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DAX: Data-Driven Audience Experiences in Esports

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ABSTRACT

Esports (competitive videogames) have grown into a global phenomenon with over 450m viewers and a 1.5bn USD market. Esports broadcasts follow a similar structure to traditional sports. However, due to their virtual nature, a large and detailed amount data is available about in-game actions not currently accessible in traditional sport. This provides an opportunity to incorporate novel insights about complex aspects of gameplay into the audience experience – enabling more in-depth coverage for experienced viewers, and increased accessibility for newcomers. Previous research has only explored a limited range of ways data could be incorporated into esports viewing (e.g. data visualizations post-match) and only a few studies have investigated how the presentation of statistics impacts spectators' experiences and viewing behaviors. We present Weavr, a companion app that allows audiences to consume data-driven insights during and around esports broadcasts. We report on deployments at two major tournaments, that provide ecologically valid findings about how the app's features were experienced by audiences and their impact on viewing behavior. We discuss implications for the design of second-screen apps for live esports events, and for traditional sports as similar data becomes available for them via improved tracking technologies.

CCS CONCEPTS

• **Human-centered computing → Human computer interaction (HCI)**; User studies.

KEYWORDS

Esport; Data-Driven Storytelling; Dota 2; Game Analytics; Artificial Intelligence; Machine Learning; AI; Broadcasting; social viewing

1 INTRODUCTION

Esports - video games played by professional gamers that are broadcast online [23, 45] - have attracted 454 million global viewers in 2019, with a projected year on year growth of 15% over the next four years [24, 36, 39, 56]. While Esports encompass digital versions of traditional sports (such as *FIFA* [19]), the most popular esports by viewership and price pool are first-person shooters (e.g. *CS:GO*, *Overwatch* [6, 64]) and team-based, magic-themed fantasy games (e.g. *Dota2*, *LOL* [46, 63]). Most mainline esports titles organise professional leagues that conclude in international tournaments, which in some cases have had prize pools that exceeded those of many traditional sports [31, 42, 70]. The viewing experience in esports is similar to traditional linear sports coverage. Pundits provide in-depth analysis before and after the match. During the match, virtual cameras capturing the in-game action are interleaved with physical camera shots of players and audience, complemented with audio commentary.

Esports have also introduced a series of changes and innovations in regards to broadcast and audience engagement. Esports fans are relatively young, tech-savvy, early adopters and have a growing appetite for social, interactive and personalised viewing experiences [7, 39, 41, 44]. Most esports are broadcast online via live streaming platforms such as Twitch [4] and Mixer [38].

Such platforms typically facilitate social viewing, for instance by providing live chat rooms in which viewers can exchange reactions during the broadcast. Twitch and Mixer have further introduced interactive elements to the linear broadcast, such as the ability for viewers to pull up interactive statistics and infographics [15, 16]. Likewise, many game clients (the software running the esports game itself) provide spectator modes that give users the ability to watch live games interactively, for instance, enabling users to adjust camera angles dynamically [63]. To enable this functionality, game publisher broadcast matches as raw data streams that contain full state information on the ongoing match, including players position in the virtual arena and any actions they take (similar to tracking data in traditional sports [3, 33]).

In contrast to traditional sports, tracking data is available publicly and free of charge for many esports.Esports has been a fertile environment for the innovation of experiences that leverage data and statistics to enrich the linear one-for-all coverage, such as interactive mobile apps [20, 40, 62], live statistics websites [57–61] and virtual reality spectator modes [65]. However, research in this area has been sparse. The design space for such interventions is vast, rich in potential applications for research and commercial application, and is still mostly unexplored, both in esports and traditional sports.

In this paper, we present a first large-scale case study of Data-Driven Audience Experiences in esports (DAX for brevity).

Our contribution is two-fold: 1) After discussion of related work, we present the design process and implementation of Weavr Dota 2 Companion, a fully functional companion app for the popular esport,

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Dota 2 [63]. Weavr Companion is a mobile phone app that translates live match data into interactive narratives and visualisations for esports viewers, providing real-time updates of the virtual arena and its objectives, showcasing important performances, live statistics and providing a personalised compilation of highlights.

Weavr Companion was trialled in the context of two major international esports tournaments, ESL One Birmingham 2019 and ESL One Hamburg 2019. 2) Our second contribution is a mixed method evaluation of Weavr Companion with fans on site as well as with prominent commentators, pundits and analysts. Finally, we discuss our findings, provide a set of design implications for DAX, and laying out a roadmap for future work in this area.

2 RELATED WORK

There is a growing, interdisciplinary, body of research surrounding esports [45], traditional sports, consumer research and game analytics that inform the work presented here.

2.1 Consumer Needs in Esports

In traditional sports, data-driven content, such as visualisation of player position and ball tracking data, has been used for decades to provide insights to audiences [17, 26, 74]. Compared to traditional sports, the need to break down complexity and facilitate insight in esports is even more pronounced [23, 30]. Research on consumer needs have found that understanding gameplay and skill building are key motivators for watching esports [23, 30, 52, 71], highlighting the potential for statistics to provide insights [7, 23]. Recent consumer studies also reflect an increasing demand for personalised and interactive content, identifying data-driven technologies as key facilitators to generate new audience engagements [7, 39, 41, 44].

2.2 Data-Driven Audience Experiences

Footage of in-game action is a pivotal component of an esports broadcast, equivalent to the physical cameras in traditional sports. In some esports titles (such as CS;GO [64]), viewers are presented with more or less the same view the players see. Other esports, such as Dota 2 [63] and League of Legends [46] have introduced dedicated spectator views that enable broadcast to control additional virtual cameras and to add overlay statistics that can help the audience better gauge the action. Along the same line, a series of work has been focusing on further optimising esports interfaces for spectators [9–11, 66, 67]. An important motivation for augmenting the spectator experience is to create 'Information Asymmetry' [11], i.e. letting the viewers see more information than the actual players. This not only facilitates insights among audiences, but also creates suspense [11], much like the audience in football, having a better overview of the pitch, is able to notice a defender sneaking up an unassuming striker, even before the striker notices herself. Our prior work has shown that data-driven content can measurably improve the range and quality of storytelling, and invoke rich emotional response from the audiences [7]. This series of work underlines the broad potential benefits of DAX. Among these benefits are the facilitation of audience insights, advancing storytelling, helping audiences anticipate highlights and creating drama and suspense.

A range of research and commercial products introduce data-driven overlays that augment the linear broadcast [1, 5, 7]. Most leading content producers, such as ESL [1] and PGL [5] leverage custom broadcast solutions that present key statistics to the audience in overlays. Layerth [32] is a graphics engine for Dota 2 that adds various information display important for viewers, and supports the overlay of detailed statistics that seamlessly blend with the games own spectator interface. Block et al. introduced an AI-driven system that identifies top performances and automatically generates audience-facing graphics [7]. Other work leverages data visualisation to provide simplified and augmented maps to illustrate high-level gameplay and strategy, [67], similar to the visual overlay of tactical formations in football.

Research in esports viewing experiences that leverage interactivity is sparse, particularly experiences that, like our work, function in a live context. Charleer et al [10] have introduced interactive dashboards for League of Legends and CS:GO, which gave viewers access to live in-game statistics. Users can interactively compare different players and select different sub-sections of the statistics panel. In additional to 'native' statistics that are included in the game data stream, the dashboard also introduces novel derived metrics that translate various raw data points into new metrics that are easier to interpret for the audience. Likewise, our work goes further and introduces a substantial number of analytical features that add novel metrics and visualisations to the experience. There are also a range of mobile apps across esports and traditional sports that provide statistics and data-driven story alongside live events. Valve's Dota 2 app, the product most related to the work presented in this paper, provides league information, match schedules and also live match information, including some basic graphs and statistics. Most major sports leagues now have companion apps that provide similar live statistics for traditional sports, such as FIFA, NFL, and Soccer [20, 40, 53, 62], but with very basic functional scopes.

There are various web-based services that provide functional depth similar to what we present in this paper, such as Dotabuff [57] , OpenDota [59] and Stratz [60]. All those services provide detailed breakdowns of matches, including statistics over time, map views of key objectives, and textual highlights. Similar to our system, Dotabuff, Open Dota and Stratz also provide historic statistics that draw on a large corpus of data to evaluate various strategic aspects of the game. However, they are designed primarily for players who want to do post-game analysis of professional matches as well as their own personal matches. Neither of those services work live, or are designed as accompanying the primary live broadcast. TrackDota [61] is the only web statistics portal that presents live matches, however, it operates at a substantial delay between 3 and 5 minutes, which make it less attractive as an companion to the live broadcast. The app introduced in this paper operates live and provides a substantially larger set of data-driven features.

2.3 Esports Analytics

The data-rich ecosystem in esports has been fertile ground for research in game analytics, artificial intelligence and machine learning [2, 13, 25, 27–29, 34, 43, 48–51, 54, 69, 73]. The overall remit of this series of work is to identify pattern in gameplay data and to make predictions based on historic data. Examples include the automatic detection of highlights [49], prediction which team is likely to win a match [25, 27–29, 34, 51, 54, 69], identification of successful strategies and factors influencing gameplay [18, 43, 48, 73] as well as coaching systems that promise to improve a player's skill level [2, 13]. Most work in this areas is targeted at players and professional teams, and is designed for offline use, i.e. analyse the match after it has concluded. In contrast, in this paper we utilise statistics and machine-learning techniques for the purpose of augmenting the viewing experience of live matches.

3 CASE STUDY: WEAVR COMPANION APP FOR DOTA 2

Despite the rich potential for new esports audience expediences offered by data, the design of DAXs remains an under-explored challenge. Previous examples only address a small range ways that an esports audience experience might be enhanced by data, with a focus on visualization of raw data for consumption post-match. Moreover, very few studies have investigated how DAX are experienced by viewers and how different data-driven design features affect viewing practices. As a consequence, design conventions that would-be creators of DAX can draw upon to understand how to employ these possibilities to enrich audience expediences (i.e. the grammar of DAX) remain in their infancy. In this paper, we present the case study of a data-driven companion application for the the game Dota 2. This app is designed to be used live during esports events, both while spectating the event at the stadium itself or watching remotely via a stream on the internet. By describing and reflecting on this case study, we expand the design space of DAXs to include the novel data-driven storytelling features it comprises. Furthermore, by describing the evaluation of these features with audiences in a naturalistic setting, we progress the prevailing understanding how and when spectators might engage with data around esports competitions.

The companion app was created as part of Weavr, a large government-funded consortium project that explores new immersive data-driven experiences in Esports [**?**], which is ongoing at the time of submission. The project brings together partners with extensive expertise in a range of areas relating to the creation of DAX. From a content production perspective, this includes ESL (Electronic Sports League), a globally leading Esports company producing some of the largest international Esports tournaments across many commercial games, and Dock 10, the largest studio operator in the UK. From a design and technical perspective, this includes REWIND, the UK's leading immersive content studio with expertise of creating experiences for agencies and brands worldwide; Focal Point VR a provider of world leading live streaming VR video technology; and Cybula, a company that specialises in data mining and data analytics. Finally, we as a university research partner, bring expertise in game analytics, data-driven content forms as well as UX design and evaluation.

3.1 Dota 2

The companion app was designed to support new viewer experiences for the game Dota 2, which is a fantasy-themed competitive team-based battle game within the genre of Multiplayer Online Battle Arena (MOBA)[63]. Dota 2 was chosen as a basis for a variety of reasons. First, Dota 2 has open data interfaces which provide access to detailed historical match recordings [7]. Secondly, our esports partner ESL hosts many of the world biggest Dota 2 tournaments, which provide us with live data and access to large audiences. And thirdly, Dota 2 is rich in detail and strategic depth, making it an ideal context to evaluate data-driven experiences.

In Dota 2, two teams of five players compete to first destroy their opponent's "Ancient" (a fixed part of their base) while defending their own. Each player can choose among a pool of 117 different characters - or heroes - each with different abilities, strengths and synergies, creating a large set of potential team compositions and match-ups. Many heroes can also be played in different roles, such as damage dealers or initiators further adding to the games complexity (equivalent to strikers and linemen in American football).

Once the match starts, teams start in opposite corners of a square-shaped map, which connects both bases through three 'lanes' or roads that cut through otherwise dense forests. A river cuts the map diagonally. In this arena, teams engage in a race to break down the enemy's defense perimeters situated along the three lanes, which take the shape of towers that attack nearby enemies. Characters are initially too weak to destroy the defenses. Thus a primary objective throughout the game is to extract gold and experience (XP) from across the map to strengthen the heroes. Experience enables characters to level up and become stronger, and gold can be used to purchase items that lend their owner additional skills and strength. As part of competing for resources on the map, teams also often engage in direct fights, in which multiple heroes can die - temporarily teleporting them to their home base, and preventing them from gathering resources. Killing an enemy player also provides gold and XP and hence gives the winning team and advantage. A single match usually goes through three phases - early, mid and late game. The early game (first 10 minutes) is mostly about extracting resources in the three lanes, along which gold and experience are concentrated. In this phase, the team usually splits up to obtain resources from all three lanes. In the mid game, teams often focus on teaming up to jointly break down defenses. In the late game (30+ minutes) teams put emphasis on maximizing each characters power levels, in order to win team fights and to destroy the enemy base. Matches typically last between 20 and 60 minutes.

3.1.1 Spectating Dota 2. Coverage of Dota 2 is mainly analogous with traditional sports. A virtual observer camera provides viewers with a window into the game world, complemented with audio commentary. The observer camera, at any given point, only shows a small section of the overall map, usually set to focus on what is considered the 'primary' action. Just like in Formula 1, action in Dota 2 often unfolds in parallel. In Dota 2, the virtual camera thus frequently jumps to cover action in the various regions of the map. Live replays can also be used to present a highlight that were not captured through the primary camera.

There are various challenges for the coverage of a Dota 2 match. Due to the high degree of parallelism it is often not impossible to capture all events that are key to the match and that the audience cares about. Furthermore, tracking and understanding each player's performance is very challenging. Each player can be judged according to a range of Key Performance Indicators (KPI, [7]), for instance, how much gold they have acquired or how many times they have died in the game. Many of these KPIs, however, are not usually exposed to the audience. Even when KPIs are presented or mentioned by the commentary, they can be hard to interpret, as their meaning highly depends on many factors, such as what hero it relates to, what roles are played, or the time in the match. For instance, '1000 gold collected at minute 5' may be a good performance for one hero, but poor for another.

It is also often hard for viewers to understand at a high level the status of a match. Dota 2 has no 'score', like in football, making it non-trivial for audiences to gauge who is having an advantage. There is an indicator of how many 'kills' each team has scored, however, due to the complexity and strategic depth those are not always indicative of win probability. Likewise, it is hard to judge how teams are performing in different sub-regions of the map, for instance, how both teams compare in extracting resources from the three lanes.

The Weavr Dota 2 Companion was designed to address some of these challenges by enhancing the viewing experience through various data-driven experiences. These experiences allow the tracking and interpretation of player performance, the highlight of key in-game events, and provide an overview of a game's state and objectives.

3.2 Design and Development Process

The Weavr Dota 2 Companion was developed over a 12-month period of close design and technical collaboration between the project partners. The starting point for this process was an existing DAX created by the University and ESL, which used analytical techniques to detect extraordinary player experiences and represented them as dynamic graphics that commentators and casters could incorporate into a live broadcasts [7]. Initially, and through a series of collaborative design and technical meetings, possibilities for extending and evolving this previous DAX to enhance viewers' experiences of esports and meet broader organizational goals were developed. Key design decisions made during these meetings included the choice to develop a companion application, which was motivated by the opportunities for content personalization posed by presenting content on individual devices; the choice and prioritisation of which of the many possible data insights would be developed for incorporation in the app; and the how interaction design and visual aesthetic of the would be crafted. The app, as defined in these initial activities, quickly progressed into prototyping and production, with stakeholders continuing to work collaboratively to refine the design in response to issues, challenges, and creative opportunities that arose as the app and its underlying analytics features evolved through stages of increasing fidelity.

Throughout these processes we consulted at length with multiple game analysts and other esports professionals, with years of experience in either casting, coaching or analysing Dota 2 professionally. We did this to best ensure that app's experience, especially the choice of data insights that would be presented, was informed by their extensive experience of what kinds of insights and stories excite and interest audiences most. In many cases, this consultation happened organically during design meetings, due to multiple esports professionals being directly involved in the project consortium at an operational level. However, we also sought to broaden the range of expert input into our design process by conducting co-design activities with ESL's extensive network of professional esports storytellers. These activities ranged from online surveys about existing challenges they face and aspirations for new content experiences, to think aloud and design idea generation sessions focused around interaction with app prototypes. Particularly extensive professional feedback was gathered at a major esports tournament in May 2019, at which a fully functional prototype of the companion was presented to esports professionals in focus groups and in more lightweight interviews with further professionals at a demo stand in the tournament's VIP area. At this event, we also sought end-user feedback, which was gathered by a team of 5 roaming researchers conducting ad-hoc think-aloud interviews about the app with audience members in the venue. The outcomes of these particular activities (which are also described in our findings section) guided a subsequent period of collaborative design, which resulted in the iteration of the app that is documented in the following section of paper.

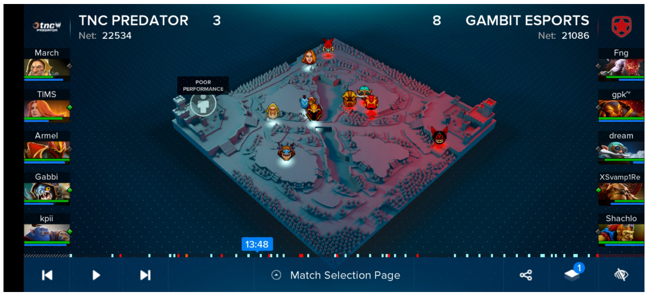
Working so closely with industry in the development of the companion app posed challenges, in particular in relation to the much more rapid timescales associated with product development vs. blue sky research. However, it also presented significant methodological advantages. Collaborating closely with internationally leading content producers in esports and traditional sports provided an opportunity to base core design decisions on in-depth engagement with expert esports storytellers, who otherwise would have been difficult to access. Moreover, collaborating with a major esports company presented a crucial the opportunity to deploy the app with large audiences at real events during the course of the research. This allowed for both formative and evaluative findings to be derived from app usage in an authentic and naturalistic setting, which, again, would have been challenging to access without direct collaboration with an esports company. We also found that conducting evaluations in such naturalistic settings also, and equally importantly, acted as a driver to reinforce that the experience developed was truly compatible with contemporary broadcast practices, due to the high stakes associated with failure (e.g. reputational damage).

3.3 Weavr Dota 2 Companion

The Weavr Dota 2 companion lets viewers augment on-demand data-driven content alongside watching the main linear broadcast. Weavr Dota 2 companion is comprised of three experience tiers that are seamlessly connected. On the first tier, the app shows a detailed overview of the map as well as each player's position and vital signs (health and mana). This gives viewers the ability to observe high level movement patterns and to anticipate upcoming team fights (see 1).

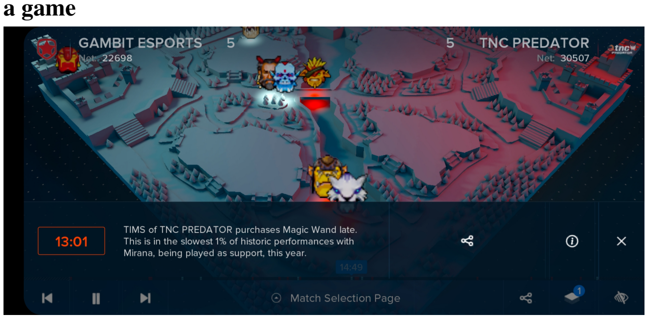
As the match progresses, important highlights pop up on the map, indicated through markers with a different symbol. Highlights include when key items are purchased (which are associated with a substantial increase in the characters' power), when parts of the defense perimeter are destroyed and when players achieve exceptionally high performance as expressed through 13 different KPIs, such as gold and experience gained. Tapping on a highlight indicator zooms into the map, and provides more information on the highlight. Figure 2 shows an example highlight. In this instance, the player named 'TIMS' of the team 'TNC PREDATOR' has purchased the item 'Magic Wand', a key early game item. In addition to bringing the event to the viewer's attention, the display also provides contextual information that tells viewers that the purchase was among

Figure 1: The overall map that allows for the constant live tracking of each individual hero.



the slowest 1%, compared to historic performances. The interpretive layer takes into account the hero that is being played (Mirana), as well as the role the hero is played in, providing meaning to the viewer. Viewers can also request more information (such as how many historic matches were considered for the contextual information), and can share the screen via social media.

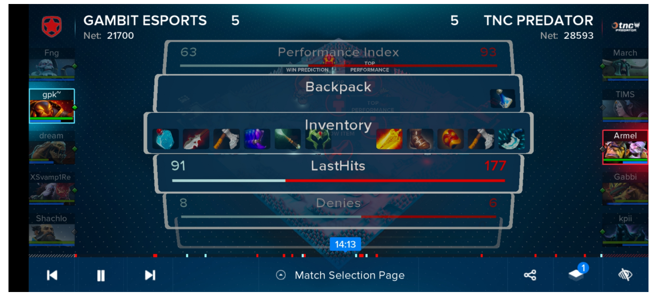
Figure 2: The story mode of that highlights important events in a game



The second experience tier adds an element of active inquiry. Contrasting the performance of players and teams is central to the esports narrative [7]. Weavr Dota 2 Companion provides various interactive features that cater for this use case. Viewers can enable various map layers that show additional information. A 'Laning View' compares both teams in terms of their regional resource extraction, showing indicators along the three lanes that visually highlight which team is in the lead in each key region on the map. A 'Defense View' shows the status of the defense perimeter of each team. Lastly, 'Win Probability' shows a percentage of which team is most likely to win, essentially providing a live 'score'. Each view aggregates a host of different performance indicators to provide a simple, at-a-glance view of important information about the ongoing match that is otherwise invisible.

Viewers can select one hero per team on each side of the display to compares performances along various KPIs (see 3. The barrel lets users track each player's current inventory of items (important to gauge progress and power) as well as 13 KPIs that give a broad view on each player's performance. The barrel makes it easy to compare any two players and to judge their respective performance.

Figure 3: Live comparison of different heroes on many different high level stats.



While the first two experience tiers were focused on map-based visualisation and story, the third experience tier lets user drill deeper into statistics. Selecting any KPI entry in the barrel brings up a line graph that compares the selected KPIs for both players over time. The line graph has a relative mode, which translates absolute values (e.g. 1000 gold at minute 5) into historic context (e.g. '99%' = performance is in the top 1% of historic performances). This enables viewers to make comparisons across different heroes and roles.

Overall, the Weavr Dota 2 Companion app creates a rich interactive experience that accompanies the live broadcast. The app presents highlights to the viewers that might have been missed on the primary coverage, and gives individual viewers a broad range of on-demand content. Personalisation is achieved through two means. The large experience space is too large to be consumed in its entirety, which means that individual trajectories through the content creates an individual experience. Viewers can also tailor their highlight stream through the user of filters.

3.4 Analytics Engine

The back-end system powering Weavr Companion consists of several interconnected components: data capture module, analytics middleware, narrative engine and datacast system. The data capture module taps into raw live game data using Dota 2's built in data APIs. While those APIs are public, true live access is password protected, and data has to be granted by the tournament organiser. The data capture converts the raw data into in-memory data structures that are accessible by the analytics engine. The analytics engine runs a series of algorithms that identify notable events and performances, much like described in [7]. The analytics engine compares Key Performance Indicators (KPIs) of all players to historic records, identifying 'top' and 'bottom' performances. For instance, the algorithm can detect when a player's gold is in the top 5% of historic performances. Just like in football, performance depends on the role a player is acting in. For instance, a goal keeper wouldn't be expected to score goals, whilst it is expected for a striker. Consequently, its extraordinary when a goal keeper scores. The analytics engine automatically detects the equivalent roles in Dota 2 [14] as well as other contextualising factors, such as time in the match and the chosen hero. This contextualising factors are then used to assign different priorities or "importance" of highlights. Similar to player performance, the analytics middleware also makes continuous historic comparisons of the different map regions (lanes), purchase of in-game items and destruction of important buildings to support respective features in the app. Lastly, the data middleware calculates real-time win prediction based on various factors (as detailed in [25].

The stream of highlights are then processed using a narrative engine. This engine annotates the thus far numeric in-memory representation of the prioritised highlights with textual representations. A simple template-based system with adaptive grammar features is used to generate the textual representation. Once the highlights are annotated they are converted to json format and broadcast to the client apps using a bespoke datacast system. This system uses Kubernetes [12] and Socketcluster.io [22] to achieve scalability to 100k+ consumers.

In parallel, the data capture also sends real-time updates of the game’s state (i.e. the player’s positions, vital signs, status of buildings) to the client app via the same datacast system. The data layer on the client side then merges the gamestate data and annotated performance highlight, and uses the combined data to support the rendering of the presented user experiences.

4 EVALUATION

We evaluated Weavr Companion in the context of two major international Dota 2 tournaments, ESL One Birmingham 2019 and ESL One Hamburg 2019. Both tournaments featured $300,000 price pools, 6,000 visitors on site and in excess of 20 million online viewers), providing a rich naturalistic setting to evaluate the app through an in-situ approach [55, 68]. The evaluation is comprised of two parts, executed in May 2019 (ESL One Birmingham) and October 2019 (ESL One Hamburg). The pilot study, conducted at ESL One Birmingham 2019 (May 2019) was of a formative nature capturing user’s feedback from a previous design iteration of the app. We present the findings here as they provide important context for the second evaluation, and underlie rationale for the final app design presented in this paper. The subsequent main study was conducted at ESL One Hamburg (October 2019), focusing on the first public release of the app.

Ethics approval for all study components were granted by the ethics committee at the University of York. Participation was completely voluntary. All participants were over 18, and gave explicit consent to be recorded about their usage and/or feedback around the Weavr app. All data was recorded anonymously, and participants were given the opportunity to drop out of the study at any time. For on-site participants informed consent was elicited, and conversations with participants were recorded and later transcribed anonymously for analysis.

4.1 Pilot Study

To gain initial insights into spectators views and perceptions of the app and its features, we spoke to 30 participants at the arena during the international ESL One Birmingham 2019. These interviews took place during tournament breaks, in-between matches. Participants were approached by researchers, consented and given a Sony Xperia XZ1 with the companion app installed. This displayed statistics for the last match that had just previously taken place at the tournament. Participants were asked to freely navigate through the app’s menu to explore its features and, while doing so, talk out loud about what they were doing and their opinions. If participants became stuck at any point, or asked asked questions about the navigation or the app’s content, the researcher would first ask them to attempt to deduce how they can resolve the problem themselves before providing guidance. In cases where participants found it difficult to describe their experiences, the researcher would ask open-ended questions in order to encourage responses. These interviews were audio recorded and subsequently analysed to find broad themes that spanned multiple participants’ responses.

4.1.1 Initial Findings. A prominent theme was a strong desire amongst the spectators interviewed to engage with the Dota 2 statistics of our app, re-inforcing the appetite for data-driven content found in [7]. Participants showed strong desire for more volume and detail of statistics when using the more exploratory interface offered by the "barrel" view (see Figure 3). In contrast, participant found the "story page" too cluttered, and expressed desire to only be presented with "hard hitting" statistics. Conceptually, the "barrel" and "story page" are fundamentally different user experiences. While the "barrel" mode caters for active information seeking (user *pulls* information), the "story page" serves the user only with selected "highlights" from the overall data space (app *pushes* information to the user). Our findings suggest that users always welcome more information to *pull*, but are averse to high volumes of information when it is *pushed* to them. Our study also brought out that what people considered a "highlight" varied widely. Based on these findings the story page was reworked in the final version to include a customizable filter as well as to better contextualise statistics and used a more conservative cut-off criteria for being presented. This reduced the visual clutter and increasing relevance of the presented story elements.

Personalization was seen as important, with participants expressing a desire to explore the app based on factors such as their own skill level and the way that they play the game, and to track favorite teams and players. Interestingly there was a desire to explore statistics in support of individually held views or hypotheses about the game and the way it should be played. When discussing potential extensions to the app, some users expressed a desire to extend the level of personalization to incorporate features that allowed them to compare data about games in the tournament with data from their own matches.

Participants also expressed some confusion about some of the higher-level statistics included in the app, including those that were derived using machine learning (particularly our win percentage and lane visualisations). In particular, participants expressed a desire to understand how these statistics were defined and determined, and a degree of frustration when they could find not this information within the app. For example, one user could not understand how the "Relative Performance Metric" was derived. They said "...Relative to what?" and later asked whether the metric was calculated based on the player’s historic performance, other players in the match or other players in the past playing the same hero. Subsequently, the final design iteration added information tooltips that provided textual explanation of the underlying algorithms.

The think aloud interviews revealed a range of usability improvements that were subsequently incorporated into an iteration of the app’s menu design and user interface, but we do not report these here for brevity. We do note, however, the importance that spectators placed on the app having a polished aesthetic, with strong positive viewpoints being expressed around the graphs that depicted stats due to those being "smooth" and "visually pleasing". This emphasises the importance of aesthetics to engage the gamer target demographics.

4.2 Main Study

The final version of Weavr Companion was launched in conjunction with ESL One Hamburg 2019. The app was available publicly on the Play store and promoted by two social media influencers via twitter. A total of 170 people installed and used the app on their phones. The main study was comprised of a quantitative and a qualitative component. The quantitative component was designed to capture overall usage patterns on the entire online sample, while qualitative interviews aimed to bring out detailed insights regarding usage and perception of the app in the context of existing viewing habits. The quantitative results capture user telemetry of all 170 people who downloaded and used the app, including the 27 subjects we recruited for the qualitative study. We could not directly tie the quantitative data of the 27 recruited subjects to their telemetry data as the technical infrastructure did not integrate user account tracking, nor would the low sample size of the qualitative study have allowed us to conduct meaningful statistical analysis. However, we will discuss themes emerging across both quantitative and qualitative study components in the discussion.

4.3 Quantitative Analysis

We recorded detailed telemetry of all app users via Google Analytic's app framework [21]. We recorded session times (start and end) as well as interaction flow between the various features provided by the app. Additionally, we recorded the times when matches were live, as well as the associated boradcast so we could cross reference app usage with in-match events.

Overall, 170 users downloaded and used the Weavr app and we collected data for 764 sessions. Across all users the average session lasted 3:45 minutes. While many sessions were brief, 55 % of all session lasted more than 1 minute while 36.6 % of all sessions lasted for more than 2 minutes. for a detailed breakdown of session duration). The average number of session per unique user was 4.55 and can be seen in the Figure 4 below. Over two-thirds (67.3%) of all users returned to the app at least once; 27.98% of users engaged in more than 5 sessions.

Of all sessions, 38.6% (295) took place while a live match was on, meaning that a substantial part of engagement with the app took place before, after and in-between matches. We visually plotted session for all unique users over the entire three day event to detect temporal patterns in usage (see Figure 5 for an excerpt of an example match). Usage was skewed towards the beginning of the event days (62.8 per cent of all sessions happened in the first half of each event day). One possible explanation for this observation could be "app fatigue", or an increasing focus on the live matches.

4.3.1 *Feature Usage.*

While all features of the app were used, not all users engaged with all features. The most popular view was the overview map, with an average of 265 seconds spend in this view per user.

Figure 4: A Histogram showcasing the number of sessions per user.

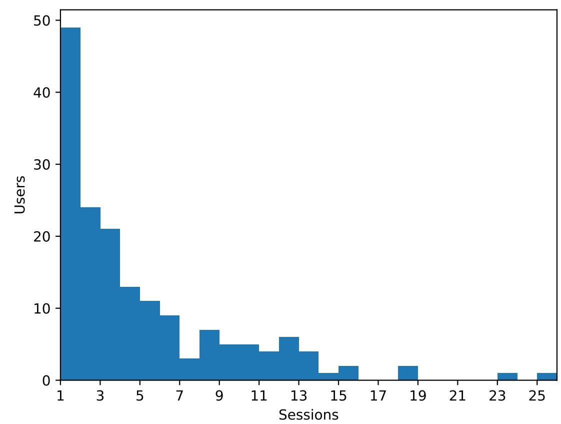
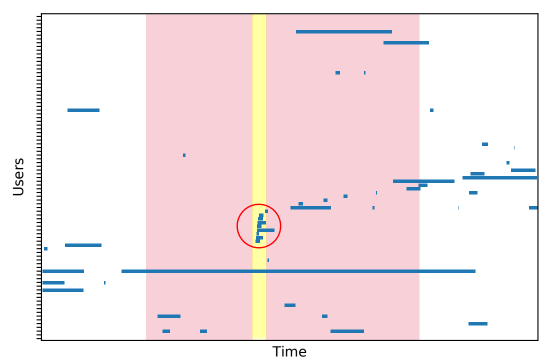


Figure 5: User activity before, during and after the first match of ESL One Hamburg. Each line represents sessions by a single user. Sessions are marked in blue. The yellow marker shows the occurrence of a big team encounter, during witch a cluster of users tuned into the app (red circle).



This is unsurprising as it is the default entry view and also serves as intermediary view when switching between features. Mirroring our qualitative findings, the player comparison - the barrel - was the feature user spend most time on with 194 seconds. This was followed by the Win Probability layer (139s), detail views of the highlights (64s), Defence Perimeter layer (41s) and Laning Layer (25s). The filter page was visited for an average of 8s.

4.3.2 *Usage Patterns.*

Many of key findings from our qualitative findings were mirrored in the our quantitative data, showing that users did engage before, during and after live matches. Observed usage was evenly distributed.

While sessions appeared to be mostly randomly distributed among users, we did find an occurrence in which multiple users tuned into the app at overlapping times. Figure 5 shows such this occurence (the cluster of parallel session in the time period highlighted in yellow). Note that for presentation purposes, users were ordered such that these sessions are visually grouped. We cross-referenced timing of this pattern with in-game events. The yellow area marks a period of an substantial team fight, followed by an instant replay recapping the fight shown in the live stream. This indicates that key events in the game may stimulate app usage. While no correlational analysis between patterns and in-game events was performed here due to the low sample size, this is possible in the future when more user have utilized the app.

4.4 Qualitative Study with Repeated Observations

While the analysis of remote telemetry provided a good overal characterisation of viewing patters, the qualitative study aimed at deepening our understanding of how the app would be experienced and affect viewing practices. 27 participants for this study were recruited in the early stages of the event. Participants were assisted in installing the app on their own Android device, given a brief introduction to its main features and instructed to use it in a naturalistic and self-driven way over the remaining three days of the tournament. Participants were given the opportunity to meet with a researcher on the second day of the tournament to clarify any questions that they had around the app and were asked to participate in an semi-structured interview with a researcher about their experiences of the app on the final day. Participants were given either a 50 EURO Amazon or merchandise voucher to compensate them for their time. Interviews were audio recorded and subsequently transcribed for qualitative analysis.

4.4.1 Usage Patterns. Participants' responses reflected the quantitative findings, suggesting that the app was used both during and between matches at the tournament, with particular ways of using the app varying within and across these periods. The most popular time to use the app was while a live match was ongoing. Most viewers who used the the app during games did so from within the arena, interacting with the apps features in direct support of live viewing. However, some others reported using the app to maintain engagement with a live game while doing something else outside of the area, such as queuing for food or drink. For instance, one participant said:" I used it most when I went to grab some beer and I couldn't see the game...and I was using the app and seeing what's happening". Other participants used it at a completely different setting as a second screen app: "...so when we were at a restaurant and then we were using the app, while watching on the restaurant screen and everything was in sync". While some participants seemed to use the app continually throughout matches or to check stats at seemingly random times, others did appear to have their usage triggered by key game events including: key moments (e.g. team fights were everyone died or when a team bought a strong item called "Divine Rapier") or during downtime and other less exciting elements of play (e.g. players re-spawning). However, we did not find any noticeable or dominant patterns in the relationship between during-match usage and particular events or happening during gameplay. Usage of the app after games also arose as a prominent theme amongst responses, with participants using it was as a tool to gain an overview or a summary of previous matches and reflect on events that took place within them. One participant said "I use it quite a bit, not during the games but when I went home...It was pretty useful to, to have, like, an overview of what was happening". However, some participants wanted to focus on more detailed time points or key moments of the match, as one participant said: " I've been using it after that, so if I want to re-visit certain situations, or like what happened here, or is that good? Is that bad?...". Participants reported using the app in these ways in a range of places, e.g. restaurants, hotels and in the arena between games.

4.4.2 Feature Use. Almost all of the app's features were explored used by our participants to some degree, reflecting the quantitative findings. However, we note that participants reported using some features more than others and some key patterns in feature usage were evident in responses. One of the most dominant and reoccurring ways the app was used was to compare players from different teams. In particular, many participants reported using the app at to view to compare statistics from players in opposing positions (e.g. those playing in a similar role to each other on different sides) across teams at different times in the game. As one participant stated: "what I loved about the app was the comparison feature...I could look at the screen for one second and already know, "Alright, this player is doing so much better than the other" because I could just check the two carry positions or mid players". A second regularly-used feature was "Win Probability", which indicated the likelihood of a team winning over the other at a point in time. Participants reported using this feature as a way to enhance their understanding of the state of the game, often to check whether their own perception was accurate in respect to the current prediction, for example: "I wanted to check my intuition about how the game was going". Thirdly, participants valued having access to the additional live statistics (not easily available by other means during the live broadcast) that the app provides, with participants noting how they used a wide range of the KPIs, and how they valued being able to break these down on a per individual hero basis where applicable. For example, one participant noted: (responding to what stats they found interesting in the app) "like the items that people are purchasing. Because again that's another thing that is so complicated in the game, so like seeing the items that people are purchasing and the builds they're going for, that was useful for me". Finally, participants also interacted with the highlight items or pop-ups, eliciting participants to share their favourite story of the match.

4.4.3 Motivations. The participants use of the app was motivated by a range of different aspirations and scenarios across the duration of the tournament. As anticipated by participants in the think-aloud interviews, the first major motivation underpinning many interactions with the app was a desire for personalization, with participants valuing the addition control over the information they were consuming about games. Some participants reported occasions where their interests did not align with what the Dota 2 hired observers (camera controllers) presented on screen, and using the app to find out the information they did want to know at that time. For example, one participant noted "...sometimes I have this question that I really want to know [the answer to] right now and, sure, I can wait three or four minutes...but why wait if I have the app and I can just quickly check it..." and another said: "Tends to be like, when I want to check like a little bit of information, like what item has somebody got, because obviously when you watch it on the stream, you can't always find the information that you want because you're dependant on JJ (virtual camera operator) clicking on whatever he wants to click". An interesting pattern amongst such app uses related to participants looking up information around support players, who generally don't receive as much attention as players in other, more *dramatic*, roles: "On the camera and in the arena they don't tend to show the support, like, hover over the support players as much. So it's nice to see like, how they're doing in general...". A second key motivator for the apps use was to gain an overall Overview or a Catch-up of a game so far. As one participant put it : "...it was to understand the game and how it's going, about some confusing moments, but also to have a better understanding of the current status of the game.". This understanding of the game was not only limited to highly experienced players but to newer players as well that wanted to understand basic level statistics and discuss them with their partners or their peers. Thus the app acted as a clarifying, anchoring point that enabled conversation at hectic in-game points. Finally, multiple participants sought to use the app as a learning tool for their own Dota 2 playing, using the app's features to draw parallels between them and the professionals players at ESL One Hamburg 2019 in order to improve their own gameplay. A common example of this was using the app to look at a pro player's item build at specific moments in time, with the aim of copying it or testing and testing and reflecting on their own skill on predicting the next purchased item.

4.4.4 Social Uses. We found that the social media features of the app were largely ignored by participants, with the majority reporting that the app did not lead to an increase in social media usage and some not even finding the share button. However, participants reported that the app was used in the context of co-located social interactions amongst friends and partners attending the tournament together. For instance, using the stats generated by the app as a talking point for a discussion. These included both controversial data the users did not agree with e.g. not agreeing with the win prediction of our app and thinking that a statistic is wrong as well as confirmatory ones where the users fully agreed with the statistics derived from the app and then going on to add their own perspectives about the match and discussing them with their friends. Moreover, a couple attending the tournament together, for whom one partner was more knowledgeable about the game, reported using the app to assist in conversations explaining complex game concepts to the less game-experienced person.

5 DISCUSSION

In this work, we have introduced and examined the concept of data-driven audience experience (DAX) in esports, using a new mobile-format app that was created through the close collaboration with leading industry stakeholders. We have presented qualitative and quantitative findings form an evaluation that was carried out in a naturalistic setting, two major international esports tournaments. We will now reflect on methodological challenges we had to overcome in the development of the presented case study, and discuss the broader themes and implications arising from across design process, quantitative analysis and qualitative interviews.

Learning as a key motivator. Our first finding validates past literature findings regarding learning as a key motivation of spectating esports [23, 30, 52, 71]. Many of our participants explained that they used the app to observe the players they think they can learn the most from. This usually included looking at player that played the same role or position as them. Many of our users said that they looked at various items timings and cross-compare them with their own performance with that hero. Thus the Weavr app and these additional statistics served as learning tool. Learning should thus be considered a key factor in the design of DAX for esports, and possibly traditional sports.

Simple statistics matter. A number of our data-driven content is based on fairly sophisticated machine learning algorithms. While those features, such as the win prediction and the historic statistics were used and were welcome by users, users also appreciated simple 'quality of life' statistics. For instance, the barrel showed many low-level statistics and simple display of what items players had purchased. Simply taking this basic data and converting it into audience-facing on-demand content created value. Consequently, translating basic but otherwise hidden data into an interactive format may constitutes an easily obtainable starting point for any DAX.

Viewers like to take control. While viewers usually have to rely on the virtual camera operator to reveal interesting details, our users saw clear value in taking charge and the ability of diving into details on demand. Analysis of user styles showed a wide variety of timings at which or app was used - before, during and after live games.

Expected and unexpected uses. Qualitative and quantitative findings confirmed many usage patterns that the app was explicitly designed to cater for. Viewers used the app to confirm their own hypotheses about the match, and to discover highlights they may have otherwise overlooked. While the app was designed as a live experience, it was also actively used before, in between and after matches to review past games. While the app was designed to accompany the primary broadcast, we found many mentions of use cases in which the app acted as a standalone experience. Users tuned into games while not at the venue to keep up-to-date and follow the event schedule. This points to an opportunity to deliberately consider stand-alone use in the design process. Our app, for instance, could have embedded push notifications when matches start, or match summaries that recap the action.

Comparing performance is a key feature. Our most popular features was the barrel, which participants tended to use to compare the performance of two players. Moreover, participants requested a feature where one could cross-compare different teams with each other. Expanding upon our previous findings showing that narratives in esports are 'all about the player' [7], we feel that comparative functions expand and refine this principle. Contrasting two competing players' performance seems an important functionality that may also resonate in other esports, and traditional sports more broadly.

There is a healthy distrust in algorithms. Those features that leveraged more complex algorithms were commonly questioned by participants. The validity of win prediction was put in question as it appeared to conflict with our users' own perception. Likewise, our app provides the possibility to display KPIs in a 'relative mode'. This, in principle, made it possible to compare players of entirely different roles. However, our participant did not commonly use the app in this way, and expressed confusion about what the relative values meant. While we are confident that his feature is valuable, we were not fully successful in creating transparency and trust for these features to develop their full potential. This points to the need to embed explanations of more complex algorithms that help users understand and trust in algorithmically generated content. At the same time, we also found that the very distrust in some of our complex features may invoke valuable dialog, such as provoke social discussions. An experience could purposefully leverage this tension, for instance, create a 'human vs. AI'-style interaction in which humans can measure how well their prediction matches with the AI.

Too much and too little - balancing information density. We received various feedback in regards to information density. The number of highlights presented on the map seemed to have sometimes overwhelmed users, noting that they prefer fewer 'hard hitting' highlights over a large quantity of 'less important' highlights. In contrast, our subjects also asked for more information when they were actively looking for it. In summary, when information is *pushed* to the user, it needs to be rare and relevant. When information is *pulled* by the user, additional layers of information have to be nested for the user to delve in. We also recommend that the user interface needs to clearly suggest when there is more information behind a content-element, to avoid disappointment when a tap doesn't bring up more content, and to ensure users can find all the information that is nested in the deeper experience tiers. In future work, we will also focus on analysis of what constitutes 'hard hitting' highlights, how what 'is important' may vary from user to user, and how this can be captured algorithmically.

Cross-platform experiences. Users want a holistic cross-platform experience that integrates with existing viewing platforms and experiences. Many users asked for integration with streaming platforms, such as twitch.com, in order to watch highlights or the full videos of their favourite teams. Moreover, many participants and spectators asked if Weavr services could be provided for their own personal games besides professional ones. Similar . In esports, most viewers are also players, and in principle, data is also available for casual and amateur matches. Similar to existing services that target players[57, 59, 60] a promising application of DAX could also be to connect personal and professional data to create a seemless experience between playing and watching. The convergence of roles - viewers are also players - coupled with the strong desire for viewers to learn new skills by watching the professionals, suggests that DAX bridging viewing and playing experiences are a promising area for future investigation.

Methodological challenges. A characterising feature of DAX, as per our definition, is that they generate user experiences in response to actions and events within the game, captured by the data that is generated during a match. How such actions and events unfold is inherently unpredictable. Consequently, any interactive audience experience has to be able to deal gracefully with any potential situation, while still maintaining a coherent user experience. From related research [8], we know that such data-driven interactivity is hard to prototype as it only becomes meaningful, and can be evaluated by users, when they are fully functional, i.e. ingest and are populated with real data. Data ingestion and analysis often involve non-trivial development work and algorithms that can hinder an agile prototyping process. Thus, it is critical that prototyping is not only done with real data, but that data is varied across different matches, so that as broad as possible an experience space can be anticipated and tested by the designer. An additional difficulty comes from having to respond to real-time data – after all, sports are often watched live. This poses a challenge to the design and evaluation process, as most light-weight prototyping tools and design techniques are less effective in simulating a realistic user experience. In our experience, creating functional prototypes that are exposed to users via RITE (Rapid Iterative Testing and Evaluation [35]) is a crucial component in design and evaluation of DAX.

Limitations. Our findings are specific to the design of our app and Dota 2. While our naturalistic case study provides an important first step in understanding DAX, it has to be established in future work if findings translate and generalise to other esports, and in potentially, traditional sports. The sample size of our quantitative evaluation was relatively small, which prevented us from examining statistical effects. As the app further matures as part of the project's delivery, we are planning to increase sample size, focusing on more closely understanding fine-grained behavioural patterns, types of uses and how usage of the app interacts with in-game events.

6 CONCLUSION

In this paper, we have presented a first case study of Data-Driven User Experience in Esports. Together with five leading industry stakeholders, we have designed and implemented Weavr Dota 2 Companion, a mobile app that provides a rich live visualisations and statistics to viewers. We have deployed and evaluated the app at two major international esports tournaments. Based on 170 users, who installed and used the app over the course of three tournament days, we found great appetite to engage with data-driven content. The majority of users tuned into the app repeatedly, and integrated use of the app with their existing social viewing habbits in a multitude of ways. Users identified clear value in the content provided. We have also identified a series of findings relating to design and methodology that can inform the research and development of DAX. Our findings were generated in the context of Dota 2 and their generalisability of our findings to other esports has to be established through further research. However, Dota 2 is one of the three most popular esports titles, part of the MOBA genre, which includes League of Legends [37, 47]. Together, Dota 2 and League of Legends attract over 120m viewers [72], a substantial portion of the 454m overall viewership. We are confident that our findings as presented are relevant for a substantial portion of the esports ecosystem. In future work, we are planning to expand our approach to other popular esports genres, as well as explore the applicability of data-driven experiences to traditional sports.

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