Designing Personal Visualizations for Different People: Lessons from a Study with Elite Soccer Teens

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ABSTRACT

This paper describes a study that sought to understand elite soccer teenagers' use of information visualizations to learn about their own sports performance, how this might motivate them to change behavior, and thus potentially improve their own performance. We specifically investigate how information visualizations support the players' data comprehension, and how their level of comprehension might depend on factors such as their general literacy, visualization literacy and maturity. We show unsurprisingly that elite soccer teenagers are able to use information visualizations to gain new information about their performance. Based on our investigation, we define a classification of the level of data comprehension. Secondly, we demonstrate a method which allows visualization researchers and practitioners to design and evaluate visualization concepts based on real data over a short time-span. Finally, we argue that designers of personal information visualizations need to consider the range of visualization literacies that are to be expected in many target populations. Our lessons provide new insights in peoples' use of visualizations and more broadly in visualization literacy. From these insights, we discuss implications for design of visualizations that consider peoples' level of visualization literacy.

Keywords: Qualitative study, Interviews, Children, Teenagers, Visualization literacy, Sports visualization, Personal visualization.

1 INTRODUCTION

Much information visualization work focus on visualizations designed for people with great expertise within a particular field tasked with complex problems. These people are often discussed as domain experts in the visualization community. In personal visualizations [5], we expect that the people using our visualizations, might come from a wide range of backgrounds and social hierarchies. However, this means that there is a wealth of differences in the target population for our designs. In this paper, we aim to shed light on these differences, and explore what they might implicate for design of personal visualizations.

We do this based on findings from a qualitative study that inquired how elite soccer teenagers (boys, 13 years) might use information visualizations to learn about their own sports performance, how they might be motivated to change their behavior, and thus potentially improve their own performance. In the study, we identify different levels of comprehension between the teenagers.

We conducted the study in collaboration with the Danish Football Club FC Nordsjælland (in the following FCN) and Eye4talent. Eye4talent develops an application for soccer players to tag and evaluate personal performance data. Their application gathers data on performance specific parameters (e.g. passing, repress, finishing accuracy) and visualizes these according to the players' personal goals. The application uses the collected data to partly show information visualizations of performance data and partly to show synchronized match video clips of the soccer field. FCN is currently evaluating the application with their youth teams. Teenagers on the team follow an elite program that combines school and training. They are highly motivated to increase their soccer skills, and so spend most of their leisure time with activities related to soccer. For example, they follow diets, watch soccer matches, play soccer console games, and reflect on their previous and upcoming matches. The teenagers have varied backgrounds, belong to different social classes, and live in different regions. They were scouted to FCN based on their soccer talent. Despite their different backgrounds, their talent and motivation is comparable. Thus, we argue that these differences enabled us to obtain a varied sample of study participants, which personal visualizations are expected to support.

Based on our qualitative study we present the following two contributions:

1. A three-level classification of people's level of data comprehension based on visualizations. We base this classification on our investigation of how information visualizations support the players' understanding of performance. The classification is introduced as a measure of analytic output, which we believe is related to the emerging visualization literacy concept [3]. We grounded this classification in data collected during design workshops, interviews and evaluations with teenagers who were motivated to improve their sports performance. Based on these findings, we suggest to a) consider a stronger focus on non-experts in designing visualizations and in talking about how they are used, and to b) identify peoples' level of understanding in visualization design, and to include people that represent the different positions along this dimension, both in designing and evaluating visualizations.
2. A method that allows early design work to be based on concrete domain-data in cases where no data exists prior to the visualizations. The method is based on study participants' own data collection. This facilitates quick and simple data collection, which allows visualization researchers and practitioners to go from concept to paper prototype evaluation within a day. The method seems particularly relevant for personal visualizations researchers.

2 RELATED WORK

We briefly review two strands of related work: First, we describe related sports visualization contributions. Next, we introduce work that considers visualizations in teaching or coaching situations.

2.1 Sports visualizations

Though people have created sports visualizations for decades, sports visualizations emerged as a subfield in information visualization and visual analytics recently. The first workshop on sports data visualization was held in conjunction with VisWeek 2013 [2]. Most importantly, Perin et al. [9] visualized soccer performance data in SoccerStories. SoccerStories provided interactive information visualizations of soccer matches, and displayed performance data according to the phases of the match

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and visualized players' positions, movements and actions on the field. The program was intended for coaches and soccer analysts. Other contributions have also considered visualizations of soccer data (e.g., [8]). Pileggi et al. [10] visualized ice hockey matches in SnapShot. The visualizations were designed to support coaches, sports journalists, and talent scouts, in providing commentary and obtain data-based insights. While these previous contributions have focused on communicating sports data to analysts, we study how soccer players themselves might use visualizations to understand and improve their performance. This bares some similarity to other types of data logging situations in individual sports, which have become ubiquitous with the rise of smartphones (e.g., RunKeeper, EndoMondo, Nike+ Running).

2.2 Visualizations as part of coaching situations

We are unaware of sports visualization work that considers the communications between players and coach. However, we found similar interactions occurring in other domains. Paay et al. [12] showed the value of personal guidance in helping people quit smoking. Based on a prior study [11], they designed a mobile application which enabled people to track their smoking habits. Employees at a national smoking cessation service provided personalized weekly counseling based on data collected in the application, and thus observed a role similar to a coach. Gasser et al. [4] suggested to use social facilitation between people using mobile and web-based applications to help them manage nutrition and physical exercise activities. MacLeod et al. [7] described how patients used information visualizations to provide a way of understanding their condition within the framework provided by their doctors.

After this brief overview of related work, we continue to describe our choice of methodology.

3 METHOD

To study the elite teenage soccer player's use of visualizations, we set up a series of inquiries (see Figure 1). In conducting the inquiries, we recorded video or audio as appropriate to the form of inquiry. We analyzed the inquiry data with inspiration from Grounded Theory [14] and interview guidelines [6]. Next, we describe each step of our approach.

First, we conducted a first round of interviews with four key stakeholders: two team members, a coach, and the chief of talent development. We conducted these interviews to learn about the teenager's background and daily life, to obtain an overview of the goals in introducing visualizations to the elite teenage soccer players, and to establish rapport with the club management – necessary for the next step in our study.

Second, we conducted a workshop with the twelve players on the soccer team, to observe how the elite teenage soccer players used the existing solution to understand their own soccer performance. The team players watched a video of a match and tagged their own performance data using the existing mobile application. Based on the mobile application, which represented the performance specific data, we collected written summaries from the players, which they were given ten minutes to produce. The workshop led to the identification of differences in the team members' abilities to evaluate their performance, based on the current application design.

Third, based on the workshop, we conducted a second round of individual interviews with three team members, to learn more about the differences in their abilities. We identified team members which we suspected had different abilities in understanding their data. We based the selection criteria on the previously collected data. This is a form of theoretical sampling; we specifically looked for interview participants that had shown different analysis capabilities. The interviews allowed us to inquire about the team members' written soccer performance evaluations and thereby determine the player's level of comprehension. We performed opinion-categorization [6] of the player's ability to explain and reflect on their performance. Next, we categorized their statements in a) explanations based on data from the Eye4talent-application, and b) explanations based on the captured video. These interviews showed that the three players' level of comprehension fit in the three different categories.

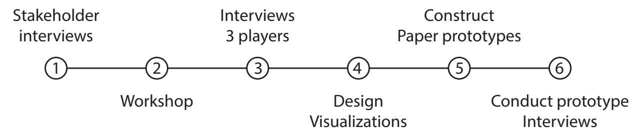

Figure 1: Study process.

Fourth, we chose to design a range of visualizations. We aimed to study the team members' abilities to understand their personal data based on these visualization designs. Using the interview insights, we created visualizations of the manually tagged data, to support the players' analysis of their own data from a football match. We sketched a range of visualizations as suggested by Tohidi et al. [15], which we condensed into two core design concepts. We based the design work on insights gathered during the previous inquiry steps.

Fifth, we selected two visualization designs, which we developed into interactive paper prototypes. We used these paper prototypes as the basis for a third round of interviews with the same three team members as previously, to once again inquire into their understanding of performance based on visualizations of personal data. Here, we were interested in observing and measuring visualization-based insights. To base these inquiries on concrete data, we repeated the data entry workshop with the team. The data for the three players that we interviewed were entered by other members of the team, to reduce potential learning effects.

Finally, we based the paper prototype interviews on concrete match data. Before the match, the interviewed players set personal goals, which we used for the paper prototype interviews. We did so to be able to correlate the players' expectations before the match to the visualizations afterwards. The manually tagged data allowed participants to compare their goals to their performance. Within a day, we collected the correlations and differences between player expectations and the tagged data in paper-prototype visualizations. We grounded and analyzed how the players used the visualizations to gain unexpected insights and how the visualizations supported their understanding of their performance.

Our study approach and intertwined analysis of the collected empirical data was inspired by Grounded Theory [14]. Throughout the study, we based decisions for next steps, on the findings emerging from analysis in the previous step. The guiding research question in the study started out as a wish to understand how the elite teenage soccer players might use of visualizations. However, we quickly identified comprehension level as an important concept, and became interested in pursuing this. By successive steps of inquiries with the team members, we aimed to saturate our empirical data about the players' information comprehension level.

4 FINDINGS

In the following, we present our findings in two separate sections: First, we describe our findings of differences in level of comprehension. Second, we describe how we examined how to support these different levels in the study. The primary source of these findings stem from the interviews and workshops conducted with the elite teenage soccer players.

4.1 Understanding Different Comprehension Levels

We analyzed the data collected from the initial workshop, in which the team members used an existing Eye4Talent application. This application provided the players with a simple visualization design, which represented their performance data in bar charts.

By analyzing data collected at the initial workshop, we identified different levels of comprehension. At one extreme, the team members were only able to explain what they saw. At the other extreme, the team members were able to explain, interpret, and evaluate the perceived visualizations, and thus discuss potential changes in behavior, which might result in performance improvements. For example, a player that did not gain additional knowledge from the visualizations, said: *"I did four forward passes, which hit in the feet. One deep, and only one miss"*. When asked how he might improve his performance, he replied: *"there's always room for improvement…[but,] I don't really know how"*.

Another player read the visualizations easily. He described data about his performance with improvement proposals: *"I can see it in the numbers, I don't have any loss of [ball] possession, because I am good at keeping the opponent away from me"*. When asked how to improve his performance, he replied: *"I need to keep training my core, because it gives me a physical advantage… also I need to be better at orientation, in order to have a better overview of where my opponent is located"*.

Naturally, we observed other team members between these two extremes. These team members were able to interpret and explain data, but did not provide suggestions for improvement. For example, when we asked a player whether his data showed good performance, he said: *"I see that I had six out of six represses. Due to my position, it's important that I don't lose the ball. It's something that I have improved"*. Thus, while he was able to interpret and explain the performance data, he simply remarked that he had improved lately, and ultimately did not use the data to gather new insights. From the workshop data, we understood the varying levels of comprehension. Thus, we became interested in supporting these different levels, to help all team members to advance their data comprehension level. In the following we define these levels. First, we considered team members that provided only data explanations from visualizations, as being at comprehension level 1. Second, we considered team members that also provided explanations and interpretations of data as being at comprehension level 2. Finally, we considered team members that realized potential behavior changes to improve their performance, as being at comprehension level 3. This classification naturally serves to consider how we might support the various levels, to allow all to gain comprehension.

4.2 Supporting different comprehension levels

By introducing the team members to the prototype, we wanted to study how personal information visualizations might help enhance the team members' abilities to understand their data, and thus increase their level of comprehension. We based the interviews on a paper prototype, which displayed visualizations of the individual players' performance data for a match they played the day prior to the interviews.

We observed that the paper prototype supported a player at level 2 in evaluating his performance and contextualize it, in relation to previous and coming matches. For example, he structured his actions by color: *"I can see that I have a surprising high amount of red actions in the end of the match. This is because I am getting tired. I should have asked for a break"*, clearly considering how he might change behavior in the future, which he did not do previously. Thus, effectively, we believe that the improved visualizations helped him to better understand his performance data. In contrast, the other team members received only marginal comprehension benefits from the paper prototype.

The player at level 1 only slightly increased his understanding of the data. We believe this stemmed from confusion caused by the visualization. For example, he said: *"This one is yellow here [points at his average performance], so it is displaying my repress like here [points at the timeline]. No, it doesn't add up, I don't get this"*. These confusions stemmed from our design choice, which we believe created a worldview gap [1] - a gap between what was being shown in the visualization and what needed to be shown, to support the players' decision-making. The player did not gain help from the visualization, to distinguish a relation between the visualization and his experiences from the match. These misinterpretations made it difficult for him to conclude any improvements, and thereby he did not gain additional insights, in contrast to the player at level 2 described previously. The player at level 3 obtained most insights, and had few problems understanding the prototype. He used most of the prototype-based interview to draw connections between his memory of the match and the visualized data in the prototypes. He used colors to cluster his soccer actions and compare them to each other, and to his memory of the match. He also used a time visualization, to understand the phases of the match, in relation to his performance. His insights and his ability to compare his performance to the match resulted in a marginally enhanced level of data comprehension. This gave him new insights and suggestions for how to improve soccer performance. For this player, we observed a low worldview gap. We believe this stemmed from his ability to draw connections between the paper prototypes and how to improve his performance.

4.3 Implications

To create better premises of understanding for all comprehension levels, we suggest creating information visualizations, with a low complexity of initial visualizations. Each view has a collection of data, which summarizes the action points of a match. The players might then be able to explore additional data levels, in order to increase complexity and challenge them to find data insights.

After interviewing the team members based on the paper prototype, we observed that the gap between the levels of comprehension significantly rose compared to their previous interpretation of video data. We believe that the initial visualization design offered by the Eye4Talent application did little to support the team members' analysis needs. We base this consideration on: first, that we noticed the players had problems elaborating on their results during the workshop, and second, that the comprehension level 2 player increased his understanding by using the visualizations during the final interviews. Going back to the early interview transcripts confirmed our suspicion. The interviews supported our belief and extended our understanding; the players explained their own performance more easily from video data, than from visualizations provided by the mobile application. All players gained a better understanding by looking at the collected video material, than by using the Eye4Talent application.

5 Discussion

We acknowledge that our study is based on very few participants (one for each identified comprehension level). To learn about differences in comprehension, we carefully selected interview participants, who we believed represented different data comprehension levels. This allowed us to study how people at different levels might benefit from visualizations, and how to best support multiple levels in a system. Thus, our deliberate choice of participants built on theoretical sampling as argued by Strauss and Corbin [14]. With this approach, we defined comprehension level, by closely examining the player's verbal expressions of understanding and the insights they gained during interviews.

Given our few samples, our findings should be considered as potential future directions, rather than as proofs. However, we still believe that we have shown, that with the right balance between visualization literacy and visualization complexity, all people might benefit from data visualizations.

This suggests to identify the range of visualization literacies within the group of people intended for a visualization design, and thus design for diversity within this group. Additionally, this suggestion points to the danger of considering domain experts in the design of personal visualizations. For addressing designs towards domain experts might take focus away from issues that might only appear for weak visualization readers. Comparing visualization literacy to textual literacy, designers should consider how they might lay out the text, such that booth novice and experienced readers are able to take something with them. For example, in children's books, authors might provide gems for the parents. How might we do similar in visualizations? We believe that using interactions or gradually introducing complexity, might be answers to this, and obviously have been applied previously (e.g., [13]). At the same time, we acknowledge that other techniques might be fruitful. Next, we discuss our use of real data in paper prototypes, which we believe other personal visualization researchers and practitioners might benefit from.

5.1 Real data in paper prototypes

To ground the third round of interviews in concrete visualization designs, we constructed paper prototypes based on data from a training match played the day before the interviews. To collect match performance data, we asked individual players to tag their own or another players match performance data. The players used the Eye4Talent application, which had support for this task.

We believe that using real data minimized the worldview gap [1]. It gave the players an opportunity to explore and interpret a realistic representation of their personal data. If we had not used real data, the players might have had difficulties mapping the prototypes to their soccer performance. This might have caused difficulties in obtaining performance insights from the visualizations. By using real data, we are aware that players might have been able to express statements of their performance by memory, rather than using the visualizations. This is both an argument for basing our study on insights and an argument for the use of real data. The insights-based approach allowed us to focus on team players' unexpected discoveries, and the real data to use insights as a measurement to study the effectiveness of personal information visualizations. Additionally, the use of real data allowed the players to provide proposals for performance improvements based on the prototype. Therefore, as a motivational aid, we exposed the players to the prototype, while their memory was still fresh, and any insights they would obtain, still useful.

The paper prototype method, gave us the opportunity to quickly and easily create a design based on the team members' real data. We expected the players to contribute design improvements, but we found that they were far more interested in their performance, than the design. The Lo-Fi design resulted in some misunderstandings rather than explicit proposals of improvements. The rough edges of our paper prototypes confused some players, as they attempted to cluster separate data categories, which were drawn in the same colour. Despite the shortcomings of the paper prototype, our method was useful, and provided an efficient way to evaluate our personal visualization design concepts. In conclusion, we observed that the study participants focused on their personal data and how they could improve their performance based on the insights they obtained in the prototype.

We believe this approach to data collection might be valuable for other researchers or practitioners that aim to build paper or other Lo-Fi prototypes based on real data.

6 Conclusion

In this paper, we provided two main contributions.

First, we classified people's level of data comprehension based on visualizations, and described three main levels. At the first level, people are able to read data from visualizations. At the second level, people use visualizations to understand previously collected data. At the third level, people consider behavior changes driven by data insights. We grounded our classification in data collected during design workshops, interviews and evaluations with teenagers who were motivated to improve their sports performance. Based on this, we suggest to first, reconsider the heavy focus on domain experts in designing visualizations and in talking about how they are used.

Secondly we suggest to identify peoples' level of understanding in visualization design, and to include people that represent the different positions along this dimension, both in designing and evaluating visualizations. Second, we described a method which allows early design work to be based on real data in cases where no data exists prior to the visualizations, and showed how this might be implemented in a concrete study. This method seems particularly relevant for personal visualizations researchers.

While many personal visualizations do not specifically aim to support children or teenagers, we still believe that the differences within this group possess relevant issues related to personal visualizations. We argue that it might even provide fertile grounds for studying differences in visualization comprehension and literacy, which seem more pronounced in this group of people.

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