Designing an Analytics Platform for Professional Sports Teams

Completed Research Paper

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Abstract

Professional sports is an area with huge economical and societal impact. However, so far it has received rather little attention by information systems research. Therefore, we design an Analytics Platform for Professional Sports Teams. We introduce Sports Analytics as an interdisciplinary research field and establish a design science research project. As part of this project, we first explore three professional sports teams and theorize meta-requirements for our platform. Second, we propose design principles that indicate how the proposed meta-requirements may be addressed. Third, we develop a prototypical web application that indicates how the proposed design principles may be instantiated. Finally, we evaluate the application with two professional sports teams and a global software vendor. As part of this evaluation, we focus on relevance and feasibility of the proposed Analytics Platform for Professional Sports Teams. We conclude this article by discussing its implications.

Keywords: Wearable sensors, sports analytics, stream computing, design science research, interdisciplinary research.

Introduction

Professional sports have an enormous societal and economic impact (Crompton 1995). The global professional sports market consisting of sponsorships, ticket fees, media right fees and fan merchandise is constantly growing and projected to reach $145 billion in 2015 (PwC 2011, 2014). 80% of this market can be allocated to team sports, with soccer alone accounting for more than all other team sports combined (A.T. Kearney 2011). Television broadcasts and the advertising markets also reflect this interest. In almost all countries and all cultures across the globe, professional team sport events are the most watched television broadcasts every year (Wikipedia 2015a). Furthermore, professional sports already account for one third of the television advertising market and one half of the digital advertising market in the US (McKinsey 2014).

This growing public interest in professional sports and its accompanied economic market also indicate an opportunity for scholars to create impact beyond their traditional research emphases. For instance, the increasing scholarly interest in the field of *sports analytics* has recently given rise to new research communities (Nylander et al. 2014), dedicated journals (e.g., Journal of Sports Analytics), conferences (Dizikes 2013), special issues (Glickman and Sonas 2015) and handbooks (e.g., Cochran et al. forthcoming; Coleman 2012). Moreover, sports analytics represents a cross-disciplinary research field that allows researchers with roots in information systems to partner with colleagues in fields such as medicine, biology and mathematics (Davenport 2014; Mueller et al. 2013). Such partnerships then may reveal new application domains for information systems.

Although research in sports analytics dates back to more than 50 years of history (Wright 2009), public attention to analytics in sports started to arise after 2004, sparked by the publication of the book "Moneyball" (Lewis 2004). In his book, Lewis proposes how statistics about players may support in enhancing a professional baseball team's performance. Ever since, there has been an explosion of interest in analytics in the sports industry. For instance, in the US, more than half of the teams from Major League Baseball (MLB), National Basketball Association (NBA) and National Football League (NFL) employ analytics professionals to facilitate decision-making through producing statistics about, e.g., players' performance and players' development (Maxcy and Drayer 2014). Apart from game officials, broadcasters and fans also benefit from a new insightful viewing experience enabled by sports analytics (Bojanova 2014).

As in other industries, the advances in analytical techniques and the abundantly available data in the domain of professional sports are an integral part of the winning strategy deployed by sports organizations that invest in such technologies (Davenport 2014). The decision-makers from such organizations gain a new and lasting competitive advantage over each other by leveraging sports analytics to gain novel insights and make timely decisions (Alamar 2013). For instance, the German national soccer team ("DFB") started using sports analytics software for analyzing video data about individual players during the FIFA World Cup 2014 (Bojanova 2014; Wall Street Journal 2014). Compared to statistics developed manually by people watching games and counting events such as goals and fouls, automatic analysis of video data allows production of statistics in sub-second intervals. However, compared to manual production of statistics, analysis of video data still has similar limitations because it requires a direct line of sight (Carling et al. 2006, 2008). For instance, analysis of video data does not allow measuring players who are partly or entirely covered by other players. Similarly, sports analytics based on GPS data are insufficient for professional sports analytics because even high quality GPS receivers are limited to an accuracy of 3.5m (11.5 ft) (GPS 2015). As a consequence, previous advancements in sports analytics focused on developing statistics about players faster. For instance, several technologies for automatic motion analysis via video and GPS tracking technologies are available such as ProZone Sports (Prozone Sports 2015), Opta (Opta 2015), and STATSports (STATSports 2015).

To tackle these limitations, researchers started analyzing data from wearable sensor-based radio devices for measuring performance of individual amateur athletes (e.g., Mutschler, et al. 2013; Velloso et al. 2013). In contrast to video, wearable sensors do not require line of sight, and, in contrast to GPS, wearable sensors enable highly accurate positing (Duffield et al. 2010; Halvorsen et al. 2013). Thereby, they are opening entirely new opportunities for detailed performance analysis such as accurately measuring the positions of all players throughout a game or training session (Davenport 2014).

However, although wearable sensors have proven to be highly accurate and valuable for athlete development (e.g., Michahelles and Schiele 2005; Morris et al. 2014; Wakefield et al. 2014), to the best of our knowledge, no published research exists that investigates the potentials of wearable sensors for analyzing tactical performance of professional sports teams. Moreover, there is no guidance for designing a software platform that would address the needs of members in professional sports teams (e.g., coaches, athletic coaches, doctors, players). However, such guidance would be valuable. For instance, it could indicate how to measure team performance more reliably than simply aggregating individual team member's performances and assist coaches in making lineup decisions. Therefore, we formulate two research questions:

Research question 1. *What are the requirements of members in professional sports teams (especially coaches, athletic coaches, doctors, and players) for a software platform that supports their daily work?*

Research question 2. *How to design an "Analytics Platform for Professional Sports Teams" that addresses these requirements?*

To address these research questions we establish a design science research (DSR) project and present the first design cycle in this article. Throughout this first design cycle, we focus on soccer as a specific team sport because (1) economically, soccer accounts for the highest share of the global sports market (A.T. Kearney 2011), and (2) societally, soccer is played by almost every nation in the world (Reilly and Williams 2003) and also attracts most TV viewers (Wikipedia 2015a). In particular, in this first design cycle, we gather concrete requirements of potential users from professional national and club soccer teams and theorize meta-requirements for a Team Sports Analytics Platform. Subsequently, we propose design principles that address those meta-requirements. Furthermore, we develop a web application in order to instantiate and evaluate the design principles.

The remainder of this article is structured as follows. Section 2 introduces sports analytics as an interdisciplinary research area. Section 3 describes our DSR project. Subsequently, we present our first DSR cycle with emphasis on the design search process (section 4), the prototype (section 5), and the evaluation (section 6). Finally, section 7 discusses our findings and section 8 concludes our work.

Background: Sports Analytics

Analytics as a research field aims at analyzing data in order to produce valuable insights. One of the most cited definitions in literature for analytics is given by Davenport and Harris (2007). The authors describe analytics as "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions. [...] It is a subset of [...] technologies and processes that use data to understand and analyze business performance" (Davenport and Harris 2007, p. 7). Analytics is an interdisciplinary field which links methods from operations research, business intelligence, data mining/machine learning, statistics, applied mathematics, and computer programming.

Building on the definition of analytics, the purpose of sports analytics is to assist decision-makers perform better rational assessments within their sports organizations. According to Davenport and Harris (2007), the goals of sports organizations are to generate high performance and achievement on the field of play, together with managing financial targets of the organization. Sports analytics have the potential to support such organizations in achieving their goals through analysis of players' performances and teams' performances (Davenport 2014). Frequently, two goals are pursued by sports analytics (Alamar 2013): (1) efficiently managing relevant data from multiple sources and (2) support optimal lineup decisions (i.e., the selection of players who are participating in a game together with their positions).

The first goal is to efficiently manage relevant data from multiple sources in order to help decision-makers evaluate player, team and organizational performance (Alamar 2013). Systematic observations are conducted to measure and analyze a valid record of players and teams performances (Bishop 2008). These records are analyzed to provide feedback on performance and to facilitate the improvement of performances. Performance analysis includes analysis of performance data during competition or training (O'Donoghue 2009; Carling et al. 2006).

Furthermore, the second goal is supporting optimal lineup decisions. Different positions require a different skill set of players both at an individual level and at a group level (Hughes et al. 2012). Due to the role of player interrelations involved in performance of a team, it becomes a non-trivial problem to make an optimal lineup decision (Boon and Sierksma 2003; Fry and Ohlmann 2012). To our knowledge, no academic research article has yet quantified sports teams' performances objectively and, thus, supported making optimal team lineup decisions.

Research Approach

We adopted a design science research (DSR) approach to address our research question because DSR is particularly suited to theoretically prescribe how to design and improve software systems for a certain situation (Gregor and Hevner 2013; Markus et al. 2002). Researchers have recommended DSR to investigate complex, non-decomposable research and business problems (Gill 2008; Kuechler and Vaishnavi 2012), understand and change generative events (Carlsson 2010), and highlight knowledge creation based on rigorous validations (Goes 2014; Nunamaker et al. 2011).

According to Hevner (2007), DSR scholars first need to become aware of the relevant business problem they intend to investigate and theorize attributes of the pursued, future system. These attributes are usually referred to as *meta-requirements* (MRs; Walls et al. 2004) because they reflect generic requirements that should be met by the future system. Next, a system needs to be designed that meets the identified meta-requirements. Therefore, *design principles* (DPs) are proposed that describe how the new system should be built in order to fulfill the identified meta-requirements. Finally, DSR scholars should implement these design principles and evaluate and refine them iteratively (Hevner 2007; Kuechler and Vaishnavi 2012).

In this article, we focus on introducing our DSR project and presenting the first DSR cycle, i.e., the first iteration. Therefore, our work is divided into the following phases: (1) a design search process which focuses on problem identification and design suggestion (presented in section 4), (2) a web application that represents a prototypical implementation of the proposed design principles (presented in section 5), and (3) a design evaluation cycle.

Data Collection

As the design search process requires flexibility for exploring the needs and preferences of potential users, we first conduct a semi-structured interview study (Eisenhardt 1989). Two professional (men's) soccer teams were selected on the basis of theoretical relevance and availability. In particular, we interviewed one national soccer team and one club soccer team. Based on the identified requirements, we theorized meta-requirements, proposed design principles for meeting those meta-requirements, and developed a web application that implements the proposed design principles.

Subsequently, we evaluated the developed web application. However, as this is the first evaluation cycle and our prototype does not allow experimental evaluation yet, we conducted semi-structured interviews with potential users from two professional (men's) soccer teams. Unfortunately, we did not receive access to another national soccer team. However, we were able to recruit interviewees from a second club soccer team. Furthermore, we interviewed experienced software developers and designers in order to get their opinions about the technical feasibility of the designed Team Sports Analytics Platform. Table 1 provides detailed information about our interviewees.

In total, we conducted 12 interviews for exploring requirements for a Team Sports Analytics Platform and 5 additional interviews for evaluating and refining the proposed design principles and their implementation. Participants were recruited upon availability. We always interviewed at least one head coach or assistant coach from each team. Besides, further participants included players, athletic coaches and doctors. Interviews were semi-structured and followed pre-defined questionnaire guidelines. The questionnaire guideline for the interviews during the problem identification phase focused on the interviewee's role and his concrete information requirements – especially key performance indicators (KPIs) that would be of interest to him. In contrast, the questionnaire guideline for the interviews during the first evaluation phase focused on receiving feedback on the proposed design principles and the implemented prototype. Therefore, the questionnaire was divided into five sections: interviewee's background, team versus individual performance, tactics, team lineup, and prototype. As needed, further questions were asked in all interviews. All interviews were conducted one-on-one, transcribed in German, and translated into English. They lasted on average 30 minutes.

Table 1. Descriptive Information about Semi-Structured Interviews.				
Team/ Organization	Team type/ Job role	League (current rank)	Interviews during *Problem Identification Phase*	Interviews during *First Evaluation Phase*
Germany ("DFB")	National Soccer Team	FIFA World Ranking (1)	2	0
TSG 1899 Hoffenheim	Club Soccer Team	Highest German league ("Bundesliga") (7)	10	1
FC Astoria Walldorf	Club Soccer Team	4th highest German league (10)	0	2
Software Vendor	Sports Analytics Developer	n.a.	0	2
Total			12	5

Data Analysis

Data analysis was supported by the use of the qualitative data analysis software package *NVivo*. The analysis involved reviewing, coding, categorizing and interpreting the data. Reviewing is the process of understanding the data by reading it several times and taking notes on the content of the data. Coding is the process of identifying and labeling common themes in the data (text segments) that corresponds with the research interest (Bhattacherjee 2012). Themes or key ideas in the data relevant to the phenomenon of interest are identified (coded) and grouped into categories. Specifically, codes are developed in the form of concepts corresponding to the evaluation of design principles and to improve the prototype. Furthermore, basic sets of similar concepts (sub-categories of codes) are grouped together.

Design Search Process

This section presents our design search process. In particular, we adopted a two-phase design search process consisting of a *problem identification* phase and *design suggestion* phase. First, during the problem identification phase, we conducted interviews with potential users of the targeted Teams Sports Analytics Platform. We abstracted their requirements and defined meta-requirements for our platform. Second, during the design solution phase, we studied extant literature in order to propose design principles that explain how the targeted Team Sports Analytics Platform could meet the identified meta-requirements.

Problem Identification

We identified four meta-requirements centering on tactics, key performance indicators, team performance, and data sources.

Tactics. We found that coaches need information about how well their team is executing specific orders such as specific tactical advice. Usually coaches define tactics for the entire team before the game or training session and the success of such tactics heavily depends on whether how well the specific tactical decision is executed by their players on the field as indicated by the following excerpt: *"I would like to obtain data on the implementation of team tactics."* (Head Coach)

Coaches described several of such tactical decisions that should be supported. A common example is focusing on counterattacks as described by one coach: *"I would like to know the average time from winning the ball to the completion [of an attack]. This would show me how the team switches [from defense to offense] and how they move forward."* (Head Coach). While different interviewees described different tactical decisions, they all differentiated defensive tactics and offensive tactics. Defensive tactics refer to tactical decisions for situations in which the opponent team is in possession of the ball, offensive tactics refer to tactical decisions for situations in which the "own" team is in possession of the ball. Thus, offensive tactics may also include defenders and the goalkeeper and defensive tactics may also include strikers. We theorize our first meta-requirement as follows.

Meta-Requirement 1. *A Team Sports Analytics Platform should support different offensive and defensive tactics.*

Key-Performance Indicators. Highly important for all interviewees have been key-performance indicators (KPIs) that measure specific performances. Overall, the 12 interviewees described 72 different KPIs that they would be interested in. Likely, this number would grow further with more interviewees. Therefore, we looked for types of KPIs that we found to be interesting. Finally, we aggregated eight types of KPIs for our Team Sports Analytics Platform: distance, player position, zone, angle, shadow, time, speed, and physiology.

These eight types of KPIs are neither mutually exclusive nor collectively exhaustive. For instance, KPIS for speed are typically measured in distance per time unit. Thus, speed KPIs by nature are overlapping with distance KPIs and time KPIs. However, we differentiated them because interviewees clearly had different intentions when talking about them. That is, while speed KPIs are associated with players movement pace, time KPIs and distance KPIs are rather associated with tactical decisions such as specific "plays" (e.g., average time for getting the ball from the left wing to the right wing when attacking) and player positioning (e.g., changes in the distance between players when a specific chain of players is moving). Table 2 lists the eight types of KPIs with an exemplary quote that illustrates the need for this type of KPI.

Table 2. Types of Required Key Performance Indicators (KPIs) for a Team Sports Analytics Platform

Type of KPIs	Exemplary Quote
Distance	*"I want to know the distance between the chains [defenders, defensive midfielders, attacking midfielders, forwards] and the distance between players within the chains."* (Head Coach)
Player role	*"Which type of players at which game positions need how many accelerations or how many sprints in how long distances as compared to different positions. This could grow a specific training theory."* (Sports Director)
Zone	*"I would like the division of the field into zones, for example wings and contact zones, in order to filter on performances in the respective zones. [For example] I would like to know in which zone the ball interception has taken place."* (Head Coach)
Angle	*"I want to know how big the average size of the angle between my position and that of the outer defense is while the ball is in possession of the opponent in the outer zone. So that I can protect my teammates and intercept passes behind the defense."* (Player)
Shadow Marking	*"I want to see how long I am in the opponent's shadow. This would show me how long I am not 'free' and my teammates cannot pass me the ball."* (Player)
Time	*"I would like to know the average time from winning the ball to the completion [of an attack]."* (Head Coach)
Speed	*"I would like to see variants of sprints such as explosive, increasing, offensive, defensive, distances, numbers."* (Athletic Coach)
Physiology	*"I want further data on a player's performance such as heart rate or lactate level, to evaluate him and to create better training plans."* (Assistant Coach)

Considering the diversity of specific KPIs, we aggregate the following meta-requirement for a Team Sports Analytics Platform.

Meta-Requirement 2. *A Team Sports Analytics Platform should allow flexible definition of specific KPIs within the eight identified types of KPIs (i.e., distance, player role, zone, angle, shadow marking, time, speed, and physiology).*

Team Performance. Another meta-requirement we identified focuses on team performance. In addition to KPIs that indicate performances of individual players, the team's performance needs to be measured specifically as indicated by the following excerpt: *"I need a way to compare players and groups of players."* (Head Coach). An assistant coach goes one step further and explains that he wants to be able to divide the whole team into groups as indicated by the following excerpt: *"I want to divide players into groups for specific exercises [e.g., 5 vs. 5, 3 offensive vs. 2 defensive] in order to evaluate them."* (Assistant Coach).

KPIs for teams are not simply sums or averages of individual KPIs. Instead, they refer to defined indicators for measuring the interplay between players: *"I would like to compare the performance of players and the interrelations between players within groups. This would allow me to identify strengths and weaknesses."* (Head Coach). For instance, each defending player "protects" a cone-shaped zone behind him into which opponent players cannot shoot or pass the ball while attacking because the defending player could easily intercept the pass (Wikipedia 2015b). This area is typically referred to as the player's *shadow marking* and should be as large as possible and mark as many attacking players as possible (from the point of view of the defending team). However, if multiple defenders are not performing well together, their shadows are often overlapping and simply aggregating KPIs that measure their individual shadows would lead to wrong results. Therefore, we define our third meta-requirement as follows.

Meta-Requirement 3. *A Team Sports Analytics Platform should support analysis of team performance, i.e., player-interplay.*

Data Sources. Another requirement we identified when talking to interviewees focuses on data sources. Currently, professional sports teams are using video data for analyzing, for example, their own performance, their opponents, and the situations that caused injuries. Since video analysis has proven to be useful and important for potential users, providing video data represents a requirement for a Team Sports Analytics Platform as an assistant coach explains: "*I would like to link video with my training sessions so that coaches and players can compare the real game situation with the calculated evaluations."* (Assistant Coach). However, the assistant coach also indicates that video data does not yet deliver the detailed computations that would be required for evaluating specific situations. Therefore, we theorize as our fourth meta-requirement:

Meta-Requirement 4. *A Team Sports Analytics Platform should link video material with a computed bird's eye perspective.*

Summary of Meta-Requirements. Overall, we theorize four meta-requirements. These are developed based on specific requirements of two professional soccer clubs. Table 3 summarizes all four meta-requirements.

Table 3. Meta-Requirements.

MR	MR Description
1	A Team Sports Analytics Platform should support different offensive and defensive tactics.
2	A Team Sports Analytics Platform should allow flexible definition of specific KPIs within the eight identified types of KPIs (i.e., distance, player role, zone, angle, shadow marking, time, speed, and physiology).
3	A Team Sports Analytics Platform should support analysis of team performance, i.e., player-interplay.
4	A Team Sports Analytics Platform should link video material with a computed bird's eye perspective.

Design Suggestion

To address the identified meta-requirements, we propose five design principles. It is important to note that there is an m:n-relationship between meta-requirements and design principles. That is, each meta-requirement may be addressed by multiple design principles and each design principle may address multiple meta-requirements.

Team-dependent KPIs in addition to Individual KPIs. We identified the needs to enable definition of KPIs (MR2) and support analysis of team performance (MR3). Performance analysis in team sports is more difficult to evaluate than individual sports because it highly depends on the interplay between individual players. Moreover, teams are dynamic wholes in which the interdependence among members can vary (Johnson and Johnson 2005; Kurt Koffka 1935). The "essence of a team" (Johnson 2003) is the interdependence among its members, which results in the team acting as a dynamic whole (Lewin 1935). Stars who do not play well with others will not benefit their team in the long run (Oldroyd and Morris 2012). As a consequence, a Team Sports Analytics Platform should highlight indicators, which represent the interplay between players. Therefore, we define our first design principle as follows:

Design Principle 1. *In order to support analysis of team performance, a Team Sports Analytics Platform should provide team-dependent KPIs, i.e., player-interplay KPIs, in addition to individual player KPIs.*

Definition of Tactics and KPI Prioritization. We found that coaches want to analyze their players for specific tactical decisions (MR1). We suggest that this can be achieved by allowing them to define certain tactics in the Team Sports Analytics Platform as well as selecting and prioritizing relevant KPIs for each tactic. As described above, potential users of our platform were able to illustrate an entire set of numerous KPIs they might be interested in (MR2). However, typically only few of those KPIs are able to indicate how well specific tactical orders have been executed and, thus, an individual's or team's performance. Therefore, we propose that users should be able to select those KPIs that they believe are good indicators for a specific tactic. Furthermore, we suggest a prioritization of KPIs according to specific tactics because although multiple KPIs might serve as indicator, they do not necessarily need to be equally good indicators. Such a prioritization could, for instance, be implemented using weighting of KPIs when computing further indicators or highlighting the most important KPIs. We define our second design principles as follows:

Design Principle 2. *In order to support tactical decisions, a Team Sports Analytics Platform should allow definition of specific tactics and prioritization of KPIs according to those tactics.*

Definition of Groups of Players. Although DP1 addresses the need to analyze team performance (MR3), it does not yet do so for different tactical decisions (MR1). Tactical orders are not necessarily "valid" for the entire team. For instance, defenders may receive specific orders that are not relevant for strikers. Thus, it would not make sense to measure the strikers' performance based on KPIs for those tactical orders.

To circumvent such a situation, we propose that users should be able to define groups of players with flexible numbers of players. For instance, a coach might want to assign all defenders to one group and be able to give them specific tactical orders while another coach might want to assign all players on the left wing to one group. This suggestion complements team-dependent KPIs as proposed by DP1. While team-dependent KPIs aim at quantifying the performance of the entire team (i.e., eleven players), defining groups allows quantifying the performance of, e.g., four players. This is important because overall team performance does not necessarily indicate how well certain groups, e.g., the defense, performed. Thus, we define as our third design principle:

Design Principle 3. *In order to support different tactics with different combinations of players, a Team Sports Analytics Platform should support definition of groups of players. The number of players per group should be flexible.*

Comparison of Groups of Players. KPIs serve to measure performance of individual players and interplay between players. Thus they support coaches in various situations. For instance, KPIs directly allow coaches to compare players and groups of players and, thus, make line-up decisions. However, while comparing KPIs for groups of players with the same number of players is a relatively easy cognitive task, it may get confusing when comparing KPIs for groups of players with different numbers of players.

This issue is directly linked to our meta-requirements because it limits the ability to analyze a team's performance (MR3) and, in particular, analyzing tactical performance (MR1). For instance, a coach might be interested in how well three defenders execute a specific tactical order in comparison to four or five defenders. That is, the coach would be interested in whether a fourth or even fifth player may further improve the group's performance. Such information would help, e.g., when making lineup decisions and discussing how many players should play defense and how many players should play offense. To support this goal, differences between different player group sizes should be made transparent. Thus, we propose as our fourth design principle:

Design Principle 4. *In order to support team lineup decisions, a Team Sports Analytics Platform should allow comparison of alternative groups of players.*

High-Level Architecture. As fourth meta-requirement, we identified the need to link video data with granular performance computations (MR4). To address this meta-requirement, we propose using data from sensors attached to players and relevant "equipment" such as the ball because sensor data allows more accurate and precise measurement of positional data or performance data (Halvorsen et al. 2013; Kencl et al. 2004). Unfortunately, traditional three-tier architectures consisting of components for data collection, data storage and processing, and data presentation are typically not suited for sensor data because sensors are providing new data records faster than physical limitations of three-tier architectures allow. Therefore, we propose a four-tier architecture that, in addition to a three-tier architecture, provides a component for pre-processing sensor data (Voisard and Ziekow 2012). Specifically, this pre-processing component receives all sensor data, aggregates and filters it, and stores the data in the middle tier component – typically a database system that directly supports data computation in order to avoid loading detailed data into the presentation tier (Voisard and Ziekow 2012). Besides granular computations, MR4 indicates the need for linking computations to videos. Therefore, the four-tier architecture needs to be linked to a media server that stores the video as, e.g., binary large object (BLOB), and uses the same presentation tier. Figure 1 illustrates the data flow for linking sensor data and video data.

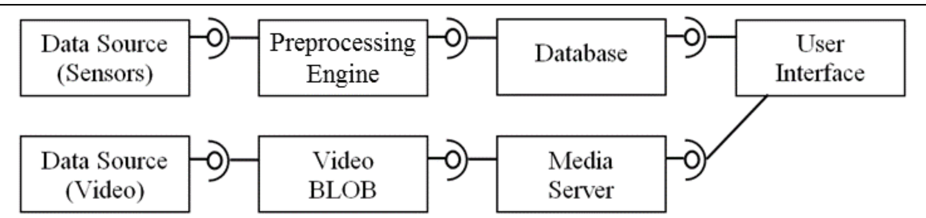

Figure 1. Proposed Data Flow for a Team Sports Analytics Platform

Building on the suggestion to use sensors for collecting granular data and linking a four-tier architecture to a media server, we define our fifth design principles as follows.

Design Principle 5. *In order to link video material with granular computations, a Team Sports Analytics Platform link data from a media server (for video data) and a four-tier architecture consisting of data collection, data pre-processing, data storage and processing, and data presentation (for low-level positional data from sensors attached to players' wear and the ball).*

Summary of Design Principles. Overall, we propose five DPs to address the identified meta-requirements. Table 4 summarizes all five design principles and shows the associated meta-requirements.

Table 4. Design Principles.		
DP	DP Description	MR addressed by DP
1	In order to support analysis of team performance, a Team Sports Analytics Platform should provide team-dependent KPIs, i.e., player-interplay KPIs, in addition to individual player KPIs.	MR2, MR3
2	In order to support tactical decisions, a Team Sports Analytics Platform should allow definition of specific tactics and prioritization of KPIs according to those tactics.	MR1, MR2, MR3
3	In order to support different tactics with different combinations of players, a Team Sports Analytics Platform should support definition of groups of players. The number of players per group should be flexible.	MR1, MR3
4	In order to support team lineup decisions, a Team Sports Analytics Platform should allow comparison of alternative groups of players.	MR1, MR3
5	In order to link video material with granular computations, a Team Sports Analytics Platform should link data from a media server (for video data) and a four-tier architecture consisting of data collection, data pre-processing, data storage and processing, and data presentation (for low-level positional data from sensors attached to players' wear and the ball).	MR4

Prototype

Based on the proposed design principles, we developed a first prototype that served as the basis for the first evaluation cycle with potential users. This section first presents the prototype and then the designed architecture.

User Interface. We developed a web application that implements DP1-DP5. This web application still represents a prototype because it is not connected to other components of the architecture and "only" uses dummy data. However, it represents a user interface (UI) that illustrates an implementation of DP1-DP5 and facilitates discussions with potential users. It may be accessed online: http://v60ycn.axshare.com/

The landing page of the web application, i.e., the first screen the user would see, provides an overview of all apps installed on the platform. An app in this regard refers to a software module that provides specific functionality to the user and/or other apps. There are two types of apps: *Basic Apps* and *Performance Analysis Apps*. *Basic Apps* are required, for instance, for maintaining metadata and master data about players or teams. In contrast, *Performance Analysis Apps* afford the user with specific capabilities for, e.g., managing tactics, defining KPIs, mapping KPIs to tactical decisions, analyzing performances, or customizing groups of players.

After a user selects an app, the respective UI is loaded. For instance, Figure 2 illustrates the UI for analyzing performances of groups of players. In the following we briefly describe the elements shown and how they implement DP1-DP5. Numbers in square brackets refer to the numbered elements in Figure 2. First, in accordance with DP1, the Team Sports Analytics Platform should provide team-dependent KPIs in addition to individual player KPIs. Therefore, the UI provides player-interplay KPIs [1] in relation to specific groups of players [2]. Besides, overall team statistics are shown [4], too.

Furthermore, in accordance with DP2 and DP3, the Team Sports Analytics Platform should allow definition of specific tactics, prioritization of KPIs, and definition of groups of players. While the actual "definition" and "prioritization" is supported by further UIs, the UI for analyzing performances of groups of players [8] provides a drop-down menu for selecting specific tactical decisions [5] as well as focusing on certain groups of players that have been assigned to a specific tactical decision [3]. Depending on which tactical scenario and groups of players the user selects, the KPIs [1] and groups of players [2] are changing. If the user clicks on a group of players, additional information about that group and its players would be shown. Similarly, if the user clicks on a specific player, detailed information about that player would be shown as well as the groups the player is assigned to ("drill-down").

Additionally, in accordance with DP4, the Team Sports Analytics Platform should afford comparison of alternative groups of players. By displaying the KPIs [1] assigned to specific tactics [5] and groups of players [2] in a tabular form, the UI implements DP4. It also allows comparison of groups of players that have different numbers of players [2].

Finally, regarding DP5, the Team Sports Analytics Platform should link video data with granular computations. The UI provides frames for video data [7] as well as a 2-dimensional graphical representation of the field based on sensor data [6]. Both perspectives, video and 2-dimensional representation based on sensor data, are important because they complement each other. The video feed provides the "real" view of the field and thereby allows interpretation of specific situations. In addition, the 2-dimensional representation displays the bird's eye view of the field and provides an interactive interface (if enlarged to full screen). The user can mark the players of interest in this graphic and, thus, visualize KPIs such as distance KPIs and angle KPIs.

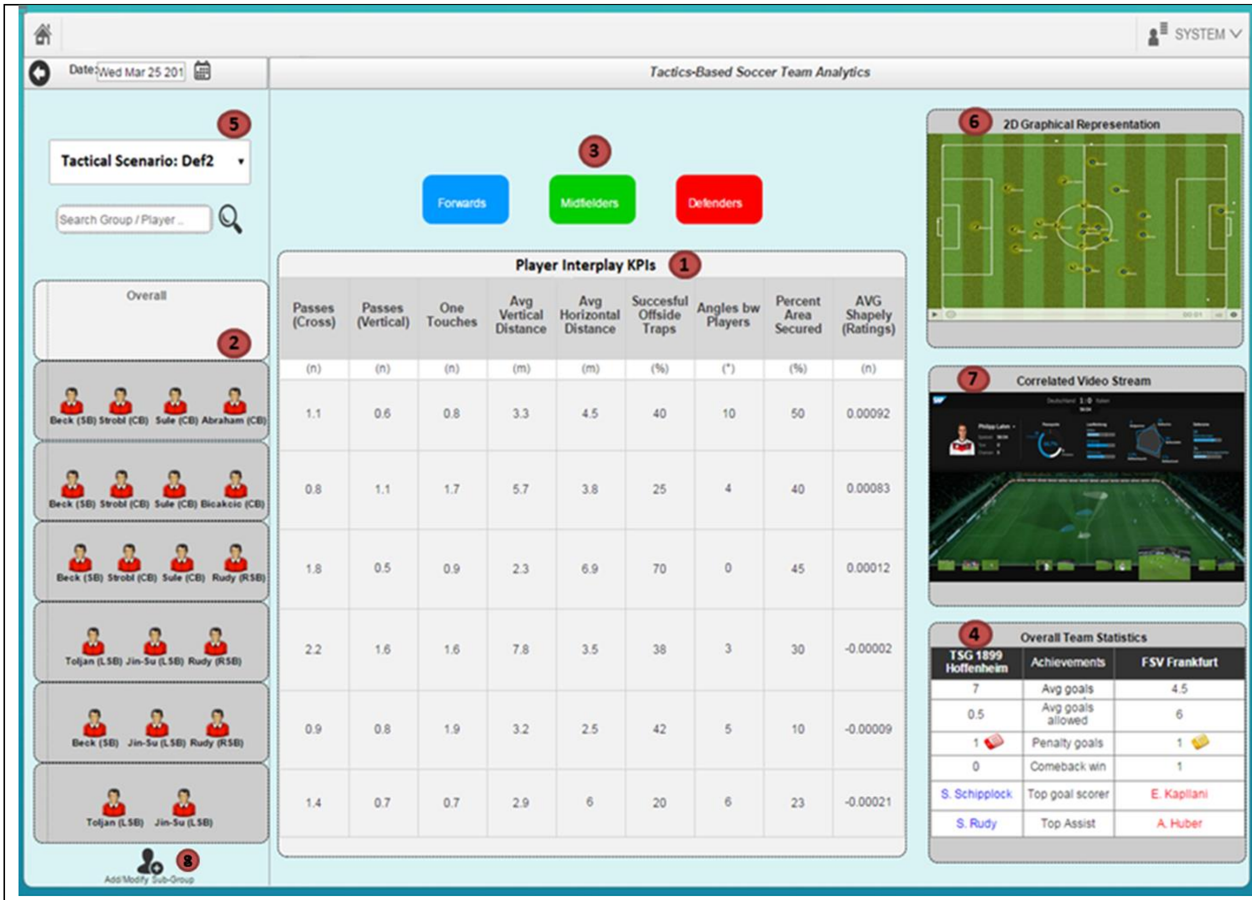

Figure 2. Screen-Shot of the User Interface for Analyzing Groups of Players

Platform Architecture. In accordance with DP5, a specific four-tier architecture that links to a media server is developed. First, sensor data is collected, transmitted, and received using the RedFIR® computer network system (Beetz et al. 2005; Fraunhofer IIS 2003). In the context of soccer, the RedFIR® system transmits data at a rate of 200 Hz (wearable sensors attached to players) and 2000 Hz (sensor implemented into the ball). Each transmitted data record indicates the sensor's position, velocity, and acceleration. Second, the raw sensor data is pre-processed by a stream computing engine (Cugola and Margara 2012; Eckert and Bry 2009; Luckham 2002). This engine aggregates the raw data to a data stream of 33 Hz. In other words, the stream computing engine creates one pre-processed data record per sensor every 30 ms. Pre-processing encompasses, e.g., data record aggregations, date and time computations, data type conversions, time measurements, and velocity and acceleration computations. Third, the pre-processed data is forwarded to the middleware tier. The middleware tier stores the pre-processed data in a main memory database system and then processes it further, e.g., joining data records and calculating KPIs (Lehman and Carey 1986). Besides, it also integrates a media server that stores and processes video streams and an application server that, e.g., runs applications for synchronizing the offset between video and positional data. The middleware tier also integrates a web server, which provides access using HTTP. Finally, the fourth tier, i.e. the presentation tier, integrates apps, creates user interfaces and processes user interactions.

Design Evaluation Cycle 1: Prototype Demonstration

As described above, the design and prototype shall be evaluated and refined iteratively. Therefore, we present the current state of our evaluation, that is, the first evaluation cycle. In particular, we demonstrated the prototype to potential users from two professional soccer clubs users to gather formative feedback towards the prototype's completeness. Moreover, the process of how to use the prototype and the information generated by the prototype is demonstrated to the participants of the evaluation study. The participants are then asked if the design has room for improvement. Thus, evaluation cycle 1 focuses on gathering support and/or criticism about the proposed design principles and the prototype. Hypotheses development and statistical confirmation or rejection is left to future evaluation studies. The combination of multiple evaluation studies is common and recommended for DSR projects (Kuechler and Vaishnavi 2012; Takeda et al. 1990). For instance, Sein et al. (2011) conduct multiple evaluation cycles and Reinecke and Bernstein (2013) conduct multiple studies with different prototypes.

Team-dependent KPIs (DP1). All participants in our first evaluation cycle have confirmed the usefulness of team-dependent KPIs. For instance, one coach explained that measuring groups of players is not "only" another statistical value because many teams with very good individual players lose against weaker teams if those weaker teams are better executing tactical orders and are better playing together. Specifically, he said: *"Often not the team with the best individual players wins. [...] Supposedly weaker teams may be successful through tactical discipline and unity. In those situations, underdogs are often able to offset individual differences."* (Coach)

Interestingly, one sports analytics developer from a global software vendor argued that the biggest impediment to computing team-dependent KPIs would be the ability to define them and that it might take some years until this issue would be resolved or mitigated: *"We all know from our experience that different combinations of players have different strengths. [...] So with the ability to define the right KPI for that, it would be absolutely possible to make an automatic conclusion of which lineup is better than others. [...] I strongly believe in that; maybe for the next generation of coaches."* (Sports Analytics Developer)

Prioritization of KPIs dependent on tactical decisions (DP2). Participants confirmed that importance of KPIs depends on specific tactical decisions. For instance, one coach explained that he would already have specific tactical decisions in his mind before he considered strengths and weaknesses of individual players and groups of players: *"In my mind I have a specific game plan, a specific tactical strategy. According to this, I am positioning my players as they are fitting best. [For example] Analyzing the covered shadow of defenders does not make any sense because players behind this line are in an offside position. It makes more sense to see how offensive players are getting into open space."* (Coach)

However, the fact that different KPIs vary in their importance for different tactics does not necessarily mean that KPIs are only relevant for one or very few tactical decisions. Rather, some skills such as speed are basic needs that are always important as indicated by the following excerpt: *"I have to compare my players with each other to decide which players go with which tactical system. [...] Some skills are more important for specific tactical requirements. For example, a player's aggressive tackling behavior. But then, there are also skills that I always need, such as speed."* (Player)

Furthermore, we also identified an important area for improvement with regards to prioritization of KPIs. That is, KPIs are strongly dependent on the opponents in the game or training exercise when the data for calculating them was collected as indicated by the following excerpt: *"Just to improve the quality of the KPIs: you have to take into account against which team or group those KPIs have been achieved."* (Sports Analytics Developer)

Groups of players of different group sizes (DP3, DP4). Evaluation study participants confirmed that dividing their teams into groups of players and defining and comparing performance indicators for such groups would be interesting and useful for them. For instance, one assistant coach explained: *"It would be useful because, for example, [if] you have already played against an opponent that has nearly the same defense tactics [...], you can analyze it. [...] You can then choose three defense players instead of four defense players. [...] And so, comparing different sizes of groups is important."* (Player)

Similarly, another coach pointed out how seeing the differences between groups of players of different group sizes would be useful for him. For instance he needs to assess whether a fourth or fifth defender contributes more to the overall team performance than an additional midfielder or striker: *"I have three to five forwards and then the midfielders. There I have specific groups and pairs of players in my head. It would make sense to compare those. [...] Comparing different sizes of groups is important to find out which lineup is the best."* (Coach).

The same coach also confirmed the importance of being able to customize groups of players. Definitions of groups of players should not be limited to players in "horizontal" chains such as the line of defenders or the line of offensive midfielders. For instance, "vertical" chains such as the left defender and the left offensive midfielder would also represent an interesting group of players: *"It would also make sense to define pairs of players across different zones. For instance, the left midfielder and the left defender."* (Coach).

Linking video and sensor data in a four-tier architecture (DP5). Our design suggestions for linking video and sensor data and the proposed platform architecture have been supported by potential users as well as software designers and developers. For instance, one coach seemed to have general concerns against performance indicators. However, he explained that he would trust the data if data would be directly linked to videos that he could watch: *"I would look again at the video to better analyze the game. Thus I am getting another trustworthy source."* (Assistant Coach). Furthermore, he argued that video would be particularly useful in order to explain to players what they did wrong in a match or exercise: "*The player looks at his game differently while playing than the coach from the outside. But with video I have evidence for the player's moves."* (Assistant Coach)

Evaluation Summary. Participants in our evaluation study supported all design principles and endorsed our prototype. However, we identified some areas for improvement such as consideration of opponents when prioritizing KPIs.

Discussion

Novelty and Practical Relevance

During the evaluation phases the designed and developed platform is presented in the form of a web application to potential users. Overall, the prototype shows that the formulated design principles address user needs and may be instantiated in one user interface. In particular, the prototype affords coaches with capabilities to prioritize player-interplay KPIs according to specific tactics. It also provides KPIs for analyzing individual players, groups of players, or the whole team. Furthermore, correlated video and graphical representation of games supports evidence-based decision making, too.

The relationship between team performance analysis and player-interplay KPIs in addition to individual player KPIs is deemed useful. This can be explained simply by the fact that player-interplay KPIs are not only based on the summation criteria of individual player KPIs but are based on filtering of KPIs between two or more individuals and then aggregations of the filtered values. Player-interplay KPIs may also take into account the overlapping values between individuals as in the case of overlapping shadow cover discussed before. As a consequence, the interrelation between players can be determined and provides new information such as the ratio of successful to unsuccessful passes between specific players.

Similarly, player group comparison and tactical decision quality is improved when player-interplay KPIs are introduced in the system. While player position-based KPIs and tactics-based KPIs depend on the subjective opinion of each individual coach, the usefulness of the platform is in providing flexibility for each user or coach to define and prioritize their own interested set of KPIs. Afterwards, the platform informs users, e.g., coaches and players, about relevant KPIs. Thereby, the platform assists, for instance, coaches in making the "right" tactical decisions and players in focusing on their weaknesses.

The newly available information leads to objective data upon which the coach can base his or her team lineup decisions. By comparing various groups of players not only by individual capabilities of players but also considering interrelations between players, the coach is able to optimize lineup decisions. Team lineup also depends on the tactics employed by the coach for a particular game. Therefore, it can be argued that group comparison is also useful in making tactical decisions and indeed this was identified during the study.

Finally, further interesting and contingent factors that may influence team performance analysis and team lineup decision quality are identified such as performing under pressure, quality of players, quality of the opponent team, the game quality, home or away match advantage and even luck. As in the case of player interrelation measurement, if these factors are incorporated into team performance analysis measures, the quality of the decisions may improve significantly.

Theoretical Contribution

In DSR, a theoretical contribution is usually regarded to be in the form of prescribing how a specific solution should be designed in order to solve a relevant real-world problem. Such prescriptive recommendations are typically coined design principles (Kuechler and Vaishnavi 2012) and guide the implementation of specific instantiations. Combined with a description of the problem a design principle intends to address (e.g., in the form of meta-requirements), each design principle represents a theoretical contribution because it prescribes how an associated problem can be mitigated or resolved (Day et al. 2009). In other words, each combination of meta-requirement and design principles represents a theoretical relationship – and thus a theoretical contribution – that could be subjected to empirical testing either by confirmatory studies or by action research (Day et al. 2009; Lee and Baskerville 2003). This kind of knowledge contribution is typically described as prescriptive knowledge contribution (Gregor and Hevner 2013).

Prescriptive knowledge can be generated through (1) inventing new solutions for new problems, (2) improving and thereby developing new solutions for existing problems, or (3) adopting known solutions to solve new problems (Gregor and Hevner 2013). We position our work as an adoption of known solutions to solve new problems. To the best of our knowledge, no other study examined the impediments of existing solutions such as BI&A platforms for analyzing team performance, yet. This is surprising because for some unknown reason professional sports teams are not using existing solutions such as BI&A platforms for team analysis. Therefore, we explored the problem domain and formulated four meta-requirements that represent the conditions that should be met by a solution, which supports team performance analysis for professional teams. We coin the solution *Team Sports Analytics Platform*.

However, while the problem we intend to solve may be characterized as new, the proposed solution rather represents an adoption of known solutions than an invention. Although a novel system for team performance analysis is proposed as a new solution, extant knowledge from the fields of Sports Science (performance tracking technologies) and Operational Intelligence (complex event processing) serve as a basis for our platform. Therefore, the knowledge contribution of our work is argued to represent an adoption of known solutions to solve new problems. Prescriptive knowledge is contributed in the form of design principles that address specific meta-requirements and an exemplary instantiation (Jones and Gregor 2007). Descriptive knowledge is expected to follow after professional sports teams have adopted the platform and a more formal empirical evaluation may be conducted.

In terms of team lineup formation, the research conducted provides a more objective information than the "player-score" and "position-score tables" used in the team formation model proposed by Boon and Sierksma (2003). This is achieved by accurately measuring different quality requirements or performance indicators for an individual as well as groups of players. Although the performance indicators for a certain playing position in soccer are based on the subjective opinion of a particular coach, the measurement and analysis techniques proposed in this research provide quantitative performance data. Therefore, the proposed platform may further support coaches in making lineup decisions.

Limitations and Future Work

Our work is subject to several limitations. First, the proposed design and prototype are evaluated qualitatively because developing a more advanced prototype which would have allowed a more comprehensive evaluation would have incurred very high costs and, thus, was not feasible during this first evaluation cycle. Second, the evaluation is based on a rather small number of study participants. This was inevitable because our platform aims at supporting coaches and players of professional sports teams and access to those people is very limited. Third, when exploring the problem domain as well as when conducing the first evaluation study, we focused on professional soccer teams (Johns 2006). However, we formulated meta-requirements and design principles on an abstract level that allows applying the insights gained to other sports, too. Besides, soccer represents by far so largest economic industry of all team sports. In fact, the soccer market is larger than all remaining team sports markets combined (AT Kearney 2011). Fourth, although the performance aspects for application design of the prototype are considered to some extent, other performance issues for processing sensor data in real-time are not considered. Fifth, many sports associations are currently not permitting the use of computer-based analytics in competitive play. Thus, the proposed Team Sports Analytics Platform is limited to the use in training sessions.

Future research should address these limitations. In particular, the proposed design should be implemented and evaluated using a working prototype with real data. Furthermore, if sufficient player data is gathered through the proposed design, it will be possible to apply predictive and prescriptive analytics instead of only descriptive reporting of team performance and health measures. For example, in health analytics descriptive statistics of individual player activity based on wearable sensors and/or biometric devices may lead to alerts for prediction of injury. Moreover, the quality of the player-interplay KPIs will increase if contingent factors (opponent team, home or away matches) are also considered in the performance data, enabling even deeper insights to support decisions. Furthermore, the proposed platform should is tested in other team sports such as basketball, cricket and hockey.

In addition, the prescriptive theoretical findings may guide future research in designing team analytics platforms in organizations where employees are frequently assigned to certain teams and are working with new colleagues. An example can be a consulting company where employees are put together in new teams every couple of months. In such situations, it could also be interesting to have some indicators about which employees could work best together in a certain situation.

Conclusion

In this article, we first presented sports analytics as an emerging area for interdisciplinary research that links information systems researchers with researchers from, e.g., sports biology, medicine, and mathematics. We believe that sports analytics provides a new opportunity for information systems scholars to provide influential research beyond its traditional emphases.

Furthermore, we designed an analytics platform for professional sports teams. In particular, we established a design science research project. We collected requirements and proposed and evaluated a platform that addresses these requirements. Each combination of design principle and associated meta-requirement represents a theoretical contribution because it indicates how a specific goal may be achieved. Besides, our platform is also relevant for system designers in practice because no alternative platform exists yet that addresses the identified requirements.

Appendix

Appendix A. KPIs for an Analytics Platform for Professional Soccer Teams

The interviews focusing on exploration of KPIs for a Team Sports Analytics Platform identified 72 different KPIs. Based on these 72 KPIs, we aggregated eight types of KPIs: distance, player position, zone, angle, shadow, time, speed, and physiology. The following table shows some of the KPIs (partially already aggregated in order to save space).

Table 5. KPIs for an analytics platform for professional soccer teams.		
Type	KPIs	
Distance	- Running distance - Distance between players within chains - Distance between specific players (e.g., distance between "assisting" and "shooting" player, distance between first and last player) - Distance to next single, two, three players	- Development of the distance between players when moving - Average distance defender to attacker - Distance between chains [defenders, defensive/attacking midfielders, forwards]
Player role	- Frequency of the central player attacking vertically - Frequency of the wing defender passing the midfielder from behind - Acceleration of players on key positions - Number of goals, assists, ball possessions, kicks, tackles	- Various sprint distances - Number of successful/bad passes, shots, tackles - Pass rate = good passes / (good passes + bad passes) - Average/Maximum strength of shots - Average/Maximum strength of passes
Zone	- Performance of players on the wing - Identification of interception zone(s) - Ball contacts in specific zones - Pass accuracy in specific zones - Heat maps for shots, tackles, passes, tackles and counterattacks - Number of outnumbered attacks (from both defending and attacking view)	- Number of players/opponents behind the ball after interception - Direct (long pass) shifts across three zones - Number of players touching the ball when shifting wings - Number of players in specific zones
Angle	- Angle to specific other players - Angle between players of the same "line" (e.g., between outer and inner defender) - Angle between player and direction of ball	- Angles in specific situations (e.g., running backwards, attack over the wings) - Optimal angle for reducing threat of long passes into defenders' backs - Optimal angle of vertical long passes
Shadow Marking	- Size of shadow marking - Overlap of shadow marking - Time in opponent's shadow	- Time/Number of players ready to receive the ball (from both defend./attack. view)
Time	- Time from winning the ball to shot on goal - Average ball possession time (single players; groups; entire team) - Average waiting time (i.e., no kicks and movement within 5 meter radius)	- Time between sprints - Time between loss of ball and first tackle/successful tackle - Time of two players entering ball zone after shift across three zones - Total time with ball
Speed	- Maximum/average sprint/movement speed - Number of sprints - Acceleration, deceleration	- Number of explosive sprints, increasing sprints, offensive sprints, defensive sprints, accelerating sprints - Attacking opponent speed
Physiology	- Heart rate - Lactate level	- Stress - Heart rate recovery

Appendix B. Evaluation Study Details

As explained above, we conducted semi-structured interviews for evaluating the proposed DPs. All interviews were conducted in December 2014 and January 2015. All participants were interviewed individually (i.e., no group interviews). Table 5 provides a list of the individual interviewees. In addition, Table 6 shows the interview guidelines for the evaluation of the DPs with the team members. While these interviews asked users to discuss the usefulness the displayed elements [1-7] as shown in Figure 2, the interviews with the sports analytics developers asked the developers to discuss the feasibility of the displayed elements [1-7] and the proposed architecture. The prototype was presented and participants were able to click on the elements of the screen in order to see detailed/aggregated information on further screens. The section “Prototype” above explains which information is shown when clicking on a specific element. Furthermore the prototype can be accessed online: http://v60ycn.axshare.com/

Table 6. Additional information about participants in the evaluation study.

Team/ Organization	Interviewee role	Duration of Interview
TSG 1899 Hoffenheim	Assistant Coach	32 min
FC Astoria Walldorf	Player	24 min
FC Astoria Walldorf	Coach	36 min
Software Vendor	Sports Analytics Developer	20 min
Software Vendor	Sports Analytics Product Owner (also former professional player)	28 min

Table 7. Interview guideline used in the evaluation study.

Goal	ID	Question
Introduction	0	Welcome, introduction of interviewers, introduction of study, assurance of anonymity, permission to record interview and publish extracts
Role and background of interviewee	1a	What is your role in the team and how would you describe it?
	1b	For how many years have you been performing this role?
Usefulness of prototype for measuring team performance	2a	Do you know an example for a situation in a game in which a team performed better although it had worse individual players?
	2x	(follow up questions depending on interviewees’ answer; e.g., regarding the importance of luck and players’ motivation)
	2x	Introduction to the prototype with a focus on explaining element [1] as shown in Figure 2. Then questions regarding the usefulness of the displayed player-interplay KPIs.
Usefulness of prototype for measuring tactics	3a	Do you know examples for different tactics that require different abilities from players?
	3x	(follow up questions depending on interviewees’ answer; e.g., regarding the importance of players’ current fitness level)
	3x	Introduction to the prototype with a focus on explaining how elements [2], [3] allow comparison of different tactics. Then follow up questions regarding the value of providing KPIs dependent on selected tactics.
Usefulness of prototype for determining optimal number of players per position	4a	How do you decide how many defenders, midfielders, and striker should start the game?
	4b	Have you experienced a situation in which an additional player for a specific situation did not add value to the team?
	4x	Follow up question depending on interviewees’ answer, e.g., regarding the value of comparing defending lines of three players against defending lines of four or five players.
	4x	Detailed explanation of elements [2], [6] and [7]. Then follow up questions regarding usefulness and visualization of those elements.
Conclusion	5	Do you have any further comments on this context and/or the prototype that have not been discussed yet?

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