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From Data to Strategy: Designing and Evaluating an Interactive Visualization Tool for Football Club Decision-Making

FELICIA ATTERLING

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Swedish title: Från data till strategi: Design och utvärdering av ett interaktivt visualiseringsverktyg för beslutsfattande i fotbollsklubbar

From Data to Strategy: Designing and Evaluating an Interactive Visualization Tool for Football Club Decision-Making

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Football clubs face complex decisions during transfer periods, yet current tools often lack interactivity to support scenario-based planning. This study explores the use of interactive data visualizations to enhance decision-making in football, building on theories from data visualization and sports analytics. The research investigates: What are the affordances and limitations of using an interactive squad planning tool during transfer decision-making? A prototype was developed through a participatory design study with Goalunit AB and evaluated using a mixed-methods approach involving club managers and analysts. The tool enables users to simulate squad changes, adjust player KPIs, and explore and compare future scenarios. Findings indicate that interactive features can support exploratory planning and the perceived affordances included improved transparency, long-term forecasting, and strategic reflection. However, limitations include challenges in modeling qualitative player traits and real-world unpredictability. The discussion highlights how such tools can complement, rather than replace, expert judgment in football strategy.

SAMMANFATTNING

Fotbollsklubbar står inför komplexa beslut under transferperioder, och befintliga verktyg saknar ofta den interaktivitet som krävs för scenariobaserad planering. Denna studie undersöker hur interaktiva datavisualiseringar kan användas för att stärka beslutsfattandet inom fotboll, med teoretisk grund i datavisualisering och sportanalys. Studien söker svar på frågan: Vilka möjligheter och begränsningar finns med att använda ett interaktivt planeringsverktyg för spelartrupper vid transferbeslut? En prototyp av ett planeringsverktyg utvecklades genom en deltagardriven designstudie i samarbete med Goalunit AB, och utvärderades med klubbchefer och analytiker. Verktyget möjliggör simulering av truppförändringar, justering av spelares KPI:er samt utforskning och jämförelse av framtida scenarier. Resultaten visar att interaktiva funktioner kan stödja utforskande planering, och upplevda möjligheter inkluderade ökad transparens, långsiktig prognostisering och strategisk reflektion. Begränsningar omfattade svårigheter att modellera kvalitativa spelar-egenskaper samt verklighetens oförutsägbarhet. Diskussionen belyser hur sådana verktyg kan komplettera, snarare än ersätta, expertbedömningar i fotbollsstrategi.

CCS Concepts: • **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

Keywords: Interactive Data Visualization, Sports Data Analysis, Football, Data-driven Decision-making, Design

Nyckelord: Interaktiv datavisualisering, Sportdataanalys, Fotboll, Datadrivet beslutsfattande, Design

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1 INTRODUCTION

The Bosman ruling [9] revolutionized football by enabling free transfers, allowing clubs to buy and sell players more freely. This development transformed the transfer market into a significant economic driver, especially in Europe, where it has become a multi-billion-dollar industry [18]. As football clubs strive for competitive and economic success, data analysis has become an integral part of decision-making [34] [23], providing insights into player performance, team dynamics, and market opportunities. The availability of vast amounts of football data provides clubs with unprecedented opportunities, but it also introduces challenges in handling and interpreting this complex information.

The true value of data lies in its ability to inform decisions, which requires presenting it in ways that are clear, engaging, and actionable. Data visualizations play a critical role in transforming complex datasets into meaningful insights, as emphasized by Tufte [36]. Effective visualizations, such as Gapminder's interactive bubble charts [28], have demonstrated their power in uncovering patterns and supporting decision-making.

While football clubs rely on data visualization to interpret player performance and market trends, existing tools often lack the interactivity needed to explore and manipulate squad data dynamically. Most current football analytics tools provide static representations, making it difficult for managers to adjust lineups, test hypothetical scenarios, or modify key performance indicators (KPIs) in real time.

Goalunit is a company that has developed a data analytics tool for football clubs, with its most widely used feature being a transfer KPI plot. This visualization displays a team's transfer KPI based on its current players, but it lacks interactive features that allow clubs to simulate potential transfers or future squad compositions. This thesis is conducted in collaboration with Goalunit to address these challenges by developing an interactive visualization tool and evaluating how that allow managers to modify squad data, simulate scenarios, and enhance decision-making efficiency.

1.1 Problem Statement

Football clubs face significant challenges during transfer periods, where effective squad planning and decision-making are critical. Current tools provide static visualizations that limit interactivity and fail to meet the needs of managers [8], such as simulating squad modifications, evaluating transfer KPIs, and projecting future scenarios. These limitations hinder strategic planning and alignment across different roles within the club. Moreover, existing tools struggle to effectively represent both individual player performance and overall team strength, making it difficult to assess the impact of transfers on squad composition and future performance [29].

1.2 Research Question

What are the affordances and limitations of using an interactive squad planning tool for football club managers during transfer decision-making?

- In what ways can a squad planning tool improve football squad planning during transfer periods?
- To what extent do interactive visualizations enable football club managers to effectively simulate and critically evaluate potential transfer scenarios?

1.3 Contribution

This thesis contributes to the fields of interactive visualization and sports analytics by addressing a specific gap in football decision-making tools: the lack of support for exploratory planning and real-time simulation during transfer windows. While many existing tools offer static analytics dashboards, few enable managers to simulate squad changes, compare multiple scenarios, or adjust key parameters to inform strategic choices.

The project presents an interactive squad planning prototype that allows football club managers to model hypothetical transfers, adjust player KPIs, and explore how these changes affect squad balance and overall team value. By integrating editable simulations and visual feedback, the tool supports data-driven, scenario-based decision-making.

The prototype is empirically evaluated through a mixed-methods user study involving domain experts (club managers and analysts), providing insights into the affordances and limitations of simulation-based planning interfaces in real-world football contexts.

The findings of this work are valuable to researchers in HCI and data visualization, as well as to sports analysts, scouts, and developers building future decision-support systems for professional sports organizations.

2 BACKGROUND

This section explains the football transfer market, data-driven desicion-making in football, as well as data visualizations and the advantages of adding interactive features. There is also a section on the tools used in this project and the hypothesis.

2.1 The Football Transfer Market

One of the most critical aspects of football economics is the player transfer market. With the increasing costs of salaries, severance payments, and performance bonuses, identifying talent early and securing them under favorable contract conditions has become more critical than ever [18]. Traditionally, transfer decisions have been made based on experience and gut feeling, which sometimes is great but can also be unreliable [15]. Today, we live in a data-driven society, and with the huge amounts of football data that exist, club managers have a great opportunity to use data analysis in their decision-making process and make more informed decisions regarding player transfers [18].

Clubs have started to rely on data to support their decisions [34] [23], but one problem with player transfers is that existing visualization tools display outdated data during the transfer period. This limitation results in an incomplete and potentially misleading representation of squad performance during the transfer periods.

Despite the growing reliance on data in football, there remains a notable gap in dedicated tools for interactive squad planning. Most existing solutions, whether internal club systems or external platforms, focus on match analysis or historical performance, offering limited support for scenario simulation or future squad forecasting [29]. Current tools rarely allow clubs to dynamically adjust player values, simulate transfers, or explore long-term planning strategies in a visual and interpretable way.

2.1.1 Transfer KPI. Based on certain metrics, players are benchmarked against each other by a calculated metric that indicates their transfer value by key-performance indicators (KPI) [21]. The transfer KPI value that Goalunit has deployed aims to provide clubs with an easy and objective way to get a transfer value and is calculated by age, remaining transfer windows left on contract, position, share of playing time, and share of points relative to position.

2.2 Data-driven Decision-making in Football

Professional football teams are using data to make decisions about player acquisitions to get an advantage over competitors on the field [35]. The data can tell whether a player really is worth a $60 million dollar contract or not [13]. Data-driven methods offer advanced analytics and statistics that support talent identification and player recruitment. These methods enable clubs to evaluate player performance, potential, and team fit, facilitating informed decision-making in the transfer market [3]. There is evidence to suggest that analytical decision-making produces a better and more accurate outcome. However, if the manager doesn't understand the data, she or he will not feel comfortable making a decision based on it [10].

A notable example is Brentford F.C., who have successfully applied data-driven scouting to identify undervalued players, spending approximately £75 million on transfers while generating over £190 million in sales, an impressive return that demonstrates the effectiveness of their analytics, based recruitment strategy [2].

Sports teams today are dealing with vast amounts of data, offering significant opportunities but also emphasizing the need to effectively manage actionable information. By leveraging actionable data, teams can implement more effective data-driven strategies [23]. As the amount of data grows, so does the complexity of the problem. This requires effective tools to manage the cognitive load during analysis. Properly applied visualization techniques has been shown by research to help analysts concentrate on the most relevant information, leading to a deeper understanding of the insights hidden within the data [5].

2.3 Data Visualization

Data visualization can be seen as a way to transform complex data into understandable insights [16]. Through thoughtfully designed user interfaces, visualizations aim to provide users with a clear understanding of the data. However, poorly designed visualizations can risk misleading users with incorrect interpretations [20]. To address this problem, Edward Tufte [36] emphasizes the need for simplicity in design that matches the complexity of the data, ensuring that visualizations are both elegant and effective.

Munzner [24] identifies three levels of actions that define user goals in data visualization. In the context of this project, the primary user goal is to analyze and consume existing data. This can be broken down further into three more specific user goals: discover, present and enjoy. Discover involves using visualizations to uncover new insights or verify hypotheses, while present focuses on utilizing visualizations for decision-making, planning, and forecasting. Interactivity plays a key role in achieving these goals. Visualizations are particularly valuable when users are uncertain about what they are looking for in the data [24], as they enable exploration and discovery. A taxonomy of interactive dynamics, discussed in 'Interactive Dynamics for Visual Analysis' [14], identifies 12 task types grouped into three high-level categories: data and view specification, view manipulation, and analysis process and provenance. These categories highlight the importance of iterative visual analysis tasks, including visualization creation, interactive querying, multi-view coordination, and collaboration.

This project emphasizes both discover and present goals. By enabling exploratory data analysis, the visualization allows users to uncover new knowledge about squad composition, transfer KPIs, and player performance. At the same time, it facilitates effective decision-making and strategic planning by providing clear visualizations that support transfer forecasting and planning.

The combination of exploratory data analysis (EDA) and interactive visualization techniques significantly enhances the depth and effectiveness of data-driven decision-making in football. Visualization tools support club managers and analysts in interpreting complex datasets, enabling more informed and strategic decisions [3]. Integrating EDA methods, such as scatter plots, allows for an initial understanding of the distribution and relationships within player statistics and match events, which forms the foundation for deeper analytical exploration. Furthermore, the use of performance metric illustrations, such as bar graphs and radar charts, facilitates the communication of key statistics like player ratings and team attributes. Radar charts, in particular, are well-suited for comparative analysis, as they enable side-by-side assessment across multiple dimensions. This makes them especially relevant when evaluating how individual player metrics contribute to composite indicators such as a player's transfer KPI [3].

2.3.1 Interactive Data Visualization. Interactive data visualizations enable users to explore information dynamically by selecting, filtering, and modifying data representations. Unlike static visualizations, interactive tools allow real-time exploration, supporting insight generation and decision-making [11]. By engaging directly with the data, users can uncover patterns, relationships, and anomalies through an iterative process of discovery.

One essential interactive technique is filtering, which helps users refine their focus by adjusting parameters and removing irrelevant data points. This is often achieved through dynamic queries, allowing users to immediately see the impact of their interactions, such as modifying data ranges or focusing on specific attributes. Such interactivity is particularly valuable when exploring unfamiliar datasets, as it provides real-time adjustments and feedback, enhancing insight generation [24].

To structure interaction in visual analysis, Ben Shneiderman introduced a taxonomy [32] of tasks that can be performed with graphical interfaces in data visualization and identified three key stages. The first is providing an overview of the data, the second, enabling zoom and filtering to focus on specific subsets, and finally offering details on demand. This emphasizes the importance of designing visualizations that give users support at multiple levels of interaction and exploration [20].

In the context of football analytics, interactive visualizations enable club managers to explore potential signings, simulate different team compositions, and analyze individual player profiles in greater depth. These tools support more informed decision-making by presenting complex data in a more intuitive and accessible format.

2.3.2 Visualization tools. Choosing the right visualization tool can be challenging due to the many options available. The company currently uses Chart.js, which is great for quickly creating attractive charts but lacks flexibility for highly customizable and interactive visualizations. An alternative is D3.js, a powerful JavaScript library for building complex visualizations from scratch [25]. However, D3.js can be hard to integrate with React—used at Goalunit—because both manipulate the DOM, potentially causing conflicts. Visx addresses this issue by combining D3's power with smooth React integration, enabling performant, reusable, and interactive charts.

This project compares Chart.js, D3.js, and Visx to determine the best fit, examining each tool's strengths and limitations.

2.4 Hypothesis

An interactive squad planning tool will significantly enhance football club managers' ability to conduct exploratory transfer planning, by enabling clearer comparisons and simulations of squad scenarios. However, if the tool fails to support users in identifying actionable insights, or introduces usability barriers that outweigh its benefits, it will not be perceived as a useful aid in strategic decision-making.

3 METHOD

This section outlines the methodology used to design, implement, and evaluate an interactive visualization tool for football squad analysis and planning during transfer periods. The approach follows a participatory design process and includes requirements gathering through stakeholder workshops, iterative prototyping, and two rounds of user evaluation. Evaluation methods combine task-based usability testing, the System Usability Scale (SUS) survey, think-aloud protocols, and semi-structured interviews. Together, these methods provide both qualitative and quantitative insights into user interaction, perceived affordances, and areas for improvement.

3.1 Research Approach

This research follows a participatory design study approach, a methodology becoming increasingly popular in problem-driven visualization research. In participatory design domain experts are treated as co-designers throughout iterative cycles of requirement gathering, ideation, and evaluation [33]. A design study typically consists of four stages: discover, design, implement, and deploy, and therefore involved close collaboration with the domain experts at every step.

The objective of this study is to investigate the affordances and limitations of an interactive visualization tool in supporting football club managers' squad analysis and strategic planning during transfer periods. To effectively evaluate these aspects, implementations will be assessed through a user-centered evaluation, specifically involving actual end-users performing realistic tasks. Such user involvement is essential, as it provides meaningful insight into practical improvements, such as task efficiency, increased analytical accuracy, or the introduction of entirely new analytical possibilities, that the visualization can offer. This evaluation will be structured as a case study, an established method for validation within visualization research, where real users engage directly with realistic scenarios and data from their daily workflows [31].

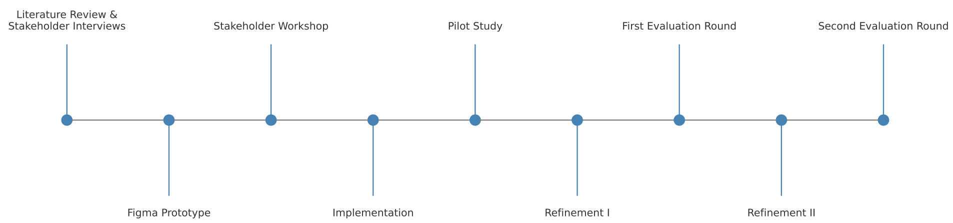

Figure 1: Timeline of the design and evaluation process, from initial research to final user study.

3.2 Discover & Design

The initial phase of this study, Discover, involved systematically gaining knowledge about the target users, their current practices, key problems, and specific requirements for the visualization tool. This stage is critical in design studies to deeply understand the users' context and requirements [31]. To accomplish this, I conducted a thorough literature review focusing on existing research in interactive visualizations and football data analytics. This review provided a strong theoretical foundation and identified best practices in visualization design.

To complement the theoretical insights and gain a practical understanding of the problem space, several stakeholder meetings were conducted. Participants included the founders and software developers from the collaborating company. These discussions clarified the company's vision, practical needs, and the specific challenges football club managers face when analyzing squad data and planning transfers.

From the literature insights and stakeholder consultations, three core user needs were identified, defining clear implementation requirements:

- Ability modify individual player values.
- Capability to simulate hypothetical squad changes.
- Clear visualization and communication of the teams and players' transfer KPI values and underlying components.

In the subsequent Design phase, to validate these identified user requirements and ensure alignment with the stakeholders' expectations and vision, a prototype was developed using Figma (See figure 2).

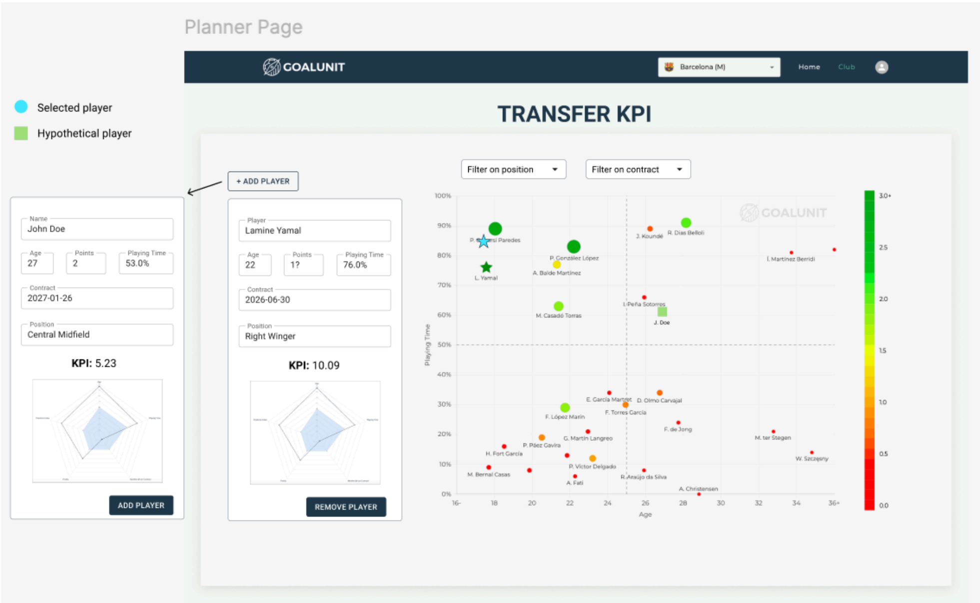

Figure 2: First Design Proposal of the planning tool using Figma.

The initial prototype prioritized simplicity and decision-making relevance. A dedicated component was created to allow users to add or edit player values. Input fields were limited to only those directly affecting the transfer KPI, namely: age, playing time, points, contract length, and position, as well as the player's name. This was done to reduce cognitive load and ensure that all editable inputs were clearly linked to strategic outcomes.

A radar chart was included alongside each player to visualize how each attribute contributed to their transfer KPI. This aimed to increase transparency and help users quickly interpret how performance and context translated into value. In line with Shneiderman's mantra: "overview first, zoom and filter, then details-on-demand" [32], a filter system was added to narrow the view by position and contract status. These filters were chosen because contract situation is a key factor in transfer decisions, and filtering by position helps users focus on a relevant subgroup rather than the entire squad.

A meeting with the developers was then conducted to review this prototype. During the meeting, we evaluated and discussed the prototype's features, interactions, and visualization choices, enabling clear validation, refinement, and final confirmation of the requirements before proceeding to implementation.

Following feedback from the initial prototype, several changes were introduced to improve usability and consistency in the revised design (see Figure 3). First, the player detail view and the add/edit form were redesigned as a right-hand sidebar. This change aimed to create a more consistent layout and reduce user confusion by keeping interaction elements within a fixed spatial context.

The playing time interaction was also reworked. In the original design, users could increase a player's time allocation without clear feedback on trade-offs. To better reflect real-world constraints, where total playing time is limited, a new squad list interface was introduced. In this view, all players were displayed with sliders to allow quick adjustment of playing time across the entire squad. If no players were sold, increasing one player's allocation required decreasing another's. This mechanic enforced realistic trade-offs and better supported scenario-based planning.

Additional exploratory changes included testing the inclusion of non-visible player metrics, such as points and contract expiration indicators, to supplement the visual overview with contextual data. One idea was to consolidate all editing actions (e.g., remove, edit) directly into the squad list, but this approach was discarded after testing due to interface clutter and decreased clarity. Also, players were sorted by position to facilitate filtering and reduce visual overload.

3.3 Implement & Deploy

To ensure efficient development and validation of the implemented features, an iterative prototyping approach was followed. Prototypes were frequently and iteratively tested throughout the implementation process. Such early and regular testing provided continuous validation, enabled quick feedback from stakeholders, and ensured the correct alignment of implemented features with the practical needs of the intended users. A functional, interactive prototype resulting from this implementation phase was essential to enable the user-centered evaluation described in the following sections of this thesis. Details of the implemented system, including design rationale, technical stack, and key interface components, are presented in Chapter 4.

3.4 Evaluation Strategy

To address the research questions, the interactive visualization tool was evaluated through user studies involving football club managers, familiar with the company's current visualization tool.

The evaluation employed a mixed-methods approach, resulting in both qualitative and quantitative data. The advantage of a mixed-methods approach is to be able to draw a more meaningful conclusion when answering the research question, that quantitative or qualitative data alone might not have [30].

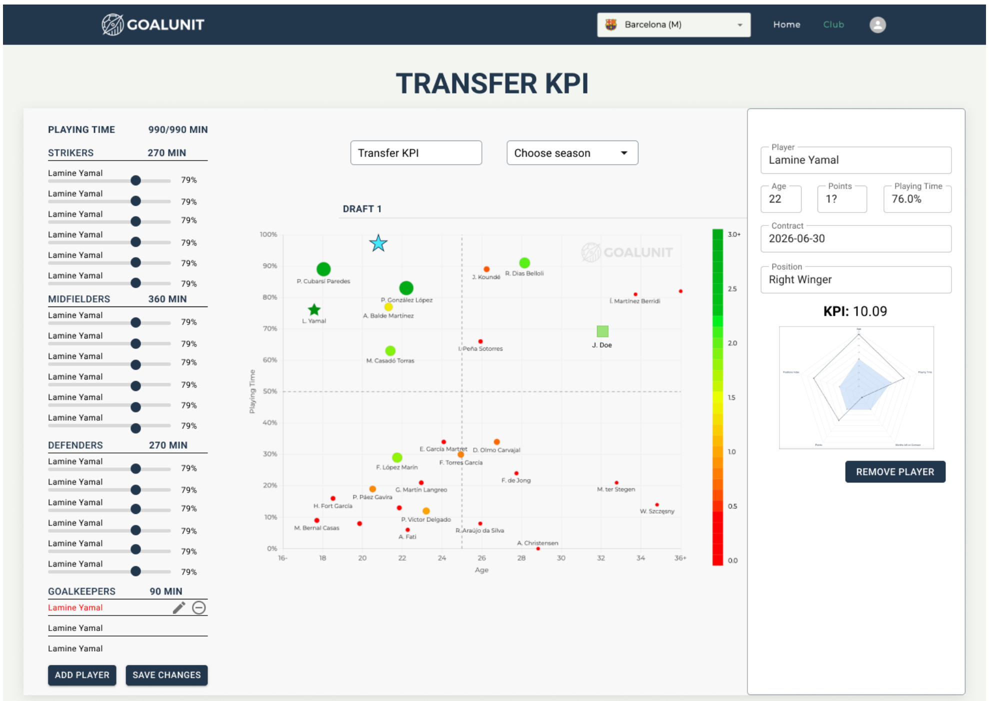

Figure 3: New Design Proposal made in Figma with improvements.

Quantitative data was gathered through structured task-based usability tests [17], measuring managers' task completion efficiency (time and clicks) and feature usage. This was complemented by responses to a usability survey and the standardized System Usability Scale (SUS) questionnaire [7], to be able to compare the systems perceived usability against industry standards. Qualitative insights was captured through the think-aloud protocol [12], enabling real-time exploration of user thought processes during task execution, and through semi-structured interviews [1], allowing in-depth discussions about perceived affordances, limitations, and usefulness of the interactive features, as well as possible improvements.

While usability metrics (e.g., SUS scores, task completion) were collected to ensure baseline functionality, the core purpose of the evaluation was how the interactive visualization tool supported decision-making. The goal was to identify how participants used the simulation features to explore and compare strategic scenarios, and whether these visual elements influenced their reasoning processes.

3.4.1 Iterative User Evaluation. Nielsen's research suggests that approximately 80% of usability issues can be identified after testing with just five users [26]. Based on this guideline, the user study was conducted with 10 participants, divided into two rounds of five. The first round consisted of one pilot study with an early prototype, and before more user studies were conducted some improvements to the prototype was made and a few evaluation questions added and re-framed.

In the first round of the user study, an early prototype with basic squad planning features was tested. The aim was to observe how participants used the tool for planning and to collect their experiences, opinions, and ideas through semi-structured interviews.

Based on insights from this round, the prototype was further developed, and a second round of user testing was conducted with new participants. This second round focused on evaluating the improvements made and identifying any remaining issues or new design opportunities.

To identify the most important improvements to make, an importance matrix was used based on impact and effort. All feedback was labeled based on how big impact it would have and how much effort it would take to implement. Based on this I focused on the tasks with biggest impact with minimal effort since time was constrained.

3.4.2 Participants. Participants were recruited with assistance from the company, primarily from among existing users of their current service with whom they have established connections. The participant group consist mainly of club managers from football clubs in Sweden. Additional participants include football scouts, sport managers of Swedish elite football, and experts in data analysis.

Participant demographics, including role, years of experience, comfort with digital tools, organization, and gender, are summarized in Table 1.

Table 1: Participant Demographics

User	Role	Experience with Squad Planning	Comfort with Digital Tools	Organization	Gender
Pilot	Technical Manager	4 years professionally, 16 years as hobby	Very comfortable	Hammarby	Male
User 1	Sport Manager	6 years, 11 years as club director	Somewhat comfortable	SEF	Male
User 2	Data Analyst	1 year	Very comfortable	Linköping University	Male
User 3	Club Manager	2 years at top level, 9 years as coach and scout	Very comfortable	Sirius	Male
User 4	Scout, Former Club Manager	2.5–3 years	Not very comfortable	Helsingborg	Male
User 5	Recruitment Analyst	1–3 years	Very comfortable	Hammarby	Male
User 6	Scout, Recruitment Manager	30 years	Not comfortable	Hammarby	Male
User 7	Assistant Coach, Recruiter	0.5 years	Very comfortable	Hammarby	Male
User 8	Assistant Coach	2 years in football, 0.5 years in strategy	Very comfortable	Karlsberg	Male
User 9	Sport Manager	0 years	Not comfortable	EFD	Female

All participants were informed about the purpose of the study, what it would involve, and their right to withdraw at any time without consequences. Participation was entirely voluntary. No incentives or pressure were applied.

3.4.3 Tasks. Each evaluation session followed a structured protocol designed to assess the usability and strategic affordances of the interactive planning tool. The tasks took approximately 20 minutes for participants to complete, and during the tasks, participants were first guided through warm-up tasks to become familiar with the interface, followed by three scenario-based planning tasks designed to simulate realistic transfer decision-making processes. Think-aloud protocols were encouraged throughout the task phase, after warm-up, and screen recording was used to capture user interactions. The tasks are described in detail below. The participants were free to make as many or few changes as they wanted when planning and during the third task they were asked to explain how they compare the two drafts.

- Warm up tasks: Add a player, Sell a player, Adjust players playing time, Change a contract, Adjust player points
- Task 1: Plan a squad based on how you want it to look like next season
- Task 2: Plan a squad based on how you think it will actually look like next season.
- Task 3: Compare the two drafts and decide on which one is best and why

3.4.4 Interviews. As mentioned earlier, the interviews conducted were semi-structured. The questions aimed to gain a deeper understanding of how participants usually plan, how the tool supported or limited their planning, whether anything was missing, and what could be improved. All interviews were conducted in Swedish, and both the interview questions and participant quotes have been translated into English for this report.

3.4.5 Data collection methods. Quantitative usability data was systematically gathered during structured user tasks. Specifically, metrics such as task completion time, number of clicks, and use of features was measured to evaluate user performance with the tool. These metrics were mainly collected for the warm-up tasks to identify pain points with the different features. Additionally, user sessions was recorded through screen-captures to enable detailed observational analysis of interactions, task completion strategies, and identification of any usability challenges encountered.

To complement the quantitative usability metrics, participants completed the standardized System Usability Scale (SUS) survey immediately after task completion. SUS provides a reliable quantitative measure of users' overall satisfaction and perceived ease-of-use, with scores above 68 indicating good usability [7].

Qualitative data collection involved semi-structured interviews and think-aloud protocols. Interviews was conducted post-tasks to capture insights into perceived affordances, limitations, user satisfaction, and overall usefulness of the tool, as well as suggestions for future improvement. Think-aloud methods offered valuable real-time insights into the users' cognitive processes, problem-solving strategies, and interactions while performing tasks.

To ensure participants were comfortable with the study and the recording of both their screen and our discussion, each participant was asked to sign a consent form prior to the session.

Together, these complementary quantitative and qualitative methods provided comprehensive and nuanced insights into user interactions, task performance, and the practical impact of the implemented interactive visualization tool on football club managers' decision-making processes.

3.5 Data Analysis

Quantitative data was analyzed using descriptive statistics [22], with the aim of identifying general patterns in usability and interaction behavior. Given the small sample size (n = 10), no inferential statistical methods were applied. Instead, the quantitative results serve to complement the qualitative findings by providing structured insight into user behavior and task efficiency. Qualitative data was systematically analyzed through thematic analysis [6]. This structured approach enabled a robust validation and nuanced understanding of whether and how the interactive visualization tool enhance decision-making processes. Analysis tools mainly included Google Sheets, Google Docs and Figma.

3.5.1 Quantitative Data. The quantitative data collected during the usability evaluation were analyzed using basic descriptive statistics, primarily by calculating mean values and summarizing feature usage across participants. This provide a straightforward overview of user interaction patterns and highlight features that were perceived as more or less intuitive. In addition, usage logs were reviewed to understand how frequently each feature was used. While no inferential statistics were applied due to the small sample size, the quantitative results serve as a complement to the qualitative findings by identifying general patterns and supporting usability observations made during testing. Additionally, the collected SUS survey responses were calculated according to the standardized SUS scoring methodology [7] to provide clear, quantitative metrics of perceived usability and satisfaction.

3.5.2 Qualitative Data. Qualitative data from transcribed think-aloud sessions and semi-structured interviews was systematically analyzed through structured thematic analysis [6]. Initially, the transcripts was thoroughly read and carefully reviewed to familiarize myself deeply with the content. Next, relevant statements highlighting affordances, limitations, usage, and improvement suggestions was coded, assigning descriptive labels to each meaningful phrase or segment of text.

After coding, similar codes was iteratively grouped into preliminary themes using affinity diagramming, which is a formative process for organizing qualitative data [4]. These themes did then undergo further iterative refinement, merging similar themes and splitting overly broad themes into narrower, more specific categories until each theme was clearly defined and sufficiently distinct. The final themes was clearly documented and exemplified with direct quotes from participants to provide transparency and rigor in qualitative reporting.

As mentioned earlier, all interviews and think-alouds were held in Swedish, so all the statements and codes were translated to English.

Lastly, the quantitative and qualitative findings was integrated through triangulation, explicitly matching and comparing them for consistency and clarity. This integration helped to clearly validate findings, identify areas of agreement or divergence between data types, and ultimately provide comprehensive answers to the defined research questions.

4 SYSTEM DESIGN AND IMPLEMENTATION

The implementation phase involved developing the interactive visualization tool using the company's established full-stack development environment, with technologies such as Go, PostgreSQL, Google Cloud, React, and Chart.js. Additionally, a comparative evaluation of alternative visualization frameworks (D3.js and Visx) was performed, exploring their potential advantages for advanced interactivity compared to the currently used Chart.js.

4.1 Visualizations

The starting point for the visualization was the company's existing implementation: a bubble chart displaying each team's players and their associated transfer KPI values (see Figure 4).

In preparation for a redesign, I explored several alternative chart types and axis encodings, guided by stakeholder input and visualization design principles. While the tool needed to support interaction tasks such as adding, editing, or removing players, a key design goal was to enhance the tool's ability to support strategic decision-making.

Through discussions with stakeholders, I identified three recurring decision-making needs:

- Identifying players with high resale potential (i.e., high transfer KPI, often driven by age and playing time),
- Detecting young players with soon-to-expire contracts (to prioritize contract extensions), and

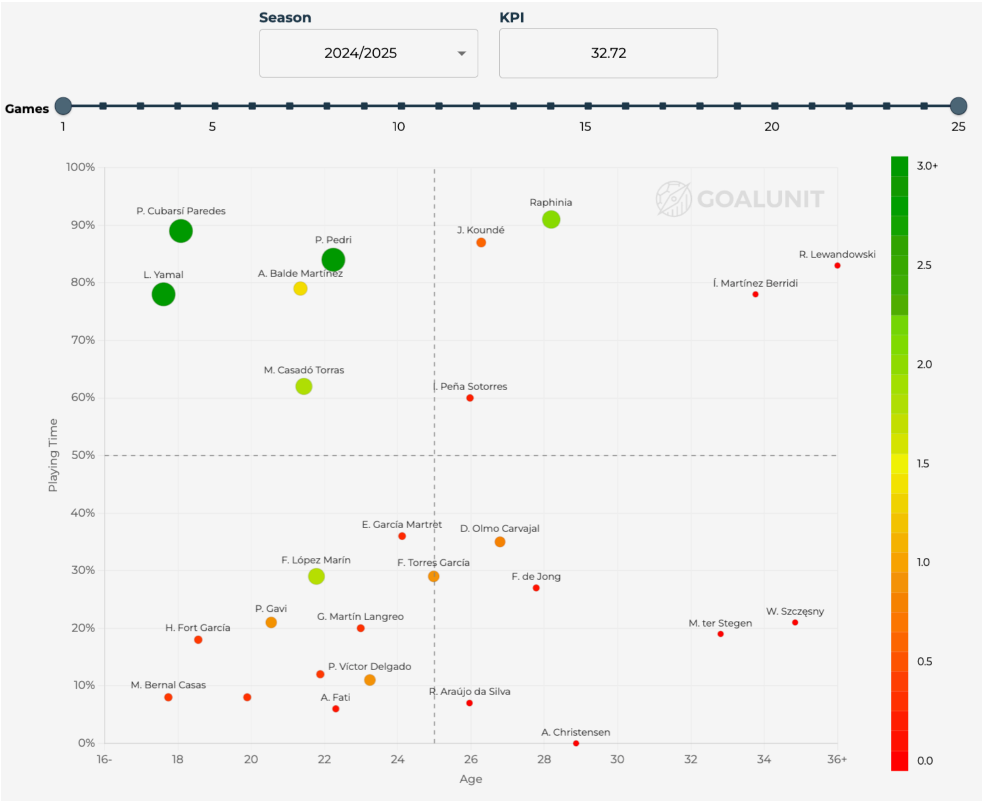

Figure 4: Existing visualization of Barcelona's Men's Team on the website.

- Highlighting high-cost players with low playing time and little future value (i.e., players for release or transfer).

These insights pointed to a core set of relevant attributes for decision support:

- Transfer KPI (composite value metric),
- Age
- Playing time
- Contract expiration status
- Cost

I prototyped a range of visualization alternatives, including bar charts and parallel coordinates plots, as well as variations of the existing bubble chart with different axis mappings (e.g., contract length, transfer KPI, salary). In collaboration with stakeholders, I ultimately retained the bubble chart but refined the encodings with bubble size representing salary. (See figure 5)

Unfortunately, salary wasn't available for the Swedish clubs so instead this was discussed as an option in the interviews. Additionally, players with contracts expiring within the current year were given a distinct color, drawing attention to urgent decision points regarding extensions or transfers.

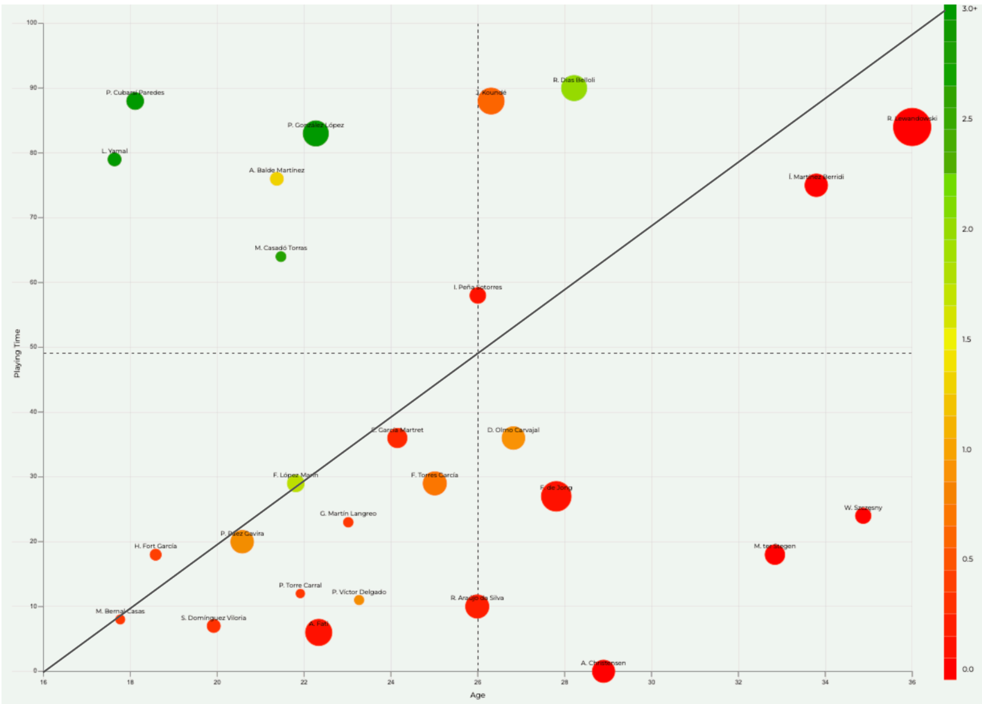

Figure 5: Visualization with playing time and age on the axis, transfer KPI as color and player salary as bubble size.

This visual configuration was chosen to reinforce a clear quadrant logic that supports rapid situational awareness. For instance, big bubbles in the lower-right quadrant highlights high-cost, low-playing-time players, typically seen as opportunity costs, while the upper-left quadrant highlights young, high-performing players with high sales potential. This layout was informed by Munzner's visual encoding best practices, which rank spatial position as the most perceptually accurate channel for quantitative data, followed by size and color [24]. The design prioritizes position for the two most important values for transfer KPI (age and playing time), while using size and color to convey secondary variables relevant to strategic planning.

During the pilot study, a key insight emerged: managers typically plan their squads using a formation-based view. This layout allows them to quickly assess depth at each position and identify first- and second-choice players. To accommodate this familiar mental model and support existing planning practices, an additional formation visualization was introduced (see Figure 6). The formation view is based on visualizing all players based on their positions on the field, sorted by playing time. To add more strategic metrics into this visualization, the color of the player card, represents the players quadrant position in the bubble chart and the highlighted border represents players with soon expiring contracts. This visualization aims to combine the financial strategy aspects of the bubble chart with the more classic whiteboard squad planning.

While the transfer KPI bubble chart was retained as the primary tool for strategic analysis, the formation view served as a complementary interface for tactical and positional reasoning. A simple prototype was developed to test the concept, and preliminary feedback from participants informed a set of improvement suggestions, which are discussed further in Section 6.3.

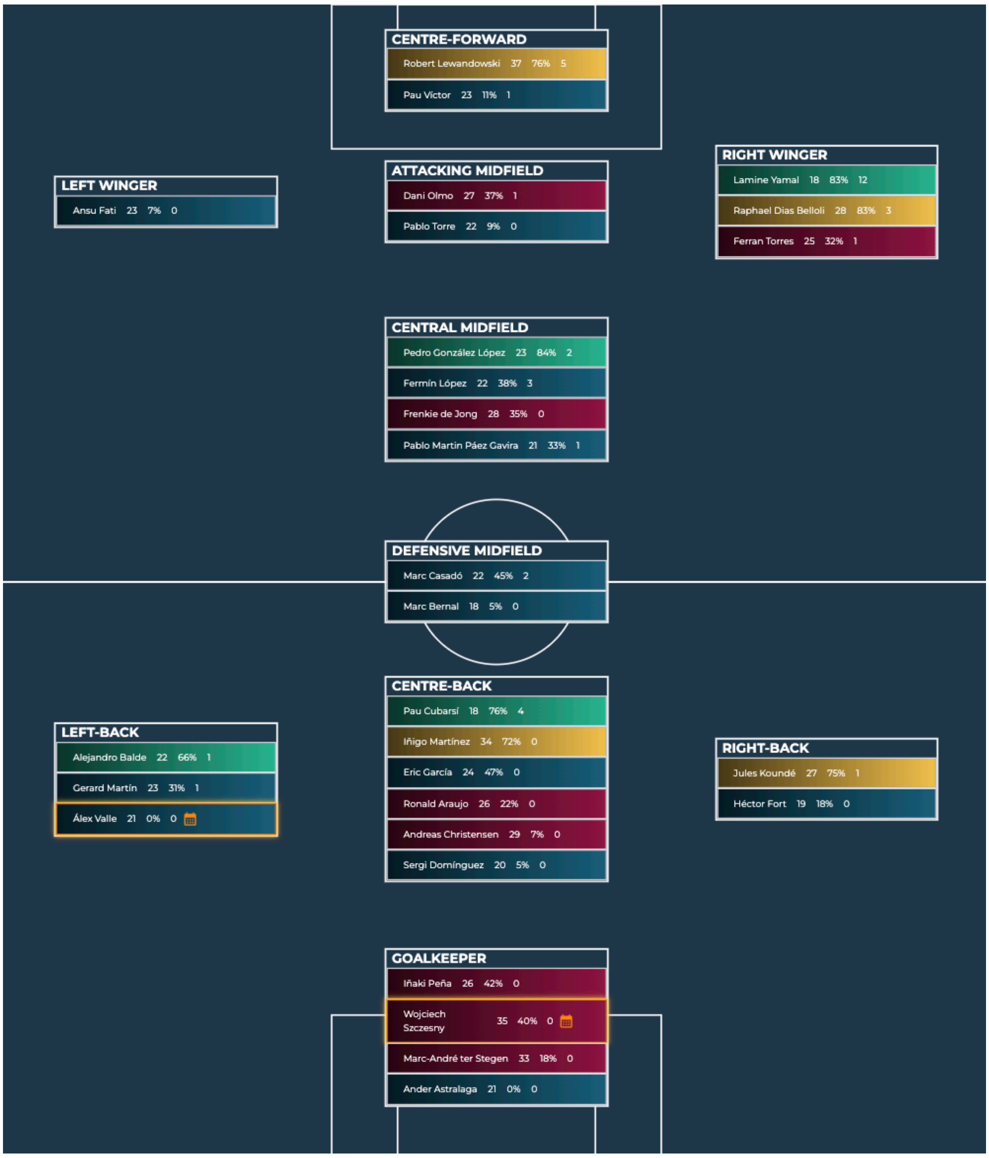

Figure 6: Formation visualization with positions placed on a football field with player names, age, playing time percentage and transfer KPI.

Another key insight from the pilot study was the desire to plan not just for the upcoming season, but across multiple future seasons. To support this, a time slider concept was introduced, allowing users to scroll through upcoming years and observe how the squad evolves over time. Although this feature was not fully implemented, the intended functionality was to dynamically update player age and contract status, highlighting upcoming expirations and shifting player positions within the quadrant layout. This forward-looking perspective could help managers anticipate future gaps and make more proactive strategic decisions.

4.2 Editing player values

This visualization was progressively expanded and enhanced by introducing the interactive features aligned explicitly with the user requirements identified earlier. The core features implemented included:

- Player KPI adjustments: Selecting players and interactively adjusting their KPI values to simulate potential future performance scenarios.
- Player removal: Allowing users to interactively simulate transfers out by removing players from the visualization and squad list.
- Hypothetical player addition: Adding new players by inputting hypothetical player data to simulate potential transfers into the squad.
- Detailed KPI breakdown: Visual exploration of the components influencing a player's overall KPI value.
- Position-based filtering: Applying position filters to facilitate clearer player comparisons within specific roles or areas of the squad.
- Playing time adjustments: Allowing users to adjust the players playing time to simulate potential future scenarios, with limitations to not allow too much playing time.

One of the key interaction challenges addressed during implementation was the management of playing time distribution across the squad. When users are allowed to freely add, remove, and edit players, there is a risk that the total playing time allocated no longer reflects realistic match constraints. To address this, the system prevents users from saving changes unless the total allocated playing time equals the expected total.

An early design alternative involved automatically decreasing the playing time of players in the same position group when another was increased. However, this was discarded to preserve user autonomy and avoid overcomplicating the interaction. Instead, the interface includes a summary display showing the total minutes allocated per position group (e.g., strikers, midfielders, defenders), along with directional arrows to indicate whether the total increased or decreased compared to before. This allows users to reason about changes while maintaining tactical consistency across scenarios.

A slider-based interface was chosen for playing time allocation, rather than direct text input, to make the interaction more intuitive and fluid. Given that the system is intended for future-oriented planning rather than match-level analytics, playing time was represented as a percentage of the total season rather than in raw minutes. However, numeric minute values were still displayed next to position group summaries to aid interpretation.

To prevent confusion and reinforce realistic planning behavior, changes to the main visualization (e.g., player bubble positions) are not applied until the user confirms the allocation. This reduces the risk of interpreting scenarios based on incomplete or invalid inputs.

Feedback from the first evaluation round revealed several usability pain points in the original implementation. Participants had difficulty distributing 100% of the time, in part because the list of players was long and the distributed percentage indicator was fixed at the top, while the save button was anchored at the bottom. To address this, the player list was made scrollable with playing time distribution and save button always visible, allowing users to monitor progress and confirm changes without excessive scrolling.

Figure 7: Improved version of playing time allocation.

Additionally to the position filtering, player filtering was added: when hovering over a player's name in the list, the corresponding bubble is highlighted in the main visualization. This enabled quicker cross-referencing between the list and the graph. Other improvements included clearer contract labels (changing "contract" to "contract expiration"), and a default contract end date (2026-12-31) was introduced based on common industry practice.

4.3 Draft Comparisons

To further support strategic decision-making, the ability to save and compare different squad planning scenarios was introduced. Since the bubble chart focuses primarily on transfer KPI, one planning objective is often to maximize the squad's overall transfer KPI while maintaining balance and strategic fit. Enabling comparisons between different drafts allows users to evaluate trade-offs and iterate on their planning logic.

Several comparison techniques were explored. One idea involved overlaying the original player bubbles with reduced opacity ("ghost" bubbles), allowing users to visually track changes to position and transfer KPI. However, this quickly became visually cluttered, especially when multiple changes were

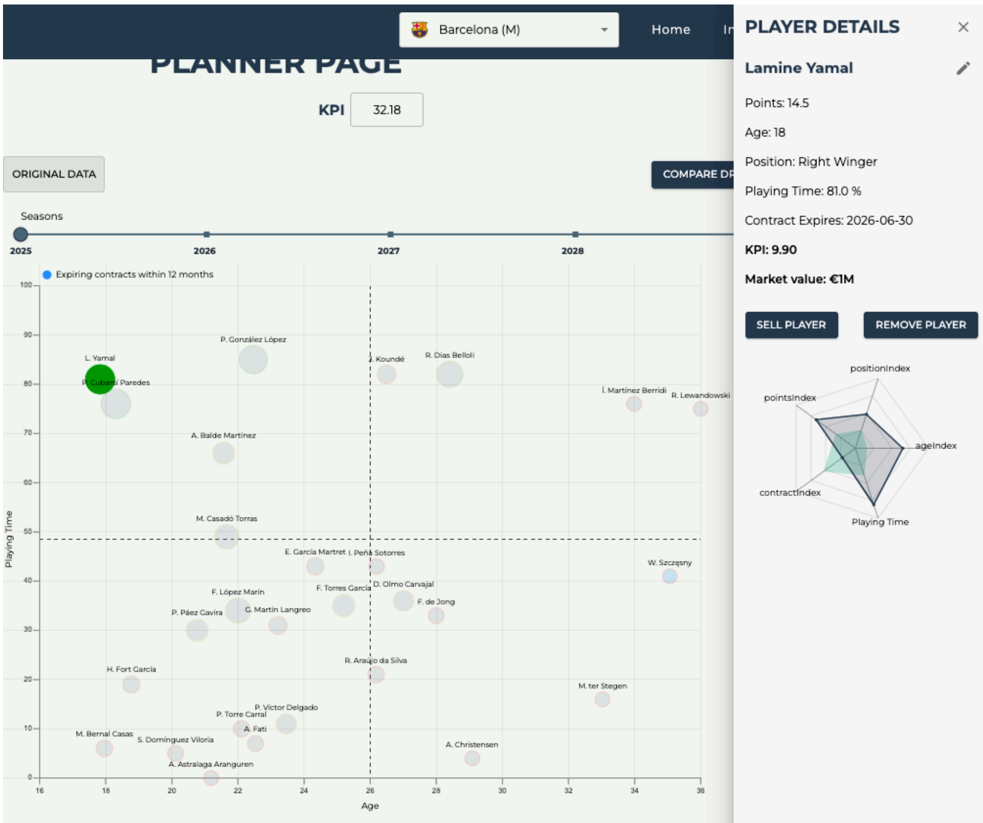

Figure 8: Sidebar with player details on selected player.

made. Similarly, arrow trails or transition paths between player states were considered, but discarded due to cognitive overload and visual noise.

Instead, a tab-based interface was implemented, allowing users to switch between different draft states and the original data.

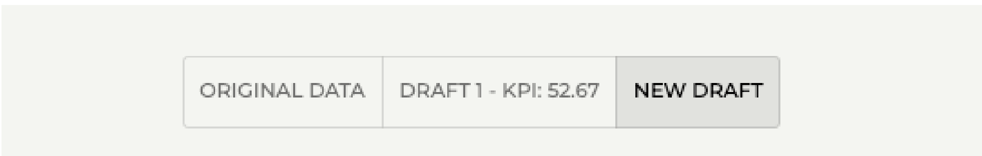

Figure 9: Tabs between original data, saved draft and new draft.

Additionally, a dedicated side-by-side comparison view was introduced, enabling users to load any two saved drafts (or a draft and the original squad) and view them in parallel (see figure 10). This structure preserved clarity while allowing meaningful comparison across planning scenarios. A small visual cue was also added by setting a black border on all edited player bubbles.

An initial enhancement following the pilot study was the addition of a small visual indicator, an arrow and numeric label, showing whether the total transfer KPI increased or decreased following a change, and by how much. This provided immediate, lightweight feedback on the impact of user actions.

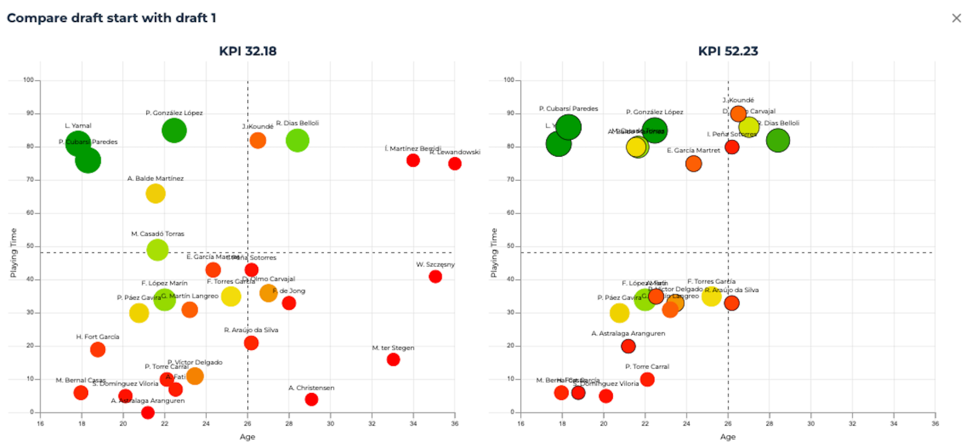

Figure 10: View for comparing two drafts.

Some other minor usability issues were observed in the pilot study, and further refinements were made. Saved drafts were integrated into the tab bar for quick toggling, and both original data and all saved drafts were made accessible in the comparison interface. These changes aimed to streamline the comparison workflow and ensure that users could easily evaluate the implications of different strategic decisions.

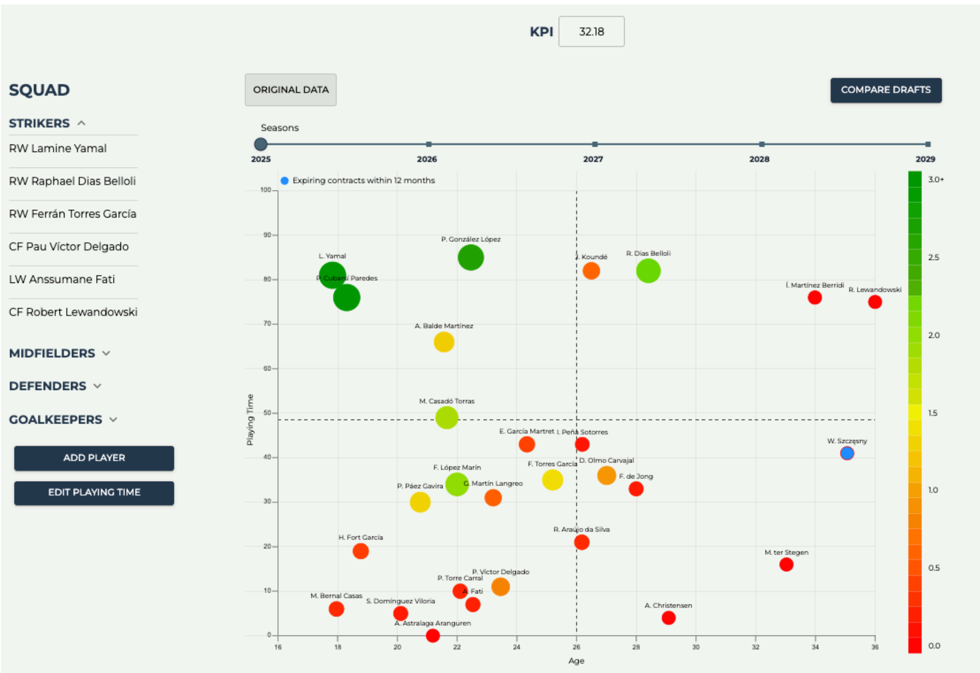

Figure 11: Final version of the prototype.

4.4 Tool Comparison

A key early step in development was selecting a suitable visualization framework. The company uses Chart.js, known for its simplicity and React compatibility, but it lacks the customization and interactivity required for this project.

Alternatives were explored, including D3.js, a powerful, highly customizable library for web-based visualizations. However, integrating D3.js with React proved complex due to conflicting DOM rendering models. This led to the consideration of Visx, a library built on D3.js primitives but designed specifically for React.

All three tools were evaluated through practical implementation of the initial visualization. This hands-on testing assessed usability, visual quality, integration ease, and potential for future enhancements. Following structured discussions with the development team, Visx was chosen for its balance of customization, interactivity, React compatibility, and developer efficiency.

5 RESULTS

In this section, the result from the evaluation is presented. It is structured by resulting themes from the thematic analysis and presents the result from both the qualitative and quantitative data.

Figure 12: Participant using the interactive planner during the task-based evaluation.

5.1 Communication and Strategic Alignment

A recurring theme identified by participants was the importance of using digital tools with visualizations to support shared understanding across different roles within the club. In a football organization, it is crucial that everyone, from coaches to the board, comprehends the strategy and the reasoning behind key decisions. Participants emphasized the need for the information to be presented in a clear and simple manner to ensure accessibility across all levels of expertise. As one participant explained:

> ”The board often consists of individuals who are successful in areas outside of football, and for them to truly understand, the information must be simple, which I found this tool was.”

Beyond internal communication, the tool was seen as valuable for setting realistic expectations regarding player performance and financial investment. By estimating a player’s future transfer KPI value, clubs could better manage both internal evaluations and external negotiations.

Furthermore, one participant suggested that the tool could enhance transparency towards fans. Fans may not always be supportive, particularly when short-term results fall below expectations. By presenting clear economic realities, such as the need to sell a key player due to financial constraints, clubs could foster greater understanding and patience among their supporters.

5.2 Strategic Planning and Key Player Metrics

Table 2: Quadrant model for player categorization based on age and playing time

Value *Below 25 years of age* *Above 50% share of playing time*	**Seniority** *Above 25 years of age* *Above 50% share of playing time*
Growth *Below 25 years of age* *Below 50% share of playing time*	**Cost** *Above 25 years of age* *Below 50% share of playing time*

Y-axis: Playing Time (↑ above 50%, ↓ below 50%)   X-axis: Age (← below 25, → above 25)

When participants describe how they plan, it differs in some ways but there are also clear themes. All participants highlight the importance of focusing on young players and limiting players in the cost quadrant. As one participant mentioned:

> ”I focus on the lower right corner, aiming to remove players already positioned there or those at risk of moving there. This mainly concerns players located on the right side or in the middle. I also consider contract lengths, as players with contracts nearing expiration are at greater risk of either not receiving an extension or choosing not to renew.”

Another participants aim is to have 4-5 key players that play 100% from the seniority quadrant, 4 valuable players on 100% and 3 on 70-80%, and lastly 3-5 growth players on 20-30%.

5.2.1 Formation visualization. As one participants strategy is to play experienced players in defense and more younger players as forwards, since they often are more valuable to sell, he liked the opportunity of seeing the players on a formation in their positions. Participants also mentioned this view would help identify gaps and get an overview of where they are strong and where they need to focus, as well as which players are competing with each other for playing time. As one participant mentioned:

> "Even though we are one of the most football-economically and strategically aware clubs, it ultimately still comes down to football. While comparisons to stocks can be made, football is fundamentally about people and players, not financial assets. Therefore, I believe that to become a truly useful tool, and to avoid the need for multiple separate systems, it would be a major advantage if, when working with the coaching staff, we could focus directly on football-related aspects, such as whether a player is a right-back or a midfielder."

However, participants highlighted the importance of both visualizations, since they serve different insights and different ways of planning depending on what role you have in the organization.

5.2.2 Key Player Metrics. Based on how the participants plan a few key metrics where identified. The three most important player metrics for planning identified were: Age, contract length and position. Together with points and playing time these five metrics is the base for calculating a players transfer KPI value. Other important metrics for strategic planning were: nationality, sales value, cost and wether the player is an academy player. Finally there were a few soft skills identified: leadership, quality and potential. These values does not come from data but rather from the participants own perceived view of the player.

5.3 Decision-making and Evaluation

The decision-making process during scouting and player transfers was described by participants as highly complex, influenced by numerous unpredictable factors. A common approach involves selecting players based on both positional needs and personal attributes, considering performance on and off the field. This is not something that data can tell, the scout needs to see the player on the field.

However, the tool provided significant support in facilitating quicker comparisons between potential player acquisitions. Participants highlighted its ability to simulate how different player decisions would impact the transfer KPI next season and what player adjustments would be needed to reach certain transfer KPI goals. As one participant illustrated:

> "Let's say we have a 20-year-old forward who currently plays 30% of the time and occasionally scores. There could be three possible outcomes: he might end up playing 70% and scoring many goals, playing 50% but scoring fewer goals, or remaining at 30%. Depending on the contract length, age, and performance, we can then assess what we could sell the player for."

Additionally, the tool allows users to retrospectively assess whether past decisions aligned with their strategic objectives. By analyzing outcomes at each transfer window, users could verify if previous choices had the intended effects, strengthening decision-making for future windows. Comparing potential outcomes between different player options was seen as particularly valuable for refining long-term strategies.

5.4 Future forecasting and Scenario Planning

While football matches are played in the moment, participants emphasized that squad planning and strategic decisions must be made with a much longer time horizon in mind. Although predicting the future with certainty is impossible, the tool was seen as offering a way to anticipate and explore potential future scenarios.

Participants described how the tool enabled them to account for different transfer possibilities and visualize how the squad composition and transfer KPIs might develop over several years. This feature was highly valued for long-term planning and goal-setting. As one participant explained:

> (Without this tool) "You have to try to form an understanding based on other players who, in previous years, have played about the same amount and scored a similar number of points."

However, participants also highlighted the importance of maintaining a critical perspective. They stressed that forecasts generated through the tool are ultimately based on assumptions, and that numerous unpredictable factors, such as injuries, can significantly impact the outcomes.

5.5 Data-driven Decision Support and its Limitations

Participants emphasized the increasing importance of data-driven decision-making in modern football. They described how digital tools could help clubs stay competitive by providing dynamic, up-to-date information that can easily be adjusted as new data becomes available. This flexibility was seen as a major advantage, allowing clubs to make more informed and timely decisions in a rapidly changing environment. One participant mentioned:

> "In football, decisions are often heavily influenced by gut feeling, and we try to minimize relying on gut instinct as much as possible. But it is a challenge, and I think this tool is very helpful to illustrate: okay, if we bring in the player that our gut feeling says is really good, what will actually happen then? Well, then he needs to have 90% playing time, which means that these other players will get 0% playing time. I think it then becomes quite clear that you can support smarter decisions."

However, participants also highlighted several limitations associated with relying solely on quantitative data. They noted that while metrics such as transfer KPIs can offer valuable insights, they do not capture the full complexity of a player's value. Personal characteristics, leadership qualities, and off-field behavior were mentioned as critical factors that are difficult to quantify but nonetheless crucial for long-term team success. And as one participant mentioned, you might not play because you're the best but because you are a leader and make the rest of the team better.

Moreover, the human dimension of football, including aspects such as team dynamics, player morale, and unforeseen events like injuries, was seen as something that data-driven tools might easily overlook. Participants stressed the importance of balancing data insights with human judgment.

5.5.1 Limitations of data for women's football. Finally, several participants pointed out a structural limitation in the availability of high-quality data, particularly in women's football. Compared to men's football, datasets for women's leagues were described as significantly less developed, posing challenges for adopting data-driven tools equally across the sport. Participants expressed concern that without focused efforts to improve data quality in women's football, existing disparities could be reinforced as technology continues to shape the future of the sport.

5.6 Usability and Quantitative Feedback

Many participants emphasized the importance of the tool being easy to use, and several described it as one of the tool's core strengths. Instant visual feedback was repeatedly mentioned as a valuable feature, particularly when observing how changes affected the plot. Participants also noted that the tool helped them stay realistic in their planning, for example, by not allowing them to assign more than 100% playing time. Several participants highlighted that the tool could reduce their need for multiple separate systems, making the planning process more efficient.

5.6.1 Perceived Usability and User Feedback. These insights were supported by the overall positive tone in the usability survey and qualitative interviews. However, a few usability challenges still emerged. Some users required minor hints during task execution. For example, adjusting playing time was the most commonly tricky feature in the first round, but only one participant needed help with it after the improvement was implemented, indicating a successful refinement. There were also occasional questions around adding players and how point adjustments work, especially regarding real player data. The need to explain the "pen icon" for editing was only necessary for participants who self-identified as less confident with digital tools. One participant suggested adding an info section or short tutorial video to help first-time users.

5.6.2 Interaction Behavior and Feature Usage. While most participants completed their tasks without significant issues, interaction logs revealed clear patterns in how different features were used. The "Sell" function was the most frequently used feature overall, but "Edit playing time" often triggered multiple changes across several players, resulting in most feature logs, as shown in figure 13. Across all 10 participants (who each planned two squad drafts), a total of 82 players were sold or removed and 27 were added.

In contrast, certain features such as position changes, contract length adjustments, and point projections were used less frequently. For instance, only one position change was recorded, suggesting the feature may not be essential for this type of planning task. However, features like adjusting contract length and points were still important, as they influence the transfer KPI calculation.

5.6.3 System Usability Scale (SUS). The average SUS score was 82.75 out of 100, which corresponds to "excellent usability" according to standardized benchmarks. This score suggests that participants found the tool easy to use and efficient in supporting the intended planning tasks. While scores varied slightly, 7 out of 10 participants rated the tool above the threshold for excellent, which is at 80,3.

6 DISCUSSION

The purpose of this study is to explore the affordances and limitations of using an interactive squad planning tool to support decision-making among football club managers during transfer periods. The following section discusses the answer to the research question, as well as improvements. Methodological reflection, ethics and future work is also discussed.

6.1 Affordances

The evaluation revealed several key affordances provided by the interactive visualization tool, particularly in supporting strategic planning and decision-making within football clubs.

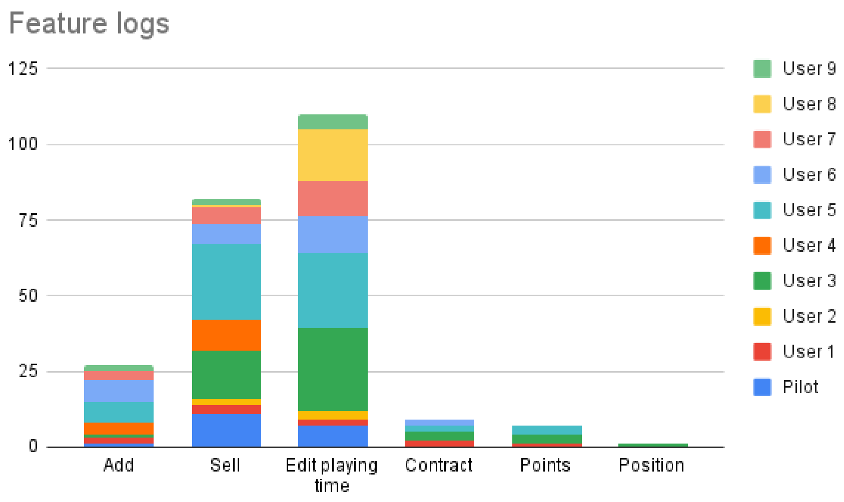

Figure 13: Number of changes made with each feature by all participants during the tasks.

6.1.1 Shared understanding across the organization. One of the most prominent affordances of the tool was its ability to foster a shared understanding of financial strategy across different organizational roles. Participants highlighted that conflicting perspectives often arise within a club due to varying priorities: coaches are focused on short-term performance and winning the next match, while board members are more concerned with long-term financial sustainability and strategic growth.

The tool enables clubs to visualize and communicate these divergent goals in a clear and accessible manner. For instance, it can illustrate a situation where a young player needs substantial playing time to increase their market value for a future transfer, even if a more experienced player might contribute more immediately to short-term match results. By making such trade-offs visible, the tool helps bridge gaps in perspective and supports consensus-building across departments and ties back to the specific user goals Munzner [24] discusses: discover, present and enjoy. This reflects the core function of data visualization: transforming complex data into accessible, actionable insights that support shared understanding and informed decision-making across stakeholders [16].

6.1.2 Data-driven transfer decision support. Although transfer decisions are often based on holistic assessments of a player, including leadership, personality, and off-field behavior, participants noted that data can play a valuable complementary role. The tool was described as particularly helpful in comparing different transfer scenarios from a financial and strategic point of view. This aligns with the findings of Link [18], who mentions that finding and securing talent early has become more critical now than ever before.

Participants appreciated being able to simulate potential outcomes of signing different players by factoring in key variables such as age, contract length, projected playing time, and transfer KPI. This enables clubs to better align transfer decisions with both team needs and financial goals. As one participant noted, the ability to quantify and compare future profitability based on projected performance helps reduce subjective bias and strengthens the rationale behind transfer choices. This aligns with what

Isichei et al. [15] mentioned in their findings, that transfer decisions traditionally have been made based on experience and gut feeling, which risk being unreliable.

6.1.3 Long-term squad forecasting. Another key affordance identified was the tool's ability to visualize and simulate future squad scenarios, enabling strategic long-term planning. Several participants described the concept of a "succession order" within the squad, a natural progression where younger players gradually replace older ones over time.

The tool made it easier to visualize such transitions and plan accordingly. For example, a club might aim for an 18-year-old player to receive 30% playing time next season and 70% the following year. This, in turn, may lead to the decision to sell a top-performing senior player to make room. Participants also used the tool to determine how much playing time a younger player would need to retain or increase their market value, and to assess the optimal contract length based on performance expectations and age.

6.1.4 Strategic alignment with club goals. Participants emphasized that the tool also acts as a strategic mirror, requiring clubs to ensure that every decision aligns with broader objectives. While clubs often state a desire to give more playing time to young talents, the practical reality is that such decisions come at the cost of reducing playing time for others.

The tool makes these trade-offs explicit. For example, increasing a young player's role may necessitate reducing the role of a senior player, which in turn could influence the timing of a potential sale. By simulating these outcomes, the tool helps users validate whether the decisions they make now are consistent with long-term strategies. This addresses the strength with interactive visualization tools: allowing real-time exploration, which would not be possible with static visualizations [11].

Overall, the tool's primary value lies in enhancing transparency, foresight, and evidence-based decision-making across multiple organizational levels. It supports internal communication, promotes alignment between strategic goals and practical actions, and helps clubs manage the inherent complexity of football squad planning.

6.2 Limitations

While the tool offers significant support for strategic planning and data-driven decision-making, several limitations were identified during the evaluation.

6.2.1 The human side of football. A recurring concern among participants was the challenge of accounting for the human side of football, qualities and dynamics that are not easily quantifiable. Soft skills such as leadership, team influence, and personality traits were frequently cited as critical factors in player evaluation, yet they are difficult to represent through data alone. Despite the increasing role of data in football, participants emphasized that certain aspects of the game remain fundamentally experiential and intuitive.

6.2.2 Unpredictable real-world events in football. Another major limitation is the unpredictable nature of real-world events in football. Injuries, sudden transfers, or fluctuations in form can dramatically alter both team dynamics and individual player value. One player's injury might open an opportunity for another, which could either elevate or diminish that player's trajectory. These unpredictable elements introduce volatility that even the most sophisticated tools may struggle to accommodate.

6.2.3 The risk of over-reliance on data. Participants also expressed concern that over-reliance on data could risk diminishing the human character of the sport. While financial and strategic planning is essential, football remains a game — with emotional, cultural, and social dimensions. When players are viewed primarily through the lens of financial KPIs, there is a risk of objectification. An observation made during the analysis was that the tool, if not contextualized appropriately, could potentially contribute to a fragmented view within the organization, particularly between staff working closely with players and those in financial or strategic roles. There is a risk that disagreements may arise if lived experience and intuitive player knowledge are not valued alongside quantitative metrics and forecasts.

In addition, the tool must accommodate a wide range of user needs and working styles. Participants held diverse roles, from coaches to scouts to directors, and naturally prioritized different goals. Some emphasized match-to-match planning and formations, while others focused on long-term financial growth and investment strategies. Designing a single tool that supports all these perspectives, while maintaining usability and simplicity, remains a considerable challenge.

6.2.4 The lack of data in women's football. Finally, a structural limitation that emerged during the evaluation concerns the lack of accessible and reliable data in women's football. This issue was explicitly raised by the two participants working in women's teams, who pointed out that even basic information, such as contract lengths, is often missing or difficult to obtain. This lack of foundational data limits the applicability of such decision-support tools in the women's game. While this report primarily explores how data can enhance strategic planning in football, it is crucial to recognize that unless efforts are made to improve data infrastructure in women's football, there is a risk that the growing reliance on data in the men's game will further widen the existing gender gap in the sport.

6.3 Suggested Improvements

As mentioned in Section 4, several improvements were made to the tool during the evaluation process, particularly between the first and second round of user studies. These changes were based on both direct participant feedback and observations made the during task-based testing.

Participants also suggested a number of future improvements that were not implemented due to scope or technical constraints. One of the most requested features was adding actual players instead of "hypothetical players", with filters such as position and nationality, which would include their age, position, market value and transfer KPI. Other improvements included real-time player values, dynamic budget tracking and more comprehensive metrics (e.g., player footedness, football skills). Some users requested features that would support deeper strategic planning, such as the ability to simulate different formations, calculate cost per played minute, or receive player suggestions based on team strategy and existing squad composition.

Finally, additional ideas emerged through the design process itself. For example, since a lot of participants mentioned that one limitation with the transfer KPI chart was that it was hard to know which players competed with playing time, the squad list can be grouped by sub-positions and ordered by playing time instead of transfer KPI. Adding more player details could be another good improvement to the tool, especially to the radar chart to provide better player comparison [3]. Future improvements could also be providing comparative views between past seasons.

6.4 Methodological Reflections

One methodological consideration is that the evaluation did not begin with an exploratory user study to investigate user needs from the ground up. Due to time constraints, the design of the prototype was instead informed by user requirements previously gathered by the company. In addition, early discussions with domain experts within the field of football strategy and planning, played a key role in shaping the direction of the design. These interactions helped identify relevant use cases and prioritize features that aligned with real-world workflows and strategic goals in professional football contexts. This approach enabled rapid development and early testing of the tool with actual users. By focusing on how participants interacted with the digital planning tool, rather than beginning from a blank slate, it was possible to collect valuable feedback on concrete features and usability.

Although this decision may have limited the opportunity to explore unmet or latent needs early in the process, the two-round user testing structure partially compensated for this. Feedback from the first round informed improvements to the prototype, which were then evaluated in the second round. This iterative process allowed for both formative and summative insights to emerge during the evaluation.

6.4.1 Participant Selection. Participants were primarily recruited from existing users of the company's current platform, which may have introduced a bias toward users already familiar with data-driven tools or open to technological solutions. From the user tests it was clear that some participants were more familiar than others with the company's current visualizations and digital tools in general, and it could have been valuable to introduce it to completely novel users. Also, since the sample size were so small and participants were all from Swedish clubs, the generalizability of the results of this study might be limited.

6.4.2 Sample Size and Diversity. While the sample included a range of roles, it was relatively small, and only two participants worked in women's football. Broader representation could have captured more diverse perspectives.

6.4.3 Challenges with Think-Aloud. Although the think-aloud protocol provided rich insight, some participants appeared less comfortable articulating their thoughts while performing tasks, which may have affected the depth of the verbal data collected. However, the semi-structured interviews was also used as a way to reflect on completing the tasks.

6.5 Ethics

In a broader context, the increasing reliance on athlete data and algorithmic evaluations also raises ethical concerns about surveillance, autonomy, and data ownership. As large volumes of personal performance data are collected, processed, and used to predict or determine player value, questions arise regarding how this data is used, who has access to it, and how transparent such calculations truly are. Complex algorithms, especially those lacking explainability, can reduce athletes to numerical profiles, potentially overlooking human context and perpetuating biases [19].

Another important ethical consideration is how certain visualization choices can unintentionally steer decision-making and affect how users interpret the data. For example, the bubble chart uses a red-to-green diverging color scale to show players' transfer KPI values. While this makes differences easy to spot, it can also create unintended associations, like suggesting green means "good" and red means "bad." This may reinforce a simplified view of players based only on numbers, which is problematic when those numbers don't capture the full picture of what makes a player valuable.

A similar issue comes up with the quadrant layout used to categorize players based on age and playing time. The current fixed thresholds (25 years and 50% playing time) create default categories that might not apply in all contexts. For example, older players with limited minutes might end up in the "cost" quadrant, even if they play an important role in the team. One way to reduce this framing effect could be to let users define their own thresholds, which would allow for more flexibility and better reflect different club strategies, especially in lower leagues where the average age and player roles might look very different.

It's also important to consider how color choices affect accessibility. The current red-green palette is difficult to interpret for users with common forms of color blindness. This can lead to confusion or misinterpretation of the data. To make the tool more inclusive, future versions could use colorblind-friendly palettes by default, or let users switch to one, and potentially use color intensity instead, to represent value differences [20].

While these concerns were not the primary focus of this study, they are important to acknowledge given the tool's alignment with wider trends in data-driven sports management and the potential influence of design choices on strategic outcomes.

6.6 Future Work

Future research could explore how decision-support tools might better incorporate soft, qualitative factors such as leadership, character, or team chemistry, alongside quantitative performance metrics. These elements are often central to real-world football decisions but remain difficult to capture through data alone. Additionally, future studies could involve a larger and more diverse group of participants, including a broader range of roles within football organizations and improved representation from women's football. Such diversity would provide a more comprehensive understanding of the varying strategic needs and planning approaches across the sport.

A longer-term evaluation would also be valuable in assessing how the tool influences actual transfer decisions, player development, and financial outcomes over time. This could provide further validation of its strategic value and highlight potential long-term behavioral changes within organizations.

Another promising avenue is the integration of predictive modeling to estimate a player's future transfer KPI based on planned playing time and projected performance. By simulating different development trajectories, clubs could assess the long-term value of investing in specific players and better balance short-term performance needs with long-term profitability. However, for such predictions to be meaningfully incorporated into decision-making, it is essential that users understand and trust the underlying models. This highlights the need for explainable AI (XAI) approaches, which can enhance transparency by showing how model outputs are derived. For instance, recent work by Procopiou and Piki [27] demonstrates how XAI can support scenario evaluation and facilitate informed planning discussions.

Additionally, future systems could explore strategic player recommendations based on squad composition, age structure, and tactical preferences. The tool could, for example, suggest profiles of players that match a club's predefined strategy, such as contract length, age balance, or positional need, or identify gaps in the squad relative to long-term goals. This would shift the tool from supporting reactive planning toward enabling proactive strategy formulation, enhancing its role as a collaborative, long-term planning assistant.

Finally, improving the quality and accessibility of data in women's football remains a critical challenge. The evaluation revealed that even basic data, such as contract lengths, is often lacking in the women's game. As data-driven systems become more central to strategic planning and scouting, the risk of widening the technological gap between men's and women's football increases unless deliberate efforts are made to strengthen data infrastructure in the latter. Addressing this disparity is essential to ensure that innovations in football technology benefit all sectors of the sport equitably.

7 CONCLUSION

This study addressed the lack of interactive squad planning tools available to football club managers by designing and evaluating a prototype that supports decision-making during transfer periods. The aim was to explore the affordances and limitations of such a tool and to identify areas for future development.

The evaluation findings suggest that the prototype enabled club managers to simulate and compare different squad compositions and observe how decisions affected strategic metrics such as transfer KPI. One of the most significant affordances was the tool's ease of use, instant feedback, and clear visualizations, which participants saw as valuable for presenting different scenarios and fostering shared understanding across organizational roles. However, the evaluation also revealed key limitations, primarily the difficulty of quantifying human aspects such as leadership, player character, and unpredictable real-world events like injuries.

This research contributes to the growing body of work exploring how data visualization and interactive tools can support sports decision-making. It also demonstrates the importance of combining data-driven insights with domain-specific expertise. As football becomes increasingly shaped by analytics and digital infrastructures, the findings underscore the need for tools that are not only data-rich, but also explainable, usable, and contextually grounded.

Future research can build on the knowledge gained from this study to further develop such tools by exploring, for example, the integration of predictive models, richer player data, and more advanced scenario planning features. By doing so, clubs can better adapt to the evolving demands of data-driven strategy in professional football.

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