A framework for Notational Analysis in Rocket League Esports: Enhancing Competitive Performance through Data-driven Insights

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ABSTRACT

In the emerging ecosystem of esports, the vehicular football-like video game Rocket League has become one of the major competitors on the market. With a dedicated playerbase of over ninety million people playing each month and over a million USD in prize money, professional teams must constantly find new ways to improve their performance to stay relevant in the competitive scene. While in traditional sports data-driven performance evaluation has become the standard, esports seems to fall behind. By looking at best practices in notational analysis of traditional sports, a framework has been developed and demonstrated to apply notational analysis to the context of Rocket League. This framework aims to provide a foundation to kick-start data-driven performance in competitive Rocket League.

Keywords

Esports, Rocket League, Notational analysis, Framework

1. INTRODUCTION

One of the fundamental aspects of any professional sport is to constantly aim to improve to be the very best. A vital element of performance improvement, which is present in all professional sports, is coaching and feedback. We can distinguish feedback between two types: intrinsic and extrinsic. Intrinsic feedback relates to the sensory input of the athletes themselves like vision and hearing. Historically, it was long believed that athlete performance was heavily reliant on their own capabilities for intrinsic feedback, also referred to as "raw talent". Nowadays, we know differently and highly prioritize both the quality and quantity of training [13]. Opposingly, extrinsic feedback refers to information about the performance from an external observer. For the majority of complex skills, extrinsic feedback is deemed vital for optimal skill acquisition [1]. Traditionally, the most common practice in coaching relied on the recall ability of the coach. This means coaches relied on their own subjective experiences to provide feedback to their athletes.

For a long time, this was standard practice in sports. However, multiple studies have revealed that there was a high probability of mistakes in coaches' efforts to reliably recall accurate information over longer periods of time. [10], for example, analysed the recall accuracy of football coaches in post-game assessment. They found that coaches were only able to remember approximately 30% of critical situations of the game and could only recollect what happened during the game with an accuracy of less than 45%. Additionally, they found that coaches were still only able to reproduce critical information from the game with an accuracy of less than 60% when allowed to take personal notes. Besides the limitations of the human memory in terms of recall ability, one must also keep in mind that the information of the coach is not free from their own bias, emotion, and experience in the moment of observation.

To tackle this problem, there was a need for an objective source of truth for coaches to rely on. What they needed was a dataset to rely on, that was free from any source of bias, emotion, or subjectivity. Inspired by best practices in dancing by Rudolf von Laban dating back to 1926 [5], coaches started to systematically write down critical events to be able to draw accurate conclusions about a player's performance, also called 'notational analysis'. Notational analysis can be defined as "An objective way of recording performance, such that critical events in that performance can be quantified in a consistent and reliable manner." [9]. Notational analysis is a descriptive form of measuring performance. The results of a notational analysis system, hereafter to be called NAS, present themselves in dependent variables, indicating the performance of outcome, rather than illustrating the cause of performance. Within traditional sports, there has been a tremendous success in using notational analysis to improve player performance. It has seen successful applications in all kinds of sports, i.e. football, rugby, basketball, volleyball, handball, cricket, tennis, padel, combat sports, target sports, swimming, running, cycling, athletics, and gymnastics. [13]. Use cases include but are not limited to rating pass effectiveness in football [18], Skill evaluation of tennis [7], evaluating team dispersion in football [11], and measuring the effectiveness of different tactics in football [23].

The success of notational analysis in traditional sports poses a question of its applicability in the environment of esports. Esports is commonly defined as "a number of different video game modalities, played competitively in controlled environments, with structure and regulations similar to traditional sport." [16]. In recent years, the growth of esports has been exponential, with millions of viewers tuning in to watch professional gamers compete worldwide [3]. Among these titles is the vehicular football game Rocket League.

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Rocket League is a video game very similar to a game of traditional football. Two teams, in the competitive environment consisting of three players, attempt to score a ball into the opponent's goal. The main difference, and the source of the game's main mechanics, lies within the modality players use to move around the field: A rocket-powered car. Initially released by game developer and publisher Psyonix under the name of "Supersonic Acrobatic Rocket-Powered Battle-Cars" in 2008, Rocket League has grown to be one of the biggest esports titles in the world. Currently gathering approximately 90 million average monthly players [25], a peak viewership of over 270.000 people and a total prize pool of over 1.3 million USD [22], pro teams are constantly aiming to find ways to improve their skills and rise to the top of the leaderboard.

The digital nature of esports and gaming makes it very easy to establish an objective ground truth of data to work with. For Rocket League, there are multiple tools that allow you to extract vast amounts of data from log files or even retrieve data from the game in real-time. As the game uses this data to present itself graphically, this provides a perfect source of information on the game state. Additionally, the noticeable resemblance of the video game with elements of traditional sports like football, implies there are valuable lessons to be learned from applying traditional analysis techniques to this competitive environment.

However, in reality, it appears to be difficult to implement notational analysis in competitive Rocket League. Due to the fast-paced nature of the game, it is challenging to incorporate a dynamic data-driven approach to strategy. There is no time to think about preferable strategies and outweighing options, as players are encouraged to follow their instinct. Some teams have tried applying data analysis to their workflow but were not able to gain any significant results. Acting on additional information creates a tactical advantage on your opponent. However, it increases your reaction time. Despite trying to act on additional information, teams ended up getting beaten by players that acted on instinct because they were slower in decision-making.

Additionally, the current state of research concerning Rocket League is very limited. For the very limited research that has been done on the game, their motives appear to be self-centred, sporadic, and ad hoc rather than serving a purpose to increase the performance of professional athletes [12], [14], [21]. For research to have the most significant impact on the performance of esports athletes, collaboration between researchers and professional teams is required.

There exists a substantial discrepancy between the potential of data analysis in competitive Rocket League and the status quo. Additionally, there appears to be a resemblance between performance in traditional sports and esports. Notational analysis promises to provide a viable use case in competitive Rocket League. However, there are currently no best practices to develop a notational analysis system in this context. Therefore, this research aims to answer the following research question:

RQ: How can conventional practices of notational analysis in traditional sports be applied to the context of competitive Rocket League?

To answer this research question, the Design Science Research Methodology (DSRM) by Peffers et al. [17] has been applied throughout the process of this research. The DSRM provides a framework for design science research in information systems. It describes the solution as an "artifact" and reaches validation of the artifact in a total of five steps. The first step, "Problem identification and motivation", and the second step "objectives of the solution" have been applied in this introduction and provide the background information, motivation, and goals for the conducted research. In the following sections, the paper will answer the research question through the remaining steps of the framework. Initially, in "Design and development", the artifact is designed. In "Demonstration", the use of the artifact is demonstrated through a practical use case. Finally, in "Evaluation", the value of the artifact is observed and discussed.

The artifact created in this paper will take shape in the form of a conceptual framework, providing an approach to applying notational analysis in the context of Rocket League. Through a demonstration of the framework, applied with coaching philosophies in similar traditional sports, the framework aims to provide a foundation for future performance research to build on. Notational analysis has the potential to have a big impact on the competitive scene of Rocket League. By creating and demonstrating a framework to apply notational analysis in Rocket League, this paper aims to discover whether conventional notational analysis techniques apply to this context. Therefore, the framework will have to include identifying the purpose of a NAS. Additionally, it must provide a step-by-step approach to developing a NAS. Finally, it must be able to apply the NAS to the context of Rocket League. Because there does not currently exist a framework to apply notational analysis to Rocket League, it is important to consider the final artifact as an initial sketch. Through validation interviews, focus points will be identified for future iterations of the framework.

2. DESIGN & DEVELOPMENT

Through the work of Hughes and Bartlett [8], five main purposes of a NAS in traditional sports have been identified. Firstly, patterns and frequencies of actions performed can be analysed through tactical evaluation. This is commonly used to prepare for opponents or derive focus points in training schedules. Secondly, execution of technique can be analysed to define where actions fail or excel through technical evaluation. This is often used to track performance over time. Technical evaluation finds great application in racket sports, because of the limited external factors involved. This makes for many set pieces of play that can be optimized. Opposingly, team sports like football or rugby have a high amount of external factors, making it more difficult to apply technical evaluation in that context. Thirdly, movement patterns and work-rate can be analysed in analysis of movement. This is often used to calculate the physical effort in traditional sports. Fourthly, notational analysis provides a purpose in development of a database and modeling. By defining a normative profile for performance, different teams and players can be compared with each other. Finally, by having players perform the notating itself, notational analysis is believed to help players get a better tactical awareness of the game. Not every type of sport or game finds a useful application in all of these purposes. Additionally, not every NAS aims to fulfill all of these purposes. Therefore, it is important when designing a NAS to initially consider its purpose(s). Therefore, the first step of the proposed artifact includes identifying the purpose(s) of the NAS.

To fulfil the main purpose(s), a typical NAS is built from a combination of up to five different elements [9]. Firstly, understanding what action a player is performing is key in fulfilling any of the purposes of a NAS in most cases. In rare occurrences, the action is not required by a NAS. For instance, in an analysis of movement it might not be necessary to provide actions performed to recognize movement patterns. However, it can be very useful to understand in what context the player moves in the pattern that is recognized. The majority of NAS keep track of the actions performed by a player. Secondly, the significant outcomes of these actions can be notated. Knowing which actions a player performed tells you about the intended playstyle of the player, but says only little about the actual performance. By knowing whether the action had a desirable outcome, we can draw conclusions on the performance of the player. However, if drawing conclusions on only the playstyle of a player is desired, notating the outcome is not necessary. Thirdly, tracking the position of the player can be key to satisfying the purposes of a NAS. Use cases include identifying movement patterns or locations of the playing field a player is most effective. Fourthly, recording by which player the action was executed can be important when personalizing the notation of performance. Finally, including a variable of time allows for analyses focusing on velocities, accelerations, or durations of tactical patterns. Not every purpose of a NAS requires all elements. Therefore, the second step of the proposed artifact includes identifying the necessary elements that are required to fulfill the NAS's purpose(s).

The different elements of a NAS can look very different for every game and should therefore be tailored to every game individually. However, many similarities in the elements of a NAS can be spotted between similar sports or games [9]. For example, NAS in both tennis [15] and padel [24] can look very similar due to their roots in being turn-based racket sports. Because there are currently no NASs in Rocket League to build on, discovering other sports that share similarities can be extremely helpful in applying notational analysis in a new context. Therefore, the third step of the proposed artifact includes discovering similar context(s) that potentially translate themselves to the context of Rocket League.

The purpose(s), elements, and similar contexts of the NAS have been identified. Subsequently, these elements can now be tailored to the new context to fulfil the purpose of the NAS. By looking at best practices in the identified similar context, and translating them to the context of Rocket League, the NAS takes shape. Firstly, to identify actions in the new context, actions of NASs in the similar context can be investigated. Furthermore, by looking at the coaching philosophies of successful teams in the similar context, actions can be identified from a higher abstraction level. This allows the NAS to incorporate game-specific actions. Secondly, to identify the most important outcomes, the purpose(s) of the actions are defined. Afterward, the most important outcomes can be identified by defining outcomes that either fulfil or deviate from this purpose. Finally, there are many ways to portray position in a NAS. It is most common to divide the playing field into a grid. The action can then be recorded according to the area they were performed in. The scale of this grid can be very dependent on the specific game it is applied to, as well as the availability and accuracy of positional data that can be extracted from the game. Therefore, one must take this into consideration when tailoring the element of position into a NAS. The way player and time elements are notated do not differ between NASs.

The step-by-step approach of applying notational analysis in a Rocket League context consists of four different steps. By identifying the purposes and elements of the NAS, discovering similar contexts and coaching philosophies, and tailoring them to the context of Rocket League, the proposed framework has taken shape:

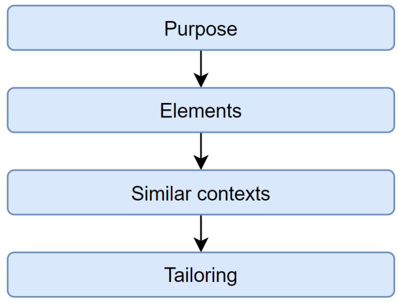

Figure 1. Framework for applying notational analysis in a Rocket League context

3. DEMONSTRATION

Professional Rocket League teams have expressed interest in applying notational analysis in their workflow. However, they have yet to find a way to give it a significant use. The goal of this demonstration is therefore to provide a foundation for future performance research to build on. By initially identifying the purposes of a NAS that best lend themselves to this initial foundation, a NAS is constructed through the proposed framework.

Following the first step of the framework, we identify the "purpose" of the NAS. The challenge for data-driven performance analysis in Rocket League is its fast-paced nature. It is considered challenging to incorporate specific strategies because acting on instinct appears to be more rewarding than acting on additional information. However, Reimer et al. [19] suggest that through proper training schedules, new habits and instincts can be taught. This is backed by Hirano et al. [6], stating that skill ceilings can be raised with appropriate training. There is a need for personalized training schedules to prepare players for their next opponent. Therefore, the purpose of a tactical evaluation is identified. Additionally, There is currently no way for teams to assess their players' performance. Coaches can more effectively track the progress of their players, as well as scout for new players that fit their team and play style, by creating a normative profile. Therefore, the purpose of the Development of a database and modeling has been identified.

Rocket League is a video game played on an enclosed playing field. This means that the ball is constantly in play until it is scored. Because of this, there are no set pieces of play besides the kick-off. This makes it very difficult to perform technical evaluation, as there are many external factors that influence the technical execution of actions. Therefore, technical evaluation is deemed too difficult to perform in the current stage of performance analysis in Rocket League. Additionally, there appears to be little use for the work-rate analysis of players due to the online nature of the game. Finally, professional Rocket League players are already considered to be at the highest level of intricate knowledge of the game. There appears to be little purpose to educate the players on the game's inner workings. Therefore, the main purposes of technical evaluation, analysis of movement, and educational use with players have been excluded from this NAS.

Following through to the second step of the framework, the "elements" of the NAS are identified. For tactical evaluation, successful action patterns must be recognized. This means notating actions and their respective outcomes, as well as the position they were performed in. Additionally, the player element must be notated to personalize focus points in training schedules. For the development of a database and modeling, aggregated data of a player's actions and outcomes must be recorded. Therefore, the elements of player, action and outcome must be notated. There appears to be no significant reason to include the time element in this NAS. This could change in the future but is currently not needed for the identified purposes and adds unnecessary complexity.

In the third step of the framework, "similar contexts" to the context of the NAS are gathered to form a starting point for the tailoring of the elements as identified in the previous step. Transitioning and applying the traditional structure of notational analysis to the context of Rocket League, means finding traditional sports that best compare themselves to the game. Hughes et al. [8] makes a classification of traditional sports. Within this classification, Rocket League identifies itself as belonging to the category of invasion games, with goal-striking games as a subcategory. This means Rocket League best compares itself to traditional sports such as football and field hockey.

The leading theory for success in invasion goal-striking games comes through the ideology of possession. International football teams like Spain or Germany, as well as professional clubs like FC Bayern München and FC Barcelona all became successful through their philosophy of an offensive game model. This means that by remaining in possession for longer, they have a better chance of influencing the outcome of the game [2]. Within Rocket League, this is emphasized even more because of the closed playing field. In football, there are many set pieces of play in the forms of corners, free kicks, and throw-ins, that allow for a controlled environment teams can prepare for. On the contrary, the ball is continuously in play in Rocket League. Having possession of the ball ensures that your team can dictate the next part of the game and is therefore an even bigger indicator of performance than possession in football.

In the final step of the framework, we "tailor" the elements from the similar context to the context of Rocket League, using the successful coaching philosophies of the similar context identified in the previous step. To identify the critical actions, purposes, and respective outcomes within Rocket League, an expert panel of players in the top 1.06% [20] of Rocket League (N=4) has been consulted. They have looked at actions in the game that lead to a gain, loss, or preservation of possession. Out of this principle, a total of six critical actions have been identified and displayed in Table 1. Note that there are always edge cases in these situations. We are noting the outcomes most relevant and important for our NAS, as identified by the expert panel.

Table 1. Actions, purposes, outcomes

Action	Purpose	Outcomes
Pass	To transfer possession to a teammate	off, blocked, successful
Shot	To score a goal	high, wide, saved, goal
Clear	To buy time to reposition or get boost	corner, middle, deep field
Control	To assess the situation of the game, or to get yourself or teammates in position for the next play by keeping possession	challenged, demolition, fumble, play
Save	To prevent a goal	corner, middle, deep field
Challenge	To break your opponent's play	forward, dead, backward

Tailoring the positional element to the context of Rocket League, it appears that dividing the playing field into a grid is also most applicable to rocket league. However, the optimal size of this grid is yet unknown. The size of the grid will ultimately depend on the amount of data that can be collected in the notational system. Therefore, more research is needed to determine the potential scale of the system in real-world applications.

To aid the validation interviews with a visual representation of the results of the framework, we first separate the to-be-collected data into three types. Firstly, summary data is provided to give a general overview of the total occurrences of actions and outcomes. This is particularly helpful to gain insight into a player's play style, giving value to both the tactical evaluation and the creation of a normative profile. Examples of summary data are the total number of shots or passes per game. Secondly, Frequency data is provided to gain insight into the success rate of actions and outcomes. This helps in identifying the strengths and weaknesses of a player. An example of frequency data is the number of goals out of shots taken. finally, sequential data is provided to get a better understanding of playing patterns and focus areas. An example of sequential data is the action occurring before a shot on goal.

These three types of data can be visualised in countless ways. However, three types of visualisations are most common in NASs [9]. Firstly, scatter diagrams provide a visual representation of the playing field, giving a medium for summary and frequency data. For each of the defined positional areas, information can be provided about the frequency of actions. An example of a conclusion drawn from scatter diagrams is whether shots are more successful from the right or left side of the field. Noteworthy is that the scale of the grid is arbitrarily chosen in the example. Secondly, frequency tables can provide a very simple and quick overview of the actions and outcomes with their frequency of occurrence. An example of a conclusion that can be drawn from a frequency table, is that a certain player shoots on goal a lot more than giving a pass. Finally, sequential systems are great for identifying strengths in playing patterns. An example of a conclusion that can be drawn from a sequential system, is the relation between the assisting player's position, and the outcome of the shot. To provide the demonstration with a visual representation of these types of data, examples were created using dummy data. These examples can be found in Appendix A.

4. EVALUATION

The artifact created and demonstrated in this paper aims to provide a foundation of performance analysis in competitive Rocket League. Additionally, it aims to discover whether conventional notational analysis techniques apply to the context of Rocket League. Therefore, the artifact has to include the identification of the purpose of a NAS, provide a step-by-step approach to developing a NAS, and be able to apply the NAS to the context of Rocket League. To identify whether the artifact has accomplished its objectives, the fifth step of the DSRM framework is dedicated to the validation of the artifact. Therefore, validation interviews were conducted with experts from the esports performance analysis environment.

Sample

The target audience for these interviews was initially coaches and data analysts from the competitive Rocket League scene. After reaching out to multiple coaches in both the global and local esports ecosystem without response, attention was focused on researchers.
Through a discord-centred international esports research community, two participants were found. The first interviewee has an Undergraduate & Postgraduate degree in Sports Coaching and 5+ years of working experience in both traditional sporting and esports. The second is an esports lab coordinator, as well as the Rocket League coach, for an American university. Their backgrounds deem them qualified enough to validate my research, as they are both experienced and knowledgeable in the field of esports and performance analysis.

Material

To evaluate whether the proposed framework has the desired value in designing a NAS in a Rocket League context, the validation interview was divided into three different topics. Firstly, the interviewees were asked whether they believe the framework fulfils its objectives. Secondly, they were given the opportunity to provide input on missing elements of the framework. Thirdly, because of their background and experience in esports performance analysis, their expectations were gauged on the process of getting professional teams to adopt this framework in a real-world environment. This is deemed important because real-world applications can allow notational analysis to become the standard in competitive Rocket League, just as it is in traditional sports. Because of the open topics, and their inherent characteristic to produce subjective answers, validation interviews were conducted on a semi-structured basis.

Procedure

Because of the inability to meet up in person, the interviews were conducted through a video call. Because of time zone differences, the interviewees were interviewed separately. The interviewees were first given an introduction to the framework and demonstration, following the same structure as given in this paper. Questions were asked based on the topics mentioned in the material. If interviewees expressed shortcomings of the framework, follow-up questions were asked to elaborate further and come to a solution to either include it in the framework or make a case for future research. The given answers were transcribed and categorized by the prepared topics. Subsequently, conclusions were extracted from the categorized results. The conclusions were used to validate strengths and adjust shortcomings for the current implementation of the framework.

Results

Both interviewees expressed the relevance and importance of the framework. They mentioned the lack of an existing robust performance analysis model in esports made it hard to evaluate the framework and demonstration. However, they see the value of creating a foundational NAS for future research to explore further. They agreed with the potential purposes of a NAS, and the identified purposes, elements, and similar context of the NAS in the demonstration. One interviewee expressed concerns about the third step of the framework, "similar contexts", seeing no different context other than the one identified in the framework. However, after a separate discussion with the second interviewee, more contexts were identified in the form of different coaching philosophies and the exploration of different sports. For instance, Manchester United has had significant success through the philosophy of counter-pressing. Additionally, ice hockey might have valuable insights due to the similar context of a closed arena.

Feedback was given on the topic of missing elements of the framework. The first interviewee mentioned that dividing the playing field into a grid is the leading methodology of recording position. Therefore, advice on the "position" element of the framework was adjusted. The importance of pressure, team dispersion, and reciprocal compensation were mentioned. However, follow-up questions led to the conclusion that an analysis of those subjects moves away from notational analysis. The second interviewee stated the importance of boost management in competitive Rocket League. Follow-up questions led to the conclusion that this is a key mechanic of the game and should therefore be included in the future. However, further research must be conducted to find the optimal way of doing so.

Both interviewees identified challenges in the practical application of the framework. The first interviewee mentioned that the framework would need to prove its use in smaller environments like college esports before gaining attention in the RLCS. The second interviewee also expressed concerns about the willingness of competitive teams to adopt such a system without proof of concept in the Rocket League environment.

5. DISCUSSION & FUTURE WORK

Most importantly, this framework aims to provide a foundation for professional Rocket League teams to start working with notational analysis. Although the framework allows for the most important aspects of a NAS to be identified in the new context, it does not provide an exhaustive overview of performance in the game. Features from traditional sports have been identified and altered to fit into the context of Rocket League. However, the validation interviews have identified core elements of the game that have to be further explored to improve the framework in further iterations. Most importantly, boost management and reciprocal compensation are deemed very important in high levels of play. Therefore, more research must be done to accommodate these components in the framework.

Additionally, notational analysis inherently allows for the collection of descriptive variables. This allows for the identification of i.e. weaknesses for focus points during training but excludes the independent variables that are the cause of these weaknesses. Due to time constraints, this was excluded from this paper. However, it seems likely there are significant results to be found there as well. It is up to the coaches and their coaching philosophies to prioritize these elements of research. However, this framework is a great tool to kick-start this data-driven process.

For a NAS to be adopted on a broad scale, first a normative profile must be identified. Meaning there has to be a large existing dataset already before the system can serve all of its main purposes. However, it is not expected to be a huge problem. In a database from ballchasing.com, there are currently over 90 million replay files stored, including players of all ranks [4]. From this website, RLCS games could be extracted to kick-start the normative profile of a system. Furthermore, the establishment of standard methodologies for collecting, storing, and sharing Rocket League data has the potential to speed up this process significantly.

Furthermore, the potential value of notational analysis to competitive Rocket League can also be seen as a starting point to branch out to other esports titles. Although this framework was designed to be applied in the context of Rocket League, it can be worth exploring other titles as well.

Finally, there is also a big potential application for the use of artificial intelligence in the future of notational analysis. In traditional sports, this is already used by incorporating computer vision to extract positional information from video material. This is not needed in an online environment like competitive esports. Where AI does find its applications, however, is in other forms of pattern recognition. By developing an AI capable of recognizing critical actions and outcomes based on replay data, a big portion of notational analysis can be automated. Furthermore, AI could be utilized to recognize playing patterns to help further augment the coach's capabilities.

6. CONCLUSION

In this paper, a framework is proposed to apply best practices in the notational analysis of traditional sports to the context of Rocket League. By first identifying the purpose(s) of a notational analysis system, a clear goal is set on the intentions of the system. In the second step, the purpose(s) are used to identify the elements of the framework as conventionally used in the notational analysis of traditional sports. The third step identifies similar contexts to the context of Rocket League, of which success factors and philosophies are explored. These success factors can then be used in the final step, where the identified elements are tailored to the context of Rocket League. By demonstrating the framework, a foundation for future research was set by emphasizing and prioritizing applications of notational analysis in the context of Rocket League. Through interviews with experienced researchers in the field of esports performance analysis, the framework has been validated and improved. Additionally, focus points have been identified for future iterations of the framework. Through the implementation of this framework, conventional practices of notational analysis in traditional sports can be applied to the context of competitive Rocket League.

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APPENDIX

A. EXAMPLES OF VISUALISATIONS

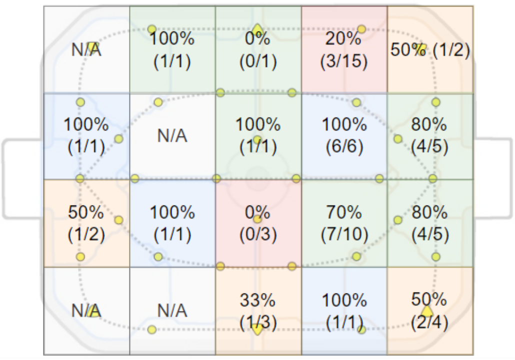


Figure 2. Grid of frequency and summary data of shots resulting in a goal in last n games

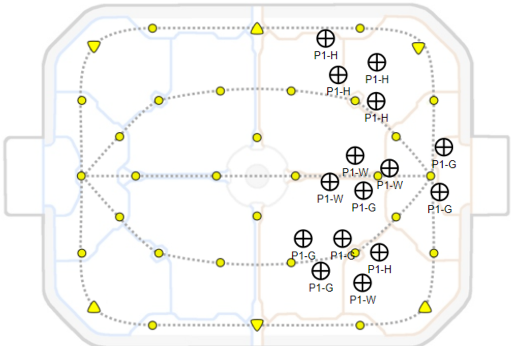
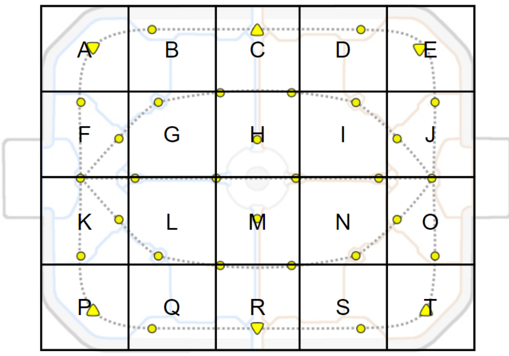


Figure 3. Scatter diagram of shots and outcomes of a single player in a single game



Assist pos.	Player	Shot pos	Player	Outcome
A	1	N	2	G
L	2	D	3	S
R	1	D	3	S
Q	3	I	2	G

Figure 4. Sequential system to identify patterns in shot outcomes by adding assist data

Frequency table Frequency data Shot outcomes (%) Last 100 games			
Player	A	B	C
High	15	60	25
Wide	15	30	25
Saved	30	5	25
Goal	40	5	25

Figure 5. Frequency table with frequential data of shot outcomes (%) in n number of games

Frequency table summary data Critical action occurrences Single game			
Player:	A	B	C
Pass	5	2	0
Shot	2	4	3
Clear	2	1	5
Control	1	5	4
Save	3	1	0
Challenge	5	2	1

Figure 6. Frequency table with summary data of critical action occurrences in a single game