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Applying and Visualising Complex Models in Esport Broadcast Coverage

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ABSTRACT

Esports has become a popular field of research, enabling advances in areas such as machine learning and environment modeling. However, complex modeling systems require complex visualisations. Despite that, visualisation of complex modeling systems within esports have been limited or fragmented, particularly when focused on the audience. Furthermore, the use of data visualisation and data-driven storytelling has been proven to be an effective and imperative method for enhancing audience experience for esport spectators. Therefore, this paper investigates data visualisation techniques within esports, and compiles design considerations for developing visualisation tools for esports broadcast. This is achieved through a case-study, in which the WARDS model was utilised in live coverage of a *Dota 2* tournament and evaluated through observational data.

CCS CONCEPTS

• **Human-centered computing → Visualization application domains**.

KEYWORDS

Visualisation, Esport, Storytelling, Audience Experience, Visualisation Design

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1 INTRODUCTION

Esports as a form of digital media is one of the larger markets for digital entertainment [17]. As a result, esport has seen a wealth of investments, including an abundance of academic interest [15, 16, 18]. One example is in the field of understanding the game environment through modeling [8, 9, 20]. Another area which has been investigated in the existing literature is audience focused visualisation [2, 4, 14].

Both areas provide indisputable contributions and insights, and generally relate and rely on each other [14, 21]. However, a detailed exploration on the steps necessary to bridge the gap between complex theoretical models to visualisation applications has not been fully investigated. This paper aims to replicate the work by Chitayat et al. [6] in modeling the "ward" mechanic in *Dota 2* and investigate how to produce and deploy a visualisation tool for this metric. This tool was later utilised in the 2021 *Promod Esports* coverage of the "Roshan Rumble" grand finals (25$^{\text{th}}$ July 2021), a UK based *Dota 2* tournament[1].

The contribution of this paper is twofold. Firstly, a case study on visualising and deploying the WARDS [6] metric is presented. This case study was deployed into a real-world tournament, enabling the collection of ecological data, as well as highlighting practical considerations when dealing with the esport broadcast field. Secondly, this paper compiles the key findings, reflecting on the data collected in the case-study, to formulate a set of design considerations, aimed at enabling the application of complex models into esport broadcast contexts for audience experience. These considerations can serve as a starting point for more in-depth studies towards developing a framework for esport audience data visualisation tools.

This paper firstly provides a general description of *Dota 2* (Section 2), to aide the reader in contextualising the work presented. A brief description of the WARDS model is also provided, however a full description of the model can be found in the original work by the authors [6]. Secondly an outline of the literature highlights existing models and visualisation techniques that are widely used and described within the domain (Section 3). This work then depicts the steps taken to design and develop the WARDS visualisation tool and provides some insights into its application within the tournament. Observational data collected in the deployment of the tool is analysed. Lastly, the findings are compiled into a series of design considerations to aide in future research and development of models catered to esport audience experience.

[1] https://liquipedia.net/dota2/Roshan_Rumble

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2 DOTA 2 AND WARDS

Dota 2 was selected as a research domain due to the wealth of knowledge available in the literature [13, 19, 22], large audience [18] and vastly accessible datasets [5, 6]. In *Dota 2*, two teams compete for in-game resources in an attempt to destroy the opponents base. The environment is split by three main paths called "lanes", where computer controlled entities will spawn periodically and move towards the enemy base.

As described in the previous work [6], *Dota 2* is an imperfect information game, i.e. players do not have access to all game state data. Due to the Fog of War (FoW) mechanic, teams can only gain information about a region of the playing field if a friendly entity is present in the area. Wards are in-game items that can be placed by players on the map. Once placed, a ward becomes a friendly entity, providing "vision" in the area, enabling information gathering as demonstrated in Figure 1.

Figure 1: A demonstration of the FoW and warding mechanics. The left side of the figure displays how there is an area under FoW (darker shaded area). The right side of the figure depicts the same area when a ward is placed down, revealing an enemy unit that was not visible beforehand.

This paper first replicates the Wards Aggregate Record Derived Score (WARDS) [6], in which the authors have created a metric for quantifying the impact of a ward in a *Dota 2* match. The authors have provided a general formula for calculating WARDS, which relays on several in-game metrics and events. This allows for more in-depth analysis of the mechanic, which is generally considered an important aspect of the game that directly impacts the outcome [6, 21].

3 RELATED WORK

In the field of esport, there has been a clear interest in visualisation of data for storytelling and audiences experience more broadly. Block et al. [2] has outlines how data can be used to enhance storytelling in the broadcast of esports. In particular, the authors depicted how historic data can allow broadcasters to draw comparisons between a current game and the existing knowledge base. This work also highlights how small understandable remarks can enable storytelling, particularly when it provides quantifiable (at-a-glance) data that was not easily accessible otherwise. Additional information about the tools utilised was later described in a Showcase Brochure [3], displaying a consistency between game and tournament branding.

Later, Kokkinakis et al. [14] developed a companion app, where audiences could access all of the historical data to draw their own narratives. This study, demonstrated the key role that the presentation of data can have into audiences, coining the term Data-driven Audience Experience (DAX). The findings of the study confirms the importance of data into storytelling, and outlines how significant points of accessible data can enable audiences to enhance their experience by providing more understanding of the events in the game, and the underlying contexts that may not by easily accessible.

While not audience focused, Afonso et al. [1] have proposed a visualisation tool aimed at players, analysts and coaches from a learning and improving perspective. In this work, the authors outline the importance spatial-temporal information, in this case represented through animations. This is relevant as esport titles are generally time sensitive, with several connected events taking place over large areas of the map through an indeterminate duration. While the work presented was not aimed at audiences, the use-case described by the author has implications into how users parse information being displayed. This was later also confirmed by Xenopoulos et al. [23].

Beyond visualisation, the use of data to model the game environment is prominent. Modeling aspects of the esport environment can serve several purposes, including classification of data [9, 20, 21] and quantification of data [8]. WARDS [6], replicated in this study, is an example of modeling the environment to quantify data. The authors outlined how a large difference in the calculated WARD score for a team, leads to a significant difference in the total resources accumulated by the team within a short duration. The total cumulative resources for a team is widely understood by the literature as one of the key metrics that determine the outcome [6, 8, 20]. In order to formulate the WARDS metric, the authors interviewed game experts who also supported the key importance of the warding mechanic for accumulating resources and ultimately winning the game. Despite that, no current visual depiction of the WARDS metric could be identified, making it not accessible to audiences and thus limiting its storytelling and DAX applications.

Furthermore, while the importance of conveying data to audiences is clear, and it is shown that modeling the game environment is an effective way to gain useful insights [5, 12, 13, 19], no current audience focused studies could be found that attempts to visualise a complex model within esports. Therefore, this paper uses the WARDS model as a case-study to compile a list of design considerations to enable to future development of audience facing visualisation tools of complex models.

4 METHODS

In order to formulate a set of design considerations, this paper describes a case-study of the WARDS visualisation tool. This tool was developed by assessing the existing literature in data visualisation for esports, borrowing from previous findings in the domain [1–3, 14, 23]. The visualisation tool is integrated into the "Roshan Rumble" grand finals, which took place in the 25$^{\text{th}}$ July 2021.

Observational data of the broadcast was collected, and analysed to evaluate the integration of the tool with a data-driven storytelling perspective. The use of observational data has been shown to be an effective method of analysing ecological data within esports [2, 7, 11]. The data is then analysed to evaluate the case-study, ensuring the integration of the tool is critically reviewed with the real-world live game coverage.

The case-study is then reflected on. Through the development and deployment of the WARDS visualisation case-study, a set of design considerations is proposed. These considerations are meant to be advisory in the development of future visualisation tools aimed at audiences, forming a starting point to a more in-depth framework for visualisation.

5 THE WARDS CASE-STUDY

5.1 Development & Deployment

Prior to replicating the WARDS model, two main factors are important to consider. Firstly, as this was to be deployed alongside the official "Roshan Rumble" coverage, leading stakeholders within *Promod Esports* were consulted through a pre/post-prototype interview. The tool was to be integrated in the post-game analysis as a info-graphic. Secondly, it was important to determine access points, and their associated needs. As this was being produced for *Dota 2* replay files were utilised, which were recorded live through the game's client and parsed using a custom built tool that utilises the Clarity parser library[2] a Java library following the methodology employed in the previous WARDS work [6].

As the original work had been designed for an older iteration of *Dota 2*, certain features of the game had changed since the publication. Therefore when working to replicate the original work, all constants and in-game values were validated with the most up-to-date versions of the game. No particular differences were identified in this instance, however any future iterations of this work may need to undergo the same process as the game updates frequently [5]. By utilising the Clarity parser library, a custom tool that replicates the steps depicted in the original work could be developed. This was done following the instructions depicted in the original work and enabled continued integration into a visualisation tool. The final WARDS function could be calculated using Equation 1. In this derived equation, K is the number of consequence kills, T is the total ward duration, D_c is the cumulative time of enemies detection, D_i is the number of items detected, D_l is the number of levels detected, O is the "optimality" score and P is the penalty score. Additional details on how the parameters are calculated can be found in the original work by the authors [6].

$$WARDS = K * (T + D_c + D_i + D_l) * (O - P) \tag{1}$$

Once the WARDS was replicated and could be readily calculated for a given ward, this case-study designed a visualisation tool using the knowledge collated from the outlined literature and stakeholder requirements. As this was integrated into the "Roshan Rumble" coverage, it was important that the visualisation followed the same branding patterns as the rest of the production. Additionally, this graphic provides insight into *Dota 2*, which also has its own branding. Merging these patters could assist to provide a recognisable interface for audiences [3].

[2]https://github.com/skadistats/clarity

In this case-study, the graphic was going to be utilised to cover the entire screen for a short duration during the post-game analysis while broadcasters provide commentary. For this reason, an appropriate game background image was used, which allowed audiences to find familiarity with the graphic [2, 3]. Furthermore, *Dota 2* UI utilise a series of dark greens panels for backgrounds, and the "Roshan Rumble" branding uses stretched and damaged edges for panels and background. Therefore, a main panel containing the information was added which takes advantage of both branding patterns as displayed in Figure 2. In addition, "Roshan Rumble" branding utilises orange and beige, which were used to provide accents and details. Lastly, as the WARDS is closely linked to a map location, it is therefore important to ensure the spatial information is conveyed [1]. Thus, the game's artistic minimap was used to allow for a locations to be highlighted.

Figure 2: A demonstration of how branding was used to guide the initial development of the WARDS visualisation tool

As shown in the literature, a small understandable amount of data can aide provide significant insight and drive narratives [2]. Additionally, as the WARDS function quantifies an aspect of the game into a numeric value, this can be used to effectively convey the information related to the ward. However, the values obtained by the WARDS metric are not easily linked to any other in-game metric and may not be quickly digested by audiences or broadcasters. To address that, two threshold values for max and min WARDS value were selected. These were chosen by calculating hypothetical maximum and minimum scores for the WARDS value. However, while hypothetically possible, those values are infeasible in nature. Therefore the thresholds were scaled by 25%. These were then used to calculate a percentage score for the WARDS, allowing any ward to be represented in a intuitive scale from *0* to *100*. It is important to note, however, that as the threshold values were scaled to arbitrary amounts and it would be possible for a ward to score outside of the thresholds. Therefore additional checks were put in place to ensure WARDS could not go below 0% or above 100%.

In addition to the WARDS value itself, some additional insight into the metric could be beneficial, to aide in audience understanding and contribute towards better narratives [14]. For this reason certain aspect of the formula were also included, as well as the player who placed the ward and their associated team. In particular, special-temporal elements used to calculate the WARD Score were included as visual or textual elements. Those were added following the same branding patterns described and are shown in Figure 3 As demonstrated by the figure, the location of the ward (spatial information) is depicted in the allocated minimap as a cross. The times of ward placement and destruction (temporal information) are denoted in text underneath the name of the player who has placed them. Lastly, the WARD Score itself is displayed in a highlighted circle, providing insight into the ward performance at-a-glance. Additionally, to further enhance the "at-a-glance" readability of the WARDS score, the radial panel containing the percentage value is also highlighted by the given WARDS amount. Thus, in this example 95% of the circular panel is outlined in bright orange and 5% in darker orange, matching the WARDS value for the hypothetical ward depicted.

Figure 3: An example of the main WARDS panel depicting the WARD Score, and relevant spatial-temporal information about the ward.

While at-a-glance information is proven to be an effective narrative strategy [2], additional context can also assist in storytelling [14]. Furthermore, the graphic has an intended use-case of covering the entire screen. Therefore, additional textual information describing the context for the WARDS can be provided. To ensure the at-a-glance content is not overshadowed by the additional information, only the at-a-glance information is given a background panel. Furthermore, additional information is spatially separated from the panel. This design aims to direct the user attentions primarily to the panel with additional information being digested auxiliary. Thus, as depicted in Figure 4, the main (at-a-glance) panel is placed on the left and additional information on the right with some padding in-between the two.

Lastly, in order to deploy the graphic, a tool that parses through a live recorded replay file was developed. When the game reaches the end state, the ward with the highest score is used to generate the graphic depicted as an image and stores it into a predetermined location in the user's file system. This tool was then used by the production team during the match ensuring the graphic was available for the post-game analysis discussion. This provides full control over the use to the production team, allowing them to choose not to include the graphic or only include the at-a-glance portion of the graphic if needed, depending on narrative or production needs.

5.2 Utilisation & Evaluation

The WARDS visualisation tool was deployed in the "Roshan Rumble" grand finals, which included a total of 5 games between "The Boys" vs "Hidden Pool Pride". Although the Twitch channel that held the tournament has been discontinued (therefore subsequent on-demand recording of the live tournament is no longer accessible) observational data of the narrative provided by the broadcasters was collected during the deployment and is used to evaluate this case-study.

5.2.1 Game 1.

The WARDS graphic was not utilised in the first game of the series. Instead the casters opted to focus the post-game analysis in a recent team-fight. This was possible because casters had control over the use of the graphic and could choose to conduct the post-game panel at their discretion. The generated graphic for Game 1 is provided in Appendix A.

5.2.2 Game 2.

The second game of the grand final series was the first time the WARDS graphic was introduced to the audience. In this 40 minutes game, the team "The Boys" lost to "Hidden Pool Pride", which was reflected in the post-game analysis commentary. The graphic generated by for this game is available in Figure 5.

When introducing the new graphics, the broadcasters highlighted the WARDS value of 84% and explained that it was related to the impact of the ward in the game. Following from this brief explanations, the broadcasters then highlighted how despite loosing the game, the ward was placed by "The Boys".

> Broadcaster 1: Oh... this [the ward] is for when they had that good Roshan team fight.
> Broadcaster 2: Yeah, that was their best chance back in the game, but it did not work out.

Their post game analysis then continued outlining several events after that ward, which lead to "The Boys" loosing the game.

5.2.3 Game 3.

Game 3 of the series was once again won by team "Hidden Pool Pride" in approximately 40 minutes. In the post-game analysis, the commentators focused on how contested the "early game" was, which refers to the large number of encounters that happened within earlier stages of the game. As shown in Figure 6 the WARD graphic supported that narrative, as the temporal information shows that the most impactful ward was in place between approximately 10 and 16 minutes and is located covering a common entrance to one of the lanes. While it is unclear if the broadcasters built their

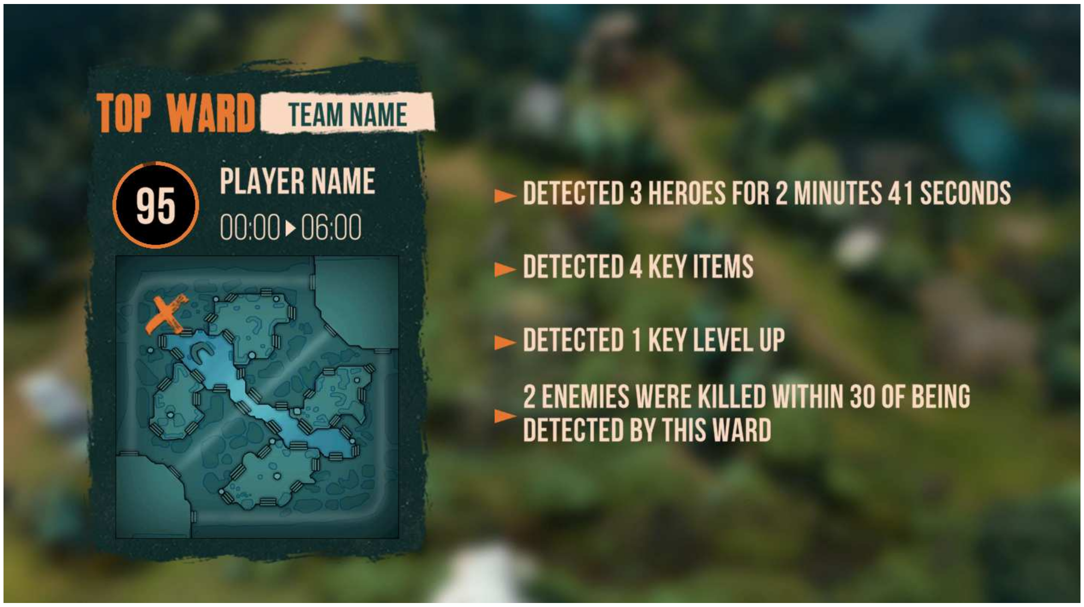

Figure 4: A depiction of the full WARDS graphic, displaying the at-a-glance panel and the contextual information

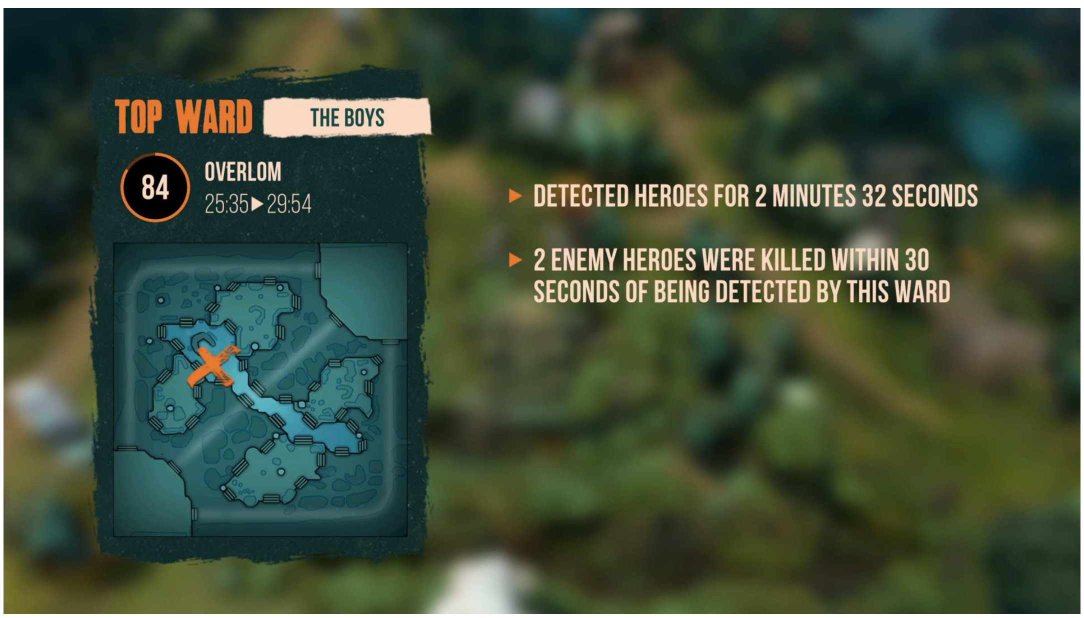

Figure 5: The generated WARDS graphic for the "Roshan Rumble" Grand Final Game 2

narrative around the graphic, or if the graphic matched their understanding of the game, it is clear that the WARD tool was integrated within the narrative delivery.

5.2.4 Game 4.

The forth match of the series was won by "The Boys", who won the game in approximately 25 minutes. This is considered to be a fast game. It was also the shortest duration of the five match series. The post game commentary identified how the vision mechanic for this match was highly contested, with most wards being destroyed quickly by the enemy teams. This was also reflected by the lowest of the WARD scores seen in the series at 56% as depicted in Figure 7.

> Broadcaster 1: The vision game was hard, both teams dewarding [destroying the enemy wards] constantly! Broadcaster 2: But Overlom's ward on the top lane really secured the safe lane for the Dire ["The Boys"]. It [the ward] stopped, I think, 3 rotations [when a

Figure 6: The generated WARDS graphic for the "Roshan Rumble" Grand Final Game 3

> player moves from another lane to force an encounter] from the mid lane.

Additionally, the commentators praised the location of the ward, as it provided strategic defensive insight to protect the players on the top lane, emphasizing the relatively high number of kills to low detection time.

5.2.5 Game 5.

The last game of the series was won by "Hidden Pool Pride", securing a tournament victory. This ward scored the highest in the series, with a 99% WARDS value. The match lasted for 32 minutes 30 seconds, although the top score used in the graphic was placed at the early stages of the game (between 2 and 8 minutes, approximately), as depicted in Figure 8.

When presenting the graphic to the audiences, the broadcaster focused on the additional information denoting four enemy heroes had been killed within 30 seconds of being detected.

> Broadcaster 1: This just shows how DNC [one of the players of "Hidden Pool Pride"] just spent the whole early game feeding [a term used when you are killed repeatedly, which consequently provides a lot of resources to the enemy]

The post-game analysis then drew comparisons between the top lane (where the ward was placed) and the other two lanes, and how "The Boys" were more successful on the top lane but "Hidden Pool Pride" were generally more successful in the other two lanes, which lead them to a ultimate victory later in the game.

6 DISCUSSION

Broadcasters had complete control over the use of the WARDS graphic. As Game 1 had a recent narrative hook, the post-game panel opted to drive the narrative towards the team-fight rather than vision. This provided the panel with greater storytelling flexibility. In contrast, the other games (particularly 3 and 4) had the overall narrative centred and complemented by the graphic tool, despite not being prompted or expected to utilise the tool if they deemed it not needed (i.e. casters choose to utilise the tool directly). This indicates a successful integration of the tool into the stream.

While a full exploration of the impact of the narrative is beyond the scope of this paper, the successfully integration and utilisation of the tool demonstrates how visual representations can aide in narrative for digital storytelling in esports.

Therefore, a set of design considerations can be drawn from this case-study and are listed below in the form of questions, formulated to aide the design and implementation of future visualisation tools:

- **Use-case**: Does the model design fit the intended use-case and are there any changes that need to be made?
- **Branding & recognition**: Are there any branding and design patterns that need to be matched, including title specific and platform branding?
- **Understandability**: Can the model provide understandable insights without the need of prior knowledge of the model?
- **At-a-glance**: What are the key parts of the model that can be understood at-a-glance?
- **Spatial-temporal information**: Are there any spatial-temporal information that needs to be depicted with animations, text or images?
- **Additional context**: Is there any fields or parameters that can provide additional information if displayed beyond at-a-glance content?
- **Controllable and delivery**: Who would have control over display and delivery, and how best to integrate it with the broadcast?

Figure 7: The generated WARDS graphic for the "Roshan Rumble" Grand Final Game 4

Figure 8: The generated WARDS graphic for the "Roshan Rumble" Grand Final Game 5

7 LIMITATIONS & FUTURE WORK

The specific use case within this case-study was limited to only one ward per post-game analysis. An extension of the tool highlighting a range of wards live could enable further stories and allow broadcasters to compare performances, as observed in the case of Games 2 and 5. Additionally, the use of quantitative data to evaluate the impact of such tools in the audiences (such as through the Audience Experience Questionnaire [10]) could provide further insights into application principles. This could be particularly relevant if applied to higher tier tournaments to the Roshan Rumble, which could also provide additional insights.

8 CONCLUSION

In conclusion, this paper has investigated the existing literature of visualisation and complex modeling of esport environment. This was used to guide the development of the WARDS visualisation tool case-study, to enable a set of design considerations to be compiled on developing other visualisation tools.

Observational data collected from the integration to a real-world live tournament suggests a a successful integration of the model into the narrative delivered. Future work in visualisation of complex models of esports may, therefore, benefit from the findings highlighted in this paper, in particular for the design and delivery process through the considerations proposed in this paper. Continued work on this topic could enable the formulation of a design framework, to further enhance future developments.

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A UNUSED GENERATED GRAPHICS

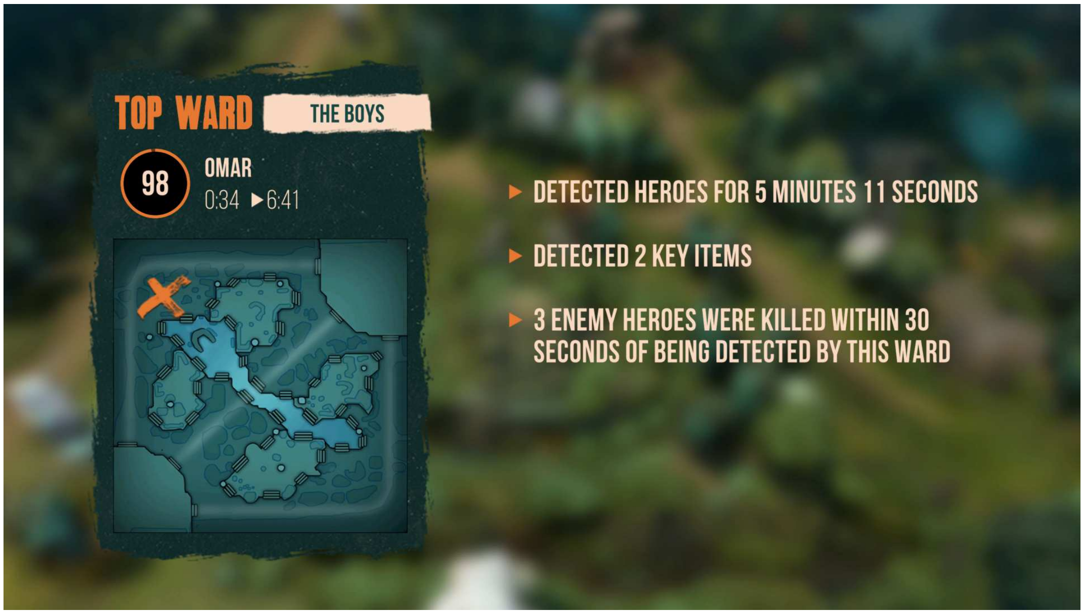

Figure 9: The generated WARDS graphic for the "Roshan Rumble" Grand Final Game 1