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From Passive Viewer to Active Fan: Towards the Design and Large-Scale Evaluation of Interactive Audience Experiences in Esports and Beyond

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Figure 1: The Dota 2 Audience Overlay

ABSTRACT

Esports - competitive video games watched by online audiences - are the fastest growing form of mainstream entertainment. Esports coverage is predominantly delivered via online video streaming platforms which include interactive elements. However, there is limited understanding of how audiences engage with such interactive content. This paper presents a large-scale case study of an interactive data-driven streaming extension developed for *Dota 2*, reaching over 300,000 people during the *DreamLeague Season 15 DPC Western Europe* tournament. The extension provides interactive live statistics, analysis and highlights reels of ongoing matches. This paper presents an analysis of audience telemetry collected over the course of the four week tournament, introducing a novel approach to analysing usage data delivered seamlessly in conjunction to a linear broadcast feed. The work presented advances our general understanding of the evolving consumption patterns in esports, and leverages esports as a lens to understand future challenges and opportunities in interactive viewing across sports and entertainment.

CCS CONCEPTS

• **Human-centered computing → Information visualization**; *Interaction design*; **HCI design and evaluation methods**; • **Applied computing** → Media arts.

KEYWORDS

esport, esports, streaming, broadcasting, data visualisation, Dota 2, audience engagement, interactive content

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1 INTRODUCTION AND BACKGROUND

Esports are video games played competitively, and attracting over half a billion viewers annually [22, 23, 32, 35, 37, 38, 41, 48, 61, 72]. Esports games come in a variety of genres, including first-person shooters (e.g. *CS:GO*[1], *Overwatch*[2]) and battle arena games (e.g. *Dota 2*[3], *League of Legends*[4]).

The viewing experience in esports is similar to linear coverage in traditional sports, blending live footage of gameplay with audio commentary, and providing pre- and post-game panel shows. Coverage is thus similar to the concept of sports broadcasts, where every viewer receives the same experience. However, the platforms of delivery and patterns of consumption differ from traditional sports [5, 8, 29, 31, 62]. Esports are predominantly broadcast online via streaming platforms such as *Twitch*[5], YouTube Live[6] and *Facebook Gaming*[7]. These platforms providing rich social interaction between viewers [5, 62]. Esport audiences are highly active on the platform's built-in live chat and social media, and increasingly demand more active ways of engaging with live events [6, 8, 29, 57]. Responding to evolving audience needs, streaming platforms have recently introduced the capability to enrich the linear video stream with interactive elements, such as informative overlays, mini-games or audience voting [12, 21, 36]. This enabled broadcasters to develop interactive interfaces [6] that allow audiences to choose when and how information is displayed to them [8]. Subsequently, previous research has explored the design of interactive spectator experiences in esports, highlighting a range of benefits brought to viewers through interactive elements alongside linear video streams, including the ability to personalise one's viewing experience, discovering additional insights, and facilitating enhanced emotional engagement with the live event [5, 8, 29, 31, 62]. However, despite the identified benefits, there is still little understanding and evidence of how the use of interactive elements practically entwine with existing passive consumption patterns, nor suitable definitions and methodology for analysing active viewing behaviour.

This paper presents the first large-scale naturalistic study of interactive viewing in esports, drawing on detailed telemetry data collected from over *300,000* unique viewers in the context of a large international esports tournament. Collaborating with one of the world's largest esports company (ESL), we designed and developed the *The Dota 2 Twitch Extension*, an interactive twitch extension for *Dota 2*, one of the top three most popular esports worldwide [58, 59]. This extension gives Twitch viewers the ability to display on-demand game statistics, highlight recaps, match (game) status and more.

The contribution in this paper is two-fold. After a review of related work, this paper introduces the *The Dota 2 Twitch Extension*, describing the 2 year iterative design process and the resulting experience for viewers, aiming to bring out design patters, UI challenges and means of integrating with linear video stream. Secondly, this paper presents the results of a longitudinal large-scale audience study of how the extension was used in a real tournament environment, providing new methodology for the analysis of interactive spectator experiences, validating various aspects of the design, and providing a detailed characterisation of observed interaction patterns. Finally, a discussion on the findings, and design implications are outlined. This work seeks to inform the design of interactive viewing more broadly, establishing foundations for design of interactive viewing experiences, and discuss the wider application of the findings to traditional sports and entertainment more broadly.

2 RELATED WORK

Esports is a rapidly growing field and the associated academic and industrial research domain is diverse, quickly evolving but also somewhat fragmented in the diversity of research available [5, 29, 48]. There is also a related cross-disciplinary body of research surrounding traditional sports and broadcasting, consumer research and behavioral analytics [14, 18, 27, 29, 45]. The case study presented here operates across a number of these lines of investigation, chiefly the interplay between *data, audiences* and *experiences*. Therefore, this section explores a range of previous work available in the literature in a range of domains. Firstly a review of previous work exploring audience needs for esports (and sports) is outlined. Secondly, this paper summarizes some of the existing work in providing advances to data-driven esport audience experiences.

2.1 Understanding Esport Audience Needs

Understanding the needs of audiences and their varied knowledge and interests is crucial to be able to deliver engaging experiences. In traditional sports, data-driven content has become more common in recent years, with visualisations of player position and ball tracking data across multiple sports, increasingly relying on GPS-based tracking data and 3D-visualisations [13, 24, 74]. For esports, there is an even greater need to break down the complexity of the gameplay and facilitate insights to the audiences [22, 31]. Indeed, consumer needs research has found that understanding the in-game actions, the skill and decisions of the cyberathletes, is a key motivator for watching because many viewers are also players [22, 31, 53, 73]. This emphasizes the potential for data-driven storytelling to provide engagement points for audiences [5, 22, 29].

Within culture, the esports literature has outlined a clear need for continued research [60, 67]. Previous work within this field has outlined several aspects of consumers that are particularly relevant for esport audiences. This includes a range of features, such as the perception on sponsorship [50], methods of engagement [34, 67] and an evolving trend of consumer needs which outlines the importance of interactive and audience focused experience [30, 47]. At the same time, consumer research in sports and esports have also highlighted the possibility space for interactive content, with data-driven content forming one venue for delivering such content [5, 37, 40, 46].

2.2 Data Driven Audience Experiences

Broadcasting and streaming of esports share many similarities with physical sports. Footage is captured through an in-game camera and transmitted in near real-time. In esports, camera position is

[1]https://store.steampowered.com/app/730/CounterStrike_Global_Offensive
[2]https://playoverwatch.com/en-us/about
[3]https://www.dota2.com/play/
[4]https://na.leagueoflegends.com/en/game-info
[5]https://www.twitch.tv/
[6]https://www.youtube.com/
[7]https://www.facebook.com/gaming/

flexible due to the virtual nature, e.g. viewing through player perspective [69] or through an isometric top-down spectator view [68]. Previous work has sought to optimise esports interfaces for spectators using data [6–8, 70, 71]. One of the underlying motivations being to create *'Information Asymmetry'*, in which the audience has more information than players [8]. This helps generate suspense in esports in the same way as in physical sports, where audiences can have a better overview of the game.

A range of products introduce some form of data-driven visualisations or overlays that augment linear broadcasts [19, 56]. Prior work have shown that data-driven content can measurably invoke emotional responses from audiences [5] and improve the range and diversity of storytelling in esports broadcasting, leading Kokkinakis et al. [29] to coin the term **Data-driven Audiences Experience (DAX)**. Most esports content producers, such as *ESL* [19] and *PGL* [56] use solutions that present key statistics to the audience in overlays on top of the main broadcast view. One example by Liebig [33], provides a graphics engine for *Dota 2* that adds non-interactive statistical information onto the spectator interface. Similarly Block et al. [5] introduced a system which utilized machine learning to identify top performances during a live match, and generate corresponding audience-facing graphics. Research in esports analytics has also focused on providing augmented maps to illustrate high-level gameplay [71], similar to the visual overlay of tactical formations in e.g. football. However, these solutions are predominantly controlled by broadcasters, and are typically delivered as part of a linear - one size fit all - broadcast feed.

Conversely, live viewing experiences that are interactive are comparatively rare. Examples include Charleer et al. [7], who introduced interactive data-driven dashboard for *League of Legends* and *CS:GO*. These give viewers access to live in-game statistics, including some performance measures which aim to be understandable to a non-expert audience. A range of commercial mobile apps exist and have been investigated in the literature [29]. These apps most commonly give users access to statistics, match schedules and simple match recaps. Similarly, major traditional sports leagues use apps to provide statistics, such as *FIFA, NFL,* and *Soccer* [17, 39, 54, 65]. Furthermore, web-based post-game analysis services also exist, which provide statistics or map-based analyses, e.g. *Dotabuff* and *Track-Dota* [25, 63]. While these services provide a more customisable user experience, they are most commonly detatched from the main broadcast platform, accessible via a companion app or a separate website. This creates a separation from the linear feed - introducing extra hurdles imposed in the audience - impacting reach, thus reducing the overall benefit associated with the experience they provide.

Despite this clear need for more interactive, audience focused, data driven experiences, no work in literature found at present has evaluated a comprehensive study of audience behaviour within an active broadcasting environment. This study aims at filling this gap by conducting the first large scale longitudinal case study of user behavioural data within a seamlessly integrated user experience deployed alongside a linear broadcasting feed. Furthermore, this study provides a design framework and its evaluation - through the implementation of the *Dota 2 Twitch Extension* - aimed at informing and advising the development of further similar features.

3 CASE STUDY: THE DOTA 2 TWITCH EXTENSION

The contributions in this paper build on a two year long process of co-design between the authors and one of the world's largest independent esports company (ESL), producing an interactive twitch extension that was deployed at a leading international esports tournament. This section describes the context of the case study, the underlying design process and the resulting *Dota 2 Twitch Extension*. The user evaluation and data analysis will be presented in Section 4.

3.1 Dota 2

Dota 2 is one of the most established and popular esports titles, attracting record price pools and consistent viewership [58, 59]. This title is a competitive fantasy game, in which two teams of five players compete for resources in a large battle arena. Each player controls a unique *hero*, picked during the "draft" phase (directly before the match starts) from a pool of over 100 available heroes. Each hero has unique strengths and abilities. Both teams tactically pick their heroes to create synergies within the team and counter their opponents strengths. Once the match starts, heroes start at their base - or *ancient*. Each base is heavily guarded by several perimeters of defenses. The aim of the game is to defend one's own ancient, while breaking down the opponent's defenses and destroy their ancient. Heroes start at a low power level and with minimal gear and need to increase their strength before attacking the enemy base. To do so, both teams collect resources within the battle arena to level up heroes and acquire new gear that gives players additional abilities. Resources are scattered around the arena in form of non-player character called *creeps*, which yield gold and experience when slain by a player. Throughout the process of levelling their heroes, both teams frequently clash, leading to spectacular engagements and team fights [51, 66] that yield gold to the winning team. When a hero dies, it re-spawns at its base after a time penalty, giving the winning team a further advantage in progressing their siege.

Dota 2 provides a rich environment for the experimentation with interactive viewing elements. Gameplay in *Dota 2* is fast-paced and involves frequent occurrence of multiple important events taking place at once. Heroes are usually dispersed across the arena to maximise resource extraction, and clusters of player frequently clash with their opponents. Broadcasters, however, can only capture a small portion of the battle arena at a time, leaving many important actions and events hidden from viewers [66]. As a consequence, commentators and audience members commonly need to draw on live statistics and additional layers of information about player performance to fully understand the unfolding action. *Dota 2* provides a wealth of open data, both live and historical, that lends itself to the creation of interactive spectator experiences. The commercial significance and large viewership, combined with its tactical depth and opportunities to reveal additional layers of information to viewers through it's available data interfaces make *Dota 2* a conducive environment for the design and study of interactive viewing.

3.2 Design Process

The case study presented here is the outcome of a two year long innovation project between the authors and ESL, one of the world's largest independent esports company. Building on our prior work in esports [5, 9, 10, 28, 29, 42, 44, 49, 66], the iterative design process included consultations with senior stakeholders at the company and close co-design with fans. Key decision makers and stakeholders were identified by the company leadership. The design process involved over 20 design iterations throughout a 24 month period, including focus groups, surveys and interviews with hundreds of fans. Company stakeholders were consulted through regular focus group sessions, in which designs and prototypes were presented throughout the iterative design process. Participants of the focus groups were identified by the company's leadership team based on their involvement in tournament production. The sessions were shadowed by all researchers, and observer notes were aggregated and translated into design requirements. We also drew on on the outcomes from surveys and interviews with fans from our prior work [5, 29], which were conducted on-site at 5 major international tournaments produced by ESL. The process generated a suite of interactive fan experiences, including an experimental mobile app and various virtual reality experiences. The *Dota 2 Twitch Extension* presented in this paper is the product of the collaboration, reflecting learning from previous design iterations and user evaluations. However, in contrast to the other apps and VR experiences, which were standalone experiences accompanying the main broadcast, the *Dota 2 Twitch Extension* was tightly embedded with the primary live broadcast of the event, delivered via Twitch. For instance, any information displayed on the Twitch extension would occlude the video feed and compete with viewers attention. This created a series of new design challenges, which the research team translated into design guidelines together with senior experts at the company from across broadcast, product and innovation divisions. The design guidelines encompass elements of user experience and usability, as well as aspects of the content of the interactive experience, i.e. what types of additional on-demand information is most suited to be delivered embedded alongside the live video stream. The final set of design principles guiding our design are as follows:

- **Unintrusive**: It is important that the user experience does not distract or obstruct main (linear) coverage permanently. Spectators need to be in full control of showing or hiding interactive content, while maintaining focus in the main coverage content at all times. This is particularly relevant for quick and time sensitive events of high narrative importance.
- **Discoverable and controllable**: Fans need to be able to easily gauge what is offered by the extension, and the mechanism for discovering interactive feature needs to be easy to learn. Users should also be able to personalise content to their specific interests, even if they diverge from the primary commentary.
- **Game status and highlight tracking**: Esport titles are complex and it often hard for fans to judge the state of the game and each player's performance. Interactive content should aim to advice and explain to audiences the key moments as well as core indicators in order to break down the state of the game in a understandable manner. A comprehensive status overview also allows the viewers to better anticipate what will happen, and sets the stage for surprise.
- **Providing context**: Due to the high complexity and varied nature of esports, it can be challenging to fully judge key events. For instance, in *Dota 2* heroes can pick up certain items that dramatically alter the power of a hero. The timing of pick-up - whether it is early or late in the game - is crucial to provide meaning to fans. Interactive overlays provide opportunity to offer such context (for instance, by taking into account historical match data), allowing fans to develop deeper understanding of key events.
- **Facilitate catch-up**: Esports audience commonly tune in late and consume live esports alongside other activities (e.g. playing games) and across different devices (e.g. through mobile devices while on the move). Interactive experience should be utilised to allow fans to catch up after missing parts of the match, provide key highlights and facilitate transition of focus between watching the live action and competing activities.
- **Tournament status**: Tournament standings and schedules are important to fans, but often located on separate website. Interactive overlays allow the provision of such information in close proximity to the actual coverage.
- **Visual integration with tournament style and game UI**: The extension had to conform to the tournament's style guide, including colour palettes, fonts and tournament branding. Similar to visual broadcast graphics, the extension also needed to be visually distinguishable from the game's visual style and user interfaces to clearly separate interactive components from the underlying non-interactive video feed.

The set of identified design principles were then translated into concrete design and working prototypes by the esports company's technical team. The extension was trialled at three international tournaments, with minor refinements being implemented following focus groups with fans. The final design and large-scale deployment are the basis for the case study presented in this paper.

3.3 The *Dota 2* Twitch Extension: Description

The *Dota 2* extension broadens the video stream with a set of interactive information panels that can be accessed any time before, during or after live matches. In order to adhere to the the "**Unintrusive**" principle, all panels are initially closed, and the extension presents itself to users as a collapsed column of five navigation button floating in the centre-left area on top of the video feed (Figure 2). This specific placement location has been selected as it does not interfere with existing elements on the video streams, such as bottom halves or in-game displays. Each button is associated with a separate information panel, which can be opened and closed at any time by the user. This allows the user to take control over what and when information is displayed ("**Controllable**"). When opened, the panel itself has a semi-transparent background to further minimise disruption from the linear broadcast.

When loading the extension, the top-most button - **Live Recap** - presents a tooltip that makes viewers aware of the Live Recap function and marks unread notifications as red dots ("**Discoverable**"). Clicking the button opens the Live Recap panel (Figure 3). The panel consists of a scroll panel that chronologically lists important highlights from the match, as well as periodically providing match summaries ('This match so far'). The Live Recap is designed to highlight notable events and performances to viewers that are usually invisible to viewers, as well as to allow viewers who join the stream at any point to catch up with the live match ("**Highlight Tracking**", "**Facilitate catch up**"). Furthermore, key moments of the match provide contextual information. For instance, when a key item is picked up, the summary states if this is "fast", "average" or "slow", by comparing timings to historical matches of the current season ("**Providing context**").

Figure 2: In its initial state, the *Dota 2* Twitch extension provides a column of five yellow buttons on the center left portion of the game footage. The top button - Live Recap - can present push notifications, informing users of key events during the match.

The second button opens the Player Performance panel (Figure 4). On the top, both teams logos and their win probability are shown, which is calculated by taking into account hundreds of key performance indicators (Section 3.4 will provide details on how data-driven content is generated). In lieu of a reliable "score" (equivalent of goals in football), the win probabilities give viewers a more refined birds-eye view on "**Game status**" and help viewers "**Catch up**" after a break to gauge the overall state of the game. Below the win prediction, the panel lists a head-to-head comparison of team and players performances, highlighting important key performance indicators and showing how well each player performs on a normalised scale from 0% (poor performance) to 100% (top performance), providing crucial context for judging each player's performance. The performance indicator is explained in detail in the previous work by Demediuk et al. [9]. The performance indicator is calculated by taking into account a range of contextual factors (the chosen hero, their role, time of the match) as well as 13 different Key Performance Indicators, such as gold earned or kills scored [9]. For each player, the top three most impactful Key Performance Indicators are listed, giving viewers insights into which aspects of the players' performance determine their performance index.

The third panel the Player HUD - presents in-depth status information about each player (Figure 5). At the top, the HUD shows the players hero, name and level, alongside primary KPIs, such as the number of kills and the effectiveness in earning gold. Underneath, the HUD visualises how each player develops the talents and skills of their in-game characters as well as provides a status of their health and resources (green and blue bars). Lastly, the HUD shows the items each player has in their positions (giving characters important power boosts), as well as their performance in obtaining

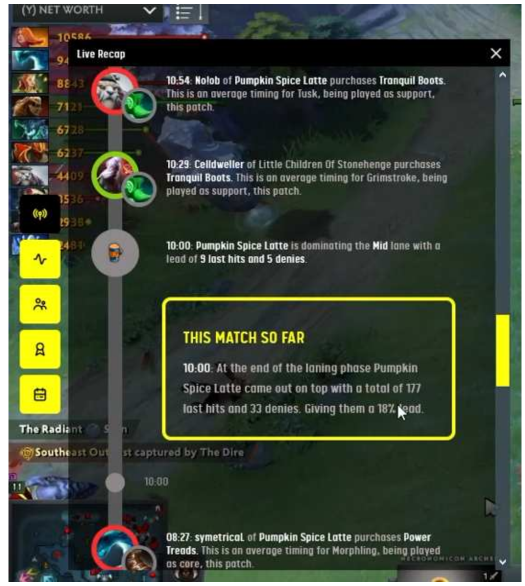

Figure 3: The live recap provides a chronological list of important highlights and outstanding performances as well as offers periodic match recaps that allow viewers who have tuned in late to catch up on the action.

Figure 4: The performance tab shows an overall win probability for each team, and lists key performance indicators of each player alongside their contribution to the team's chance of winning.

gold. Some elements in the HUD allow for additional interaction that reveals more layers of information. For instance, moving the mouse over a skill or item provides a tooltip with details about the item. The provided information gives viewers more insights and ability to explore performance beyond what is normally covered in the linear video feed ("**Game status**").

Figure 5: The player Heads-up-display (HUD) provides detailed status information about each player.

The last two interface panels provide information about standings and schedule of matches, this covers the further information needed which has been highlighted in the "**Tournament status**" requirement. The Standings panel provides a tree view of the group or knock-out stage, depending on the stage of the tournament. If a live match is on, the current match is highlighted visually within the standings. The final panel - schedule - provides information about upcoming matches. Both panels provide convenient access to information otherwise only found disparately, across multiple web-sources and apps. Both standings and schedule are available any time during the tournament (before, during and after matches).

Overall, the *Dota 2 Twitch Extension* creates a rich interactive experience that accompanies the live broadcast. The extension 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.

3.4 Implementation

The extension is developed in HTML and JavaScript, utilising the Twitch API [12] to integrate with the live video stream. The twitch extension receives its content through a dedicated data link with a bespoke data service, which was designed and implemented by the authors (a detailed description of the data analytics and machine learning techniques can be found in [9, 11, 29]). The data service has access to the live match data, which it receives from the tournament operator. The data service compares the live match data to thousands of matches from the current season, and automatically generates highlights, status overviews, analyses of performance and match predictions, which are then broadcast in form of a structured JSON packages to all viewers via Twitch's content delivery network. The extension runs in the browser of each viewer and translates the data packages into the described interactive user experience.

4 USER EVALUATION

The *Dota 2 Twitch extension* extension was used during the *DreamLeague Season 15 DPC Western Europe* for both Upper and Lower division for the period between *Apr 24 2021* to *May 22 2021*. The 4 week event provided an opportunity to study how audiences engaged with the interactive features in an ecologically valid setting. For this purpose, the extension was modified to collect anonymised telemetry data for each individual user. Full ethics approval was granted by the University of York's ethics committee. The aim of the data collection was to characterise general usage patterns of interactive features as well as validate our design principles. Specifically, the study sought to identify how do passive consumption of the linear video stream and active engagement with interactive content entwine depending on various stages of the tournament, and phases of live coverage.

In order to draw observations and comparisons from the data, several steps were followed to allow for data validation and synchronisation, in addition to analysing user activity and defining interactions between user and extension. This section first outlines the steps utilised in pre-processing user data, including steps taken for collecting data, followed by a general analysis of user interactions and how it relates to real world events, and ending on an analysis of user consumption patterns which assist in defining how an interaction behaviour can be observed across users.

4.1 User Analytics Capture

In order to collect usage data, the *Dota 2 Twitch extension* utilised the Google Analytic API [20] that allowed for several aspects of user interaction to be collected for analysis. Table 1 contains a breakdown of all of the features present in the usage dataset.

The *Dota 2 Twitch extension* deployed during the *DreamLeague Season 15 DPC Western Europe*, from the period starting **Apr 24 2021** to **May 22 2021**. During this period, the *Dota 2 Twitch extension* covered 60 matches for the upper and lower divisions, which generated data from *306,545* unique users. Data was collected for all users who enabled Twitch extensions. Some browser settings prevent google analytics from collecting data. Packet loss was also commonly observed (see next subsection). Users who did not actively engage with the extension did not generate active log entries. However, the delivery of the push notifications (the little red number flag on the "live recap" button) was recorded for all user, regardless of their activity.

4.2 Data Validation and Cleaning

Of the 306,645 total users, *101,729* users (~33%) engaged with the extension directly. The rest received push notifications, but did not otherwise engage with the extension and are therefore excluded from further data analysis. In order to evaluate interactions across the different stages of broadcast, exact timings of the different matches and their phases were collected. The two main phases of a *Dota 2* match consist of the *Draft Phase* (in which teams pick their heroes) and the *Game Phase* (the actual match). This process was automated using the OpenDota API [64]. Additionally, timings of the different phases within a match were determined utilising the Clarity Parser [55] library - a open source Java library for parsing and processing *Dota 2* replay files.

All times were converted into UTC times so the information could be synchronised with the Goggle Analytics data. An artificial delay of five minutes was added to all game times, as live video of the event, as well as the data received by the extension was delayed

Table 1: Dataset feature overview

Feature	Description
User ID	A unique ID that relates to a single user
Time	Human readable time of interaction
Delta	Time difference between two consecutive interactions
Category	A category defining the event, used to identify the event
Label	Additional context for the event when available
Value	The numerical value associated with the event when available
Action	The textual value associated with the event when available
Unix Timestamp	The time in Unix Index (seconds) that the event was performed by the user

by that amount by the tournament organiser. This is a common anti-cheat technique in esports broadcast, particularly during the COVID-19 pandemic in which players competed from home.

In order to assess and validate the dataset further, the usage dataset was pruned of errors, such as faults caused by network traffic or other similar technical issues. This was achieved by investigating the sequence of actions performed by any given user, particularly the "Category" of the events. The event categories relate to the type of event, including:

- **OpenWidget**: when a panel has been opened.
- **CloseWidget**: when a panel has been closed.
- **Hover**: when a user hovers their mouse over any relevant UI elements, which reveals additional textual information in the form of tooltips.
- **Scroll**: when the user scrolls through text.
- **Tab Open**: when the user opens an additional window within a panel.
- **RecapNotification**: when the user receives a push notification indicating there is a new live recap story element that can be read.

By identifying possible sequence of events, a simple finite state diagram - as depicted in Figure 6 - can be reproduced to validate and identify any unexpected behaviour and remove it from the dataset. For example, a user path of "OpenWidget -> Hover -> Scroll -> CloseWidget" would be a valid path, whereas a path of "OpenWidget -> CloseWidget -> CloseWidget" might indicate a problem with the logged data due to two consecutive close events.

Finally, after removing users that did not engage with the extension, and discarding faulty interactions (i.e. that have reached unexpected states) a total of *101,729* unique users were included in the data analysis.

4.3 Data analysis

In total the cleaned dataset contains *1,628,017* distinct interactions within the four week period of **Apr 24 2021** - **May 22 2021**. Figure 7 depicts the average distribution of activity events per user. Outliers above the upper quartile range were removed due to a large deviation of values between maximum and remaining values. A series of observations can be made. Given that we had removed 'passive' users from the dataset, the majority of log information relates to "active" interactions that require user input - the mean for the "passive" *RecapNotifcication* was comparably low. Secondly, users commonly inquire deeper into the interactive feature than just opening and closing the extension, with a wide range of interactions recorded (e.g. *Hover* and *Tap Open*). Both *Second Level* interactions - switching to new panel when the extension is already open, *Third Level* interaction - switching sub-panels - and *Fourth Level* interactions - inspecting additional information in the sub-panels via "Hover" as well as "scroll" - are commonly observed.

Note that across all users, the average was 8 actions combined. This average number is relatively low, given the data was collected across a four weeks period (but see Commercial Implications in Section 5). Figure 8 shows a histogram of number of interactions per user. From the *101,729* users that have engaged with the extension, *15,302* have interacted 20 or more times. Conversely, a large proportion of the population has interacted fewer than 10 times. Consequently, the majority of interactions are generated by a minority of "power users". This distribution of engagement is well known from other observational studies [4], splitting users into a large portions of "shoppers" (displaying only shallow engagement), and "power users" (show prolonged engagement and fully explore the interactive offerings).

4.3.1 Longitudinal Analysis. We analysed engagement with the extension across different stages of live coverage by synchronising log telemetry data, as well as match and game-phase timings. The majority of interactions (68.5%) occurred during the live match phase. 5.2% of interactions took place during the relatively short draft phases (15 - 20 minutes). The remaining 26.3% of interactions happened in the time period between matches. Note that the extension's full functional capacity was only available during the live match. Between matches and during the draft phase, the extension only provides tournament schedule and standings. However, the data suggests that viewers were aware of the extension during all stages of the tournament, and increased their engagement during the primary game phase. This also provides evidence that the primary data-driven content presented in the extension - providing context and in-depth analysis - provides additional value during the game phase.

Figure 9 displays user activity for the duration of the final match, during which a peak number of concurrent users can be observed. The example illustrate the slow build-up of engagement with the widget before the match (white background) and during the draft phase (light blue). In both cases, only tournament status and schedule are populated, all other tabs remain inactive until the match starts. During the live match (green background), activity across all types of interactivity increases, with notable peaks and troughs.

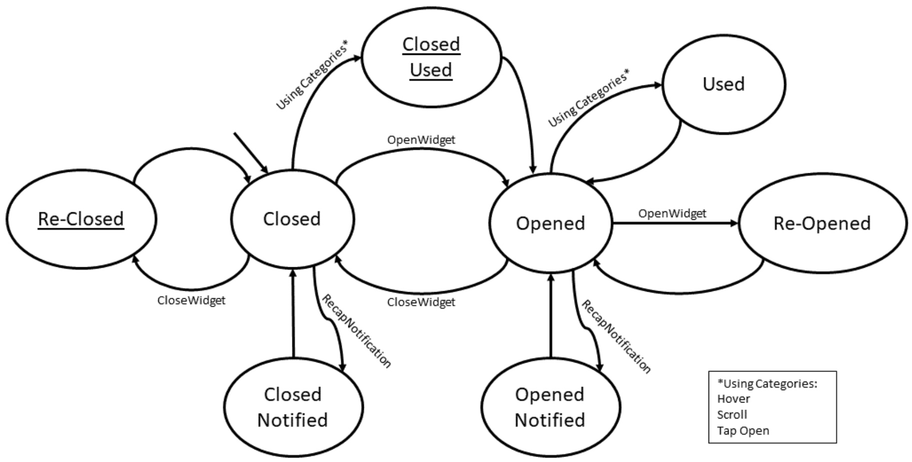

Figure 6: A graphical representation of the Finite State Machine used to parse through and join user interactions. States indicating a unexpected sequence of actions have been underlined.

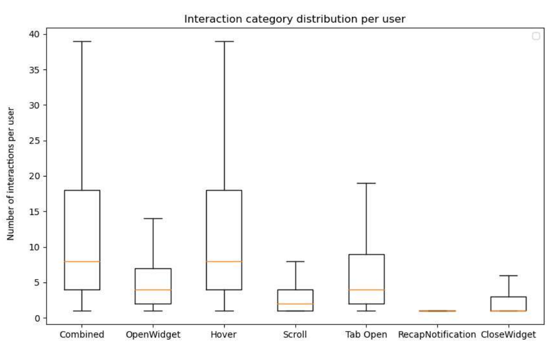

Figure 7: A box diagram depicting the distribution of user interactions per category - outliers have been removed for display purposes

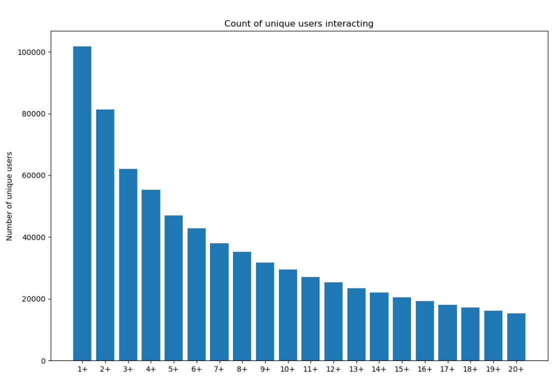

Figure 8: A histogram that displays the amount of user interactions per users

Usage of the extension builds up over the course of the example game, then drops a few minutes before the end of the match. *Dota 2* involves variable gameplay, creating both quiet periods of no conflict and short bursts of intensive team encounters, which may explain the peaks and troughs in active use. The last minutes of a match usually involves substantial action, as one of the teams invades the enemy base, which may explain the drop-off. Similar patterns could be observed across the other matches. While further analysis is required, the data suggest that the observed patterns of interaction may correlate with the cadence of the match. This is further discussed in Section 5.

Usage of the extension also increased over the four week period, peaking during the final weekend (Figure 10 depicts). This is expected, as it follows general viewership, which typically increases over the course of a tournament. The authors did not have access of match-level data on total viewership (Twitch only provides aggregate statistics of daily peak viewership), therefore a full comparison was not possible.

4.3.2 Active vs. Passive Engagement. Previously described analysis has focused on aggregate numbers of discrete activity entries. This section focuses on analysing sequences of actions performed by individual users, and how phases of "active engagement" can be further qualified. The aim is to provide additional insight of how the viewers' focus switches between active use of the extension and passive consumption of the video stream. We define active engagement as periods of time in which the user is predominantly focused on the extension. For instance, a sequence of actions where the user opens the extension, selects the Heads-up-display, a player and then hovering the mouse over an item to get a tooltip. During this time, it is likely that the user is fully focused on interacting with the extension. In an alternative scenario, a user opens the extension and leaves the live recap open for one minute, then switches to another panel, and subsequently closes the extension. In this scenario, while the extension is visible, the user is likely to split

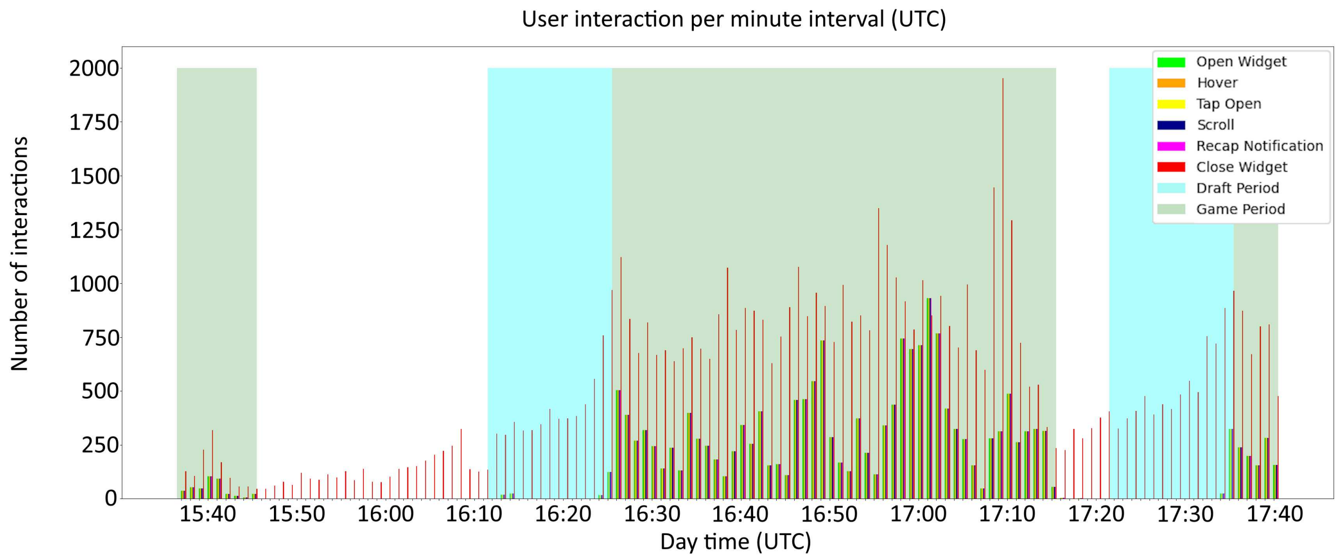

Figure 9: A demonstration of user activity in one-minute intervals for Upper Division last week final Game 1 with 30 minutes offsets

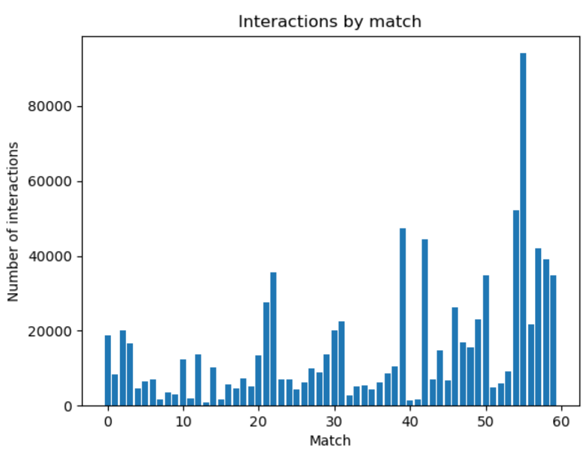

Figure 10: A histogram displaying the number of users active at all games covered in the series

their attention between the extension's information displays and the live video stream.

The challenge of characterising "active engagement" in our telemetry data is in identifying a suitable time threshold that links individual actions into sequences of active use. If time lapsed between two subsequent activity events is below the threshold, it would link them into a period of active use. Multiple subsequent events that all fulfill this criteria form a larger active period. If the time lapsed between two subsequent activity events is above a certain threshold, it is assumed that the engagement is passive, in which the user may not be fully focused on the extension. Literature suggests that user attention retention is unlikely to be maintained over long periods [52]. Particularly as the information being consumed by users is displayed alongside a *Dota 2* game, which increases the amount of overall information displayed on screen [5]. Furthermore, it is known that sports can modulate and impact audience attention retention [1], however the effects of esports has not been tested. Similarly, single interaction performed by the users are expected to retain their attention for a limited, but non-zero length of time.

To determine a suitable threshold, a histogram showing the distribution of time lapsed between any two subsequent events in the dataset (Figure 11) has been plotted. The first bar shows that around 270,000 log entries occurred less than 1 seconds from each other. Of the *768,309* total interactions, *155,145* (approximately 20%) were separated by more than 30 seconds. The distribution focuses on time scales that are reasonable to consider for an activity threshold.

Figure 11 provides a visual representation of usage patterns, displaying the number of times that users performed two consecutive actions (X) seconds apart. The data shows that the time between interactions plateaus relatively quickly at approximately 8 seconds, thus user patterns past this threshold are roughly equally distributed. By utilising the Elbow technique [15], a threshold of *5 seconds* can be established, as this the most pronounced curve in the data distribution. This time period can then be used as an approximate duration for which users are actively engaging with the extension. While this is an approximate value, it suggests that a large number of subsequent actions happen within that time period. This could assist further analysing the data and provides a starting point for quantifying user interaction based on engagement patterns.

Using the active threshold outlined, it is then possible to identify all sequences of active usage. This can be defined by a sequence of actions where all log entries succeed each other within 5 second. A sequence can contain a single interaction, if it is isolated from

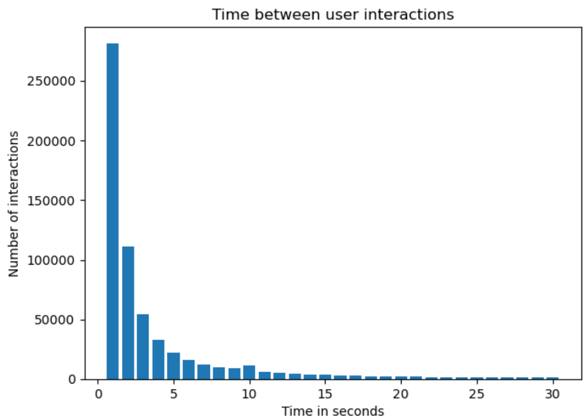

Figure 11: A histogram displaying the time difference between any two consecutive interactions capped at 30 seconds

previous and subsequent log entries by more than 5 seconds. Using this method a total of *121,101* sequences were identified across all users. Figure 12 shows a distribution of number of interactions per active sequence. The distribution shows that a large number of sequence only consist of a single isolated action. However, a total of *74,643* sequences (62% of all sequences) contain two or more interactions. The distribution also shows that the number of interactions per sequence is varied.

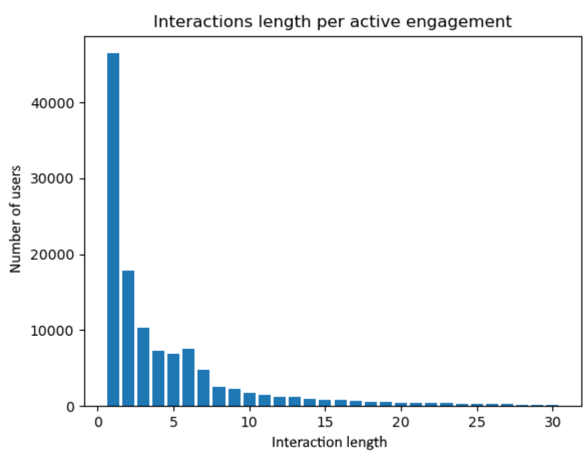

Figure 12: A histogram depicting the number of interactions for active engagement

Figure 13 shows the distribution of users based on the percentage of time spent actively engaging with the extension as per our measure. This was achieved by calculating the duration of each chain of interactions, and compared with the overall time the extension was visible. The maximum value was calculated by measuring the time difference between the cumulative time between all pairs of "OpenWidget" interaction and the subsequent "CloseWidget".

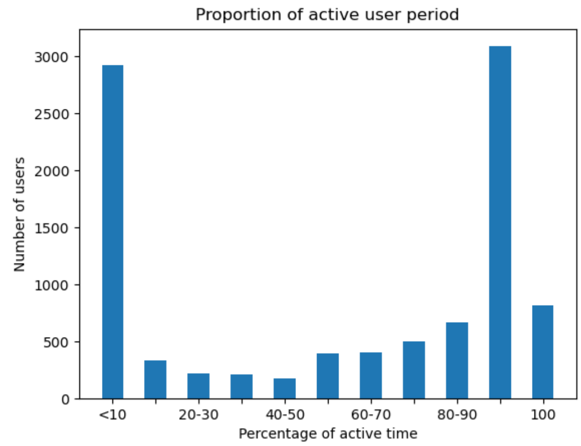

Figure 13: A histogram displaying the proportion of time users spend actively engaging with the extension in relation to the time the extension remained opened

The data shows that a large number of users spent less than 10 percent of their time 'actively' engaging with the extension - as depicted by a large peak in the "<10%" bin. However, a similarly large number of users spent the vast majority of their time (>90%) actively engaged with the extension. This usage pattern seems substantial, given that the extensions competes for attention with the live match. Additionally, the data shows that the rate of occurrence and duration of active usage may correlate with the cadence of gameplay. Figure 14 displays all active sequence performed by all users within the upper bracket Game 1 final. In this graph, every user is depicted as a thin horizontal row on the *Y-axis*, with active sequences being connected in blue. Longer horizontal lines mean longer active sequences. Short lines or dots represent short bursts of activity. All users are stacked vertically. The X-axis represents time from the start of the draft phase to the end of the match.

As depicted in Figure 14, the active engagement periods clearly cluster around certain time of the match (see regions that are more intensely blue). Other regions of the figure are mostly white and devoid of active usage, suggests that little interaction occurred across all users during this time of the match. While more in-depth analysis is required, this provides an indication that in-game aspects may affect how the extension is used, and consequently how the audience attention can shift during the match.

5 DISCUSSION

The data analysed in this paper draws a detailed picture of how users interacted with the interactive content provided by the *Dota 2 Twitch extension*. The following sub sections discuss the major findings of the analysis, with a specific focus on validating the principles underlying the design of the extension. Finally, this section outlines limitations of the presented study and identifies areas for future work.

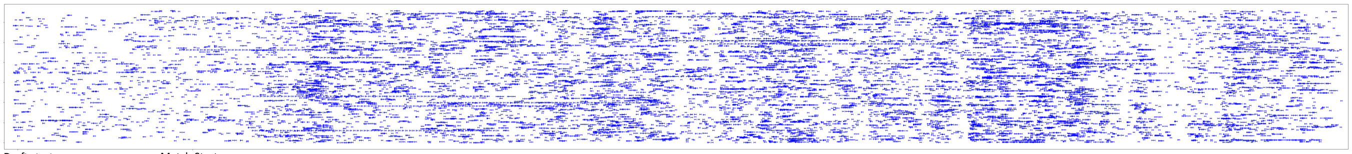

Figure 14: User activity performed in the Upper Division last week final Game 1 as chained by the Active period threshold of 5 seconds. The X-axis represents chronological time from start of the draft period until the end of the match. The Y-axis represent user activity where each unique user has been assigned a horizontal value in the axis.

5.1 Overall Characterisation of Usage

The *Dota 2 Twitch extension* introduced novel interactive content alongside the video stream. Despite not being actively advertised or explained as part of the video coverage, the extension organically attracted a substantial number of viewers. Roughly one third of all viewers captured by the telemetry data actively engaged with the extension. Of those that did engage with the extension, the depth of interaction was varied. 55% of users displayed only "shallow" engagement, dipping in an out of the extension only once and never returning. However, 20% of active viewers can be considered "power users" who displayed active prolonged engagement, and explored the full functional depth of the extension over the course of the tournament. In between shallow and power users is a varied gradient of engagement. However, while this distribution of engagement is not new in the context of prior research (e.g. visitor studies in museums [4]), this study is the first to quantify large-scale adoption of interactive offerings in the context of live esports and sports. While engagement will depend on the specific design of the interactive offering (see Limitations & Future Work), this study observed a high "organic" uptake (without additional advertisement or incentives) and good levels of engagement considering the added experiences compete with action-packed live coverage. Consequently, the data provides clear evidence that interactive content is in demand, and can help conversion of audience from passive consumers to active viewers. The varying levels of engagement and evidence for systematic functional exploration across users suggest that the design was successful in being "**Discoverable and controllable**". However, based on the data, it remains uncertain if every user was able to discover the functionality. The design was purposefully subtle, only showing five buttons in a marginal area of the screen when inactive. Two thirds of viewers never engaged with the extension, suggesting the design was also successful in being "**Unintrusive**". Unintrusiveness and discoverability are at obvious odds with each other. The measured engagement characteristics can likely swayed towards higher adoption rates by deploying animation or active guides to encourage usage. Additionally, explaining and encouraging use of the interactive extension in the main video feed (e.g. through panelists) may result in increase adoption rates.

5.2 Contextualising Interaction

The study showed that levels of engagement varied depending on the tournament stage and on the stages of live coverage during each day. Since this extension provides most of its content during live matches, this stage saw the highest usage. Viewers consistently opened tournament schedule and standings throughout the broadcast, validating our "**Tournament status**" design criteria. Within the live match, usage tended to build up as time progressed suggesting that the relevance of the provided information displays increased to viewers. A possible explanation for this observation is that judging performance and strategy in *Dota 2* matches becomes increasingly complex as the match progresses. The extension was purposefully designed to show "**Game status and highlight tracking**" as well as "**Providing Context**". The data-driven insights provided by the extension (such as win prediction and performance indicators) may thus become more valuable as the match enters later stages.

5.3 Active vs. Passive Usage

We introduce a mechanism for identifying "active" use, defined as a sequence of interaction happening in short succession, based on a 5 second threshold. This analysis brought out two common forms of interactions across users. By analysing those behavioral patterns, a set of three engagement levels can be determined. In a large number of cases, users engage with the extension in bursts of connected interactions. This can be commonly observed when users open the extension and navigate through several panels utilising features and engaging with the extension in varying ways. This interactions typically occur within short intervals of times - commonly within the highlighted threshold of 5 seconds. During this period, it is expected that the user is actively engaging and consuming the information being displayed. In another common behaviour of interaction, users open a panel that remains open for a long period of time. During this time users perform actions sporadically, with large periods of inactivity in between actions. In this case, information is being displayed and it is expected that the user is passively consuming the information with limited attention, as this is being shared with the linear coverage feed in the broadcast. Lastly, it is important to note that there are periods of time during which the extension is closed completely. This provides an insight into a third behavioural pattern, during which users and not engaging with the extension, neither passively nor actively.

5.4 Interaction with In-Game Events

The data included various indicators that usage of the interactive features and events happening in the virtual game worlds correlated. First, a sharp drop in engagement with the interaction in the final minutes of each match can be observed. This stage often entails intense action that audiences follow closely. Secondly, there were also clear peaks and troughs in usage of the extension throughout the live match across all users. These fluctuations in collective usage are likely linked to particular in-game events as well as the general cadence of the match. However, a statistical link could not yet be established and should be explored further in continued work. Identifying key events and measures for such a "cadence" are non-trivial, involving the detailed analysis of replay data. Esports such as *Dota 2* provide rich match recordings for each match, enabling the detailed correlation between audience telemetry and game analytics. This can be subject to future research.

5.5 Commercial Implications

It is important to contextualise the findings from this paper within the commercial drivers of the esports ecosystem. Most esports broadcasts are free to watch. The majority of esports revenue comes from sponsorship [37], which have been shown to have had a positive impact on brand awareness and image [16]. Consequently, the addition of new audience experiences, such as the one presented here, is ultimately driven by generating additional revenue. The collected data and presented methodology has various commercial implications. While not all viewers utilise the extension, those viewers who do, engage actively and receive added value through the contents of the extension. This can positively impact the effectiveness of advertising, as more disruptive forms for brand placements (such as rolling unskippable ads) can lead to negative impact on users, less disruptive forms have comparable brand effectiveness while reducing the negative impact to audiences [2, 43]. Sponsorship embedded in interactive experience is thus prone to generate a different depth of engagement with fans and a clearer perception of added value than traditional "passive" sponsorship displays embedded in the linear video feed [3, 26]. Even for the majority of fans who only click a handful of elements in the twitch extension over the course of the four week tournament, the short burst of interaction creates a moment of *focused and measurable attention*. From a sponsorship perspective, this interactive engagement is different to usual product or logo placements in the passive video, of which no metrics of exposure exists. Such 'interaction with brands' - similar to advertising placed within virtual game worlds - was considered valuable to the tournament organisers we worked with and deemed to create new sponsorship offerings that compliment existing inventories. It is also important to note that such interactive engagement lends itself to being personalised to each individual fan, which has been shown to offer similar levels of brand retention while reducing the negative impact to audiences [3]. Furthermore, interactive content generates detailed information about fans. While in this paper we deployed offline analysis of the telemetry data after the tournament, similar techniques could be utilised to collect real-time data about fans. A tournament organiser or brand could leverage such data to know when there is a downtime in the cadence of the match, when fans are active in the extension and what they are interested in (e.g. what player they have selected in the HUD). This could create numerous possibilities for the delivery of tailored advertisement or merchandise. Lastly, interactive extension could be leveraged to deliver premium content to fans and be monetised through subscriptions or micro-transactions.

5.6 Limitations & Future Work

The presented study provides the first large-scale analysis of how interactive audience experiences in esports are used in an ecologically valid environment. Many of the presented findings are specific to the design of the *Dota 2 Twitch extension*, and generalisation will require additional study of engagement across different esports titles and applications. The the presented design principles and methodological foundations for our analysis, including the addressed challenges of log analysis and definition of active use seek to inform future design and evaluation of interactive audience experience in esports.

Additionally, as explored in Commercial Implications, the analysis presented was performed post event. A possible extension of this work could be the use of *real-time* telemetry data to further drive fan engagement 'in situ', creating a series of interesting creative and commercial opportunities, as well as generating additional insights into audience behaviour. Combining real-time and historical engagement data from each user alongside generative AI, for instance, could enable much more sophisticated penalisation's an tailored content delivery. This, in turn, could enable better live customisation of data, catering to individual users needs and preference - ultimately generating value for fans and commercial opportunities for content creators. Similarly, analysis of live viewer engagement could also be leveraged to improve other elements of the broadcast, including social media engagement, or post-match analysis. For instance, the highlights treated during the post-match analysis could be informed by spikes in the use of the extension and automatically generate social media short-form content. This could also be further enhanced by continued work to investigate live usage with in-game "cadence" as explored in Interaction with In-Game Events.

Future work needs to also focus on greater customization in appearance and presentation. While the design language of the extension followed the "**Unintrusive**" general patterns, users may choose to customize the look to better suit their needs and preferences. Additionally, the extension also adhered to the overall tournament style guide, dictating several aspects of the look and feel. While this was a limitation in this study, future work in the domain could explore the effects of greater customization for appearance and presentation with continued engagement, in line with the "**Discoverable and controllable**" criteria discussed in this paper. Additional customizability could also have accessibility implications, allowing users to adjust the extension to suit their needs. This greater customization in addition to Real-Time Viewer Engagement Analysis could also serve to provide greater insights into why some users opted out of engaging with the app.

Lastly, it needs to be recognised that the behaviour of esports audiences - particularly of analysis-focused and data-heavy game titles such as *Dota 2* - may not generalise of the wider esports viewership. Future work has to focus on applying the analytical methods proposed here to other interactive audience experiences to generalise our understanding of audience behaviour and associated creative and commercial opportunities beyond this first case study. Similarly, the translation of interactive audience experiences to traditional sports needs to be subject to further study.

6 CONCLUSION

This paper presented the first large-scale case study of esports viewing consumption patterns an interactive, data driven audience experience in esports, used by over *101,729* people during the *2020 DreamLeague Season 15 DPC Western Europe* tournament. By investigating sequences of user interactions, this paper proposes an active period threshold of 5 seconds. This in turn allows for a more refined investigation of how users engage with interactive overlays. By studying user activity in conjunction with the active period threshold proposed in this study, this paper documents methods for detecting behavioural user patterns. Future work will investigate additional details in the potential relationship between user telemetry and in-game events, which may help explain the observed interactions. The contributions raised by this paper can also be used to assist the understanding of future challenges and opportunities in interactive viewing across sports and entertainment.

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