1. Introduction

League of Legends is a Multiplayer Online Battle Arena game produced by Riot Games. It pits two teams of five players against each other in matches which typically last between 20 and 45 minutes. Each player controls an in-game avatar, known as a “champion”, and tries to demolish the opposing team’s base structures while battling other champions and computer-controlled “minions” to gain additional power in-game. It has exploded in popularity since its release in 2009, and is the most played video game worldwide, with over 67 million players every month (Forbes 2014).

Part of the reason for this growth has been Riot Games’ global support for professional play. Riot Games has set up the infrastructure for weekly matches throughout a League of Legends season, culminating in a world championships tournament. Professional teams play in these regional tournaments to qualify for the world championships, and manage player rosters not unlike how traditional sports teams manage their own rosters, by buying and selling player contracts.

However, with between 200 and 1,000 professional players – depending on your definition of professional – professional players make up less than 0.01% of the player base. But that does not prevent the rest of the player base from being competitive in their play. League of Legends has a ranking system based off of the ranking system of chess, called elo. Players spend time playing the game to improve, but also spend time reading guides, watching professional gameplay, and reviewing their own gameplay. But, every community has its problems, and my research surfaced two problems out of the League of Legends community. One problem has to do with how players discuss professional gameplay, and the concerns players in their own development.

When players discuss professional gameplay, opinions are often divisive, and make far-reaching claims. Ragnight comments, “now just get rid of [CLG] Link”, in response to a thread concerning roster swaps on Counter Logic Gaming (CLG), one of the most prominent professional teams in North America’s League of Legends scene. wgmwgl follows up with, “…Even last year in S3 playoffs vs TSM, he just performed so poorly and threw the game…This playoffs, he had absolutely 0 presence [in the game]”. In another thread about CLG signing on a new player, Seraph, to replace another player, Nien, who recently stepped down, a poster comments, “…Nien was playing bad and he knew it, that’s why he gave up…he had huge fails and very little big plays…he was consistently the worst performing team member…”

This commentary has led to several professional players being driven out of the scene, and has also caused other top teams to institute social media bans on certain days of the week, to reduce the negative commentary that their players are exposed to. I hypothesize that part of this problem is due to the limited nature of the language and statistics players have access to and consider when making this commentary. I observe that the metrics used to evaluate players are either very high-level or very low-level and thus fail to capture the player in a holistic sense. League of Legends has a lot of room to grow when compared to other competitive activities with a more developed set of analytical tools which better capture a player’s skill in a vacuum. Baseball is one such example.
At the same time, while hindering professional level analysis, this incomplete skill discourse also prevents players from having as much success in their endeavors to grow. By obscuring areas of knowledge within the game behind large concepts, players leave each analysis without actionable items, or when they do have actionable behavior, it is so minute that it does not translate beyond a certain skill. Between this and a lack of tools which exist to aid players track their own gameplay, it renders self-tracking and self-improvement very difficult. TobiasFunkeFresh comments, “So I have been playing since S3 and I am absolute s***. Like, I lose 70% of my matches...the inability to progress at anything in the game is wearing at me...” There are many stories like this, where players find themselves unable to improve at the game, and become increasingly frustrated due to it.

2. Research Methods
Over the course of this past year, I researched the League of Legends community, specifically the Reddit League of Legends community, to assess the problems they face and better understand what I can contribute to the current base of knowledge and tools. I started off with a forum analysis of the League of Legends subreddit. My initial plan was to build a tool to help players understand how external factors affected their gameplay via reaction time. This was motivated by a greater interest in player skill, player self-tracking, and player self-improvement. The forum analysis revealed a larger issue of the limited language that the community uses to assess skill.

From this stage, we created a framework breaking the concept of video game skill, specifically that in League of Legends, down into five distinct areas to give players an easier time to analyze their prior games. After conducting a few rounds of iteration over myself and a pilot study, I conducted studies over twelve participants to determine if the framework assisted with its intended purpose. We found that the framework was an effective facilitative tool, and that players presented with the tool provided more perspectives in their gameplay reviews.

3. Related Work
While Riot Games themselves have contributed to the amount of player knowledge about their game using their own analytics, the amount of literature specific to League of Legends is sparse. In general, literature in this area is confined to computer vision and AI problems in understanding and processing gameplay, but there exists some literature concerning the components of player skill.

3.1. Huang et al. “Mastering the Art of War”
Huang et al. delve into the TrueSkill rating of Halo in this paper, observing what differentiates the top tier players from average players in the game, and what sorts of factors are important to consider in these analyses. One important takeaway from this paper is that player skill, once learned, is akin to riding a bike. Even after extended breaks from the game, player skill quickly returns. There is little evidence that says that other video games do not operate in this manner, and means that lessons that players learn in improving their gameplay are tenacious. This paper also highlights the diminishing marginal benefit per game in improving skill, indicating that beyond a set of core lessons, gameplay improvements become more and more minute. This is especially true in Halo, a first-person shooter, where twitch-based reactions are very important. That distinction aside, it indicates that a more focused framework might help this reduction of marginal benefit by helping players reach conclusions faster in a semi-mediated environment.
3.2. Duncan Shields’ “The Art of CounterStrike”
Duncan “Thorin” Shields has been an e-sports commentator and journalist for the past 14 years, and wrote a book on the intricacies of CounterStrike, one of the most popular first-person shooters for decades. This book focuses on several areas which translate to areas of skill players might be interested in. It initially details in-game mechanics, discussing weapon stats and strategies, before moving on to talking about play environments – hardware setups, and gaming posture. It dedicates sections to the mental side of the game as well as team communication and community experiences. While not a definitive resource, it begins to delve into these questions about what factors are truly important to in-game skill, and the diversity of things to take into consideration when evaluating players. Though first-person shooters are a different set of games from the Multiplayer Online Battle Arena style games that League of Legends represents, there are still similar skillsets shared between the games. Much like how hand-eye coordination and team communication are important aspects present in baseball and basketball, the lessons Thorin provides in this book cross over to some degree to League of Legends, and can inform other instructional material.

3.3. Yan et al. “Masters of Control”
Yan et al. delve into the mechanical aspect of the game Starcraft, a real-time strategy game, looking at the effectiveness of control groups in player play, and how it correlates with player skill. Yan et al. break down control group usage into various categories, detailed by the intent of the control group and the affordances it provides to the player. The majority of this paper outlines the correlation between high-skilled players and continued control group usage, but touches on the fact that even this factor of gameplay has many elements to break down, such as the timing of the groups, mindfulness in using these groups, and ease of keyboard access. The paper solidifies the importance of player skill beyond just mechanical ability in defining and utilizing skill groups. It specifies that high-skilled players are not able to merely sustain high actions-per-minute in commanding groups of units efficiently, but also have many different sets of uses which they leverage this singular mechanic for. It would indicate that even at the mechanical level of gaming, there are decision points to be made, and that that portion of the game is not purely muscle memory and repetition.

4. Initial Forum Analysis
I initially intended on surveying the effect of various physical statuses, (e.g. being hungry, cold, or sleep-deprived) on one’s reaction time, using League of Legends as the venue. In order to validate this as an interesting and useful point of research, the first step was to do a forum analysis of the community to understand their existing issues and problems that they dealt with. To do this, I performed a forum analysis of the /r/leagueoflegends community (www.reddit.com/r/leagueoflegends), analyzing top posts which were returned from a series of 16 queries. I analyzed a total of 100 posts (throwing an additional 76 posts unrelated to skill out) over the course of the forum analysis, tagging each one for later analysis.
To tag this data, I used a total of 61 codes which were developed over the course of the forum analysis, encoding both post content and top comments. This helped me understand the key themes which arose through the analysis, and provided a lens with which to view the aggregated posts. The forum analysis surfaced several key themes which informed the research going forward. At the beginning of my research, I looked at players who tracked or cared about their reaction times, and studied the interactions and relationships between players and their reaction times. As the forum analysis progressed, the findings from the analysis influenced me to adapt the research focus. The next sections detail these lessons.

5. Forum Analysis Findings
This next section is broken down into several subsections, each of which highlights a particular lesson learned from some subset of the posts from the forum analysis.

5.1. Outside Considerations
By the end of the analysis, I realized that reaction times, while something some portion of the player base cared about (43 of 100 posts tagged with “reaction time”), was not something analyzed to large degree. While players cared about improving their reaction time, consideration of other factors such as age (5 tags), hunger (2 tags), mental health (3 tags), and sleep (2 tags) were sparse. Players first turned to playing more League of Legends, or using third-party tools to improve their reaction time, before observing their lifestyle habits. In the posts as a whole, there was little discussion regarding maintaining good health or exercise habits, or maintaining healthy sleep and stress levels. However, when posts pertaining to lifestyle habits were made, they were generally well-received. On the post “The Importance of Sleep and its Effect on Knowledge Retention and Mechanical Performance”, Grimord comments, “I agree. I think one of the things holding many teams back is the lack of a good sleep schedule and eating/exercise habits…”

5.2. Improving at League of Legends
Self-improvement is something that is constantly on the mind of League of Legends players, primarily those who frequent ranked queues. Many players aim to increase their elo over time, and when they participate in the community, a consistent topic is improvement. Example threads which rise to popular conversation are “Best gameplay tip you’ve gotten”, “Consolidated top player advice on climbing out of ELO hell”, “Cloud9 Recently Published a Total of 28 Guides on Mobafire”, and “Reddit, what is your champion and how do people beat it”.

However, while the community shares a mutual desire to improve their gameplay, with members regularly going out of their way to help others (“desire to help others” – 28 instances), the community is split on the best ways to approach helping others, and what things to focus on. Two primary camps arise when entering this discussion: those who believe that game knowledge\(^1\) is the

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\(^1\) Game knowledge is the theoretical side of the game, related to how the game works, what actions are possible, and overall strategies and approaches to gameplay.
important area to focus on (12 instances), and those who believe that game mechanics are the key to improving (23 instances). SuperSov comments on “Something I noticed on my recent [elo] climb..” with “tl;dr – Mechanics aren’t as important as decision making – How can you improve at decision making?...” On the other hand, acerunner007 makes the post, “I went from gold 5 to plat 2 because of osu! I wanted to share why. Self post.”, and writes a nearly 1600 word post detailing all the mechanical benefits of osu!, finishing with “I thought that playing just League of Legends would be enough to get me out of Gold. But my skillset was underdeveloped.”

My hypothesis for this phenomenon is that players naturally have one aspect of the game (knowledge vs mechanics) which comes more easily to them, and as such, requires less focus. Whichever one is hard-fought, on the other hand, requires focused attention, and so is naturally what that player might recommend. At any given point, one or the other might act as the bottleneck of skill for an individual. This leads me to the conclusion that different players find different portions of being skilled at League of Legends easy or difficult, which would then reflect on what sorts of practices they perform to improve at the game.

5.3. Methods of Improvement

Beyond just the focus of improving, one focus of discussion was what sorts of tasks help players improve at the game. Getting better at League of Legends by practicing League of Legends (16 instances) was a fairly obvious first step, but others also believe that you can improve in League of Legends by practicing other games (12 instances). External aids also came into play, things like third-party applications to analyze or aid gameplay. While many (17 instances) believe that external aids do boost gameplay, there were some holdouts (7 instances of “external aids don’t help”, and 4 instances of “external aids are unnecessary”) who saw League of Legends by itself as the only way to improve.

For those who played other games to improve at League of Legends, two common threads were CounterStrike: Global Offensive (a first-person shooter) and osu! (a point-and-click rhythm game). These games were lauded for their ability to train reaction times, muscle memory, and mouse accuracy.

Improving with osu!

Osu! is a point-and-click rhythm game where players load music and click, drag, or spin circles on screen which appear and move in-sync with the music. Osu! was the most mentioned external tool for player development as well as a contentious method of League of Legends practice. In contrast with the post above denoting osu!’s helpfulness, heyjah comments, “no it [osu!] doesn’t [help] lmao how are people so clueless and such sheeps”, and lalalala223 comments, “I’ve [got] a secret strategy for improving my mechanics (2 diamond 1 acc), I play a game called league of legends…a lot. [Y]ou should try it”.

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2 Game mechanics are the physical part of the game, related to reaction times, actions per minute, and generally being able to control your in-game actions.
Those who claim benefit from osu! typically cite the game improving their reaction time, hand-eye coordination, or mouse accuracy. Others use osu! since they hear it helps their gameplay but do not know specifically how it might help. Players who use osu! will play in four general times – before, during, and after gaming sessions as well as outside of gaming sessions. These last two are normally used to kill time when there is insufficient time to play a game of League of Legends, while the former two are used for warm-up and practice purposes.

5.4. Reaching Out
Players commonly reached out to the community for advice in how to improve their gameplay and increase their ranks, making posts such as “I suck. Hard.”, “Best piece of LOL advice you ever received”, and “How to improve reaction time?”. When people seek advice, they often know which field (between mechanics and knowledge) they want their advice to fall in, though the comments may not always provide that knowledge. That said, whenever a comment addressed a specific area to improve in – for instance, last hitting (killing minions to receive gold), improving reaction times, or becoming better at a certain role – comments addressing the same area would often have a few themes commonly brought up. This could be due to the fact that those themes are objectively the best ways to improve, or subjectively due to the “hive-mind”, or are just tribal knowledge.

5.5. Giving Back
While not a huge part of the forum analysis, a surprising number of players shared their own knowledge with the community, unprompted. For reference, 24 posts marked as “desire to improve”, compared to 28 posts marked as “desire to help others”. This knowledge usually came in the form of text posts, either detailing a new mechanical exercise, or a new philosophical way to approach the game. Posts included “How to get better at this game. (imo)”, “Diamond Guide to Grinding Elo”, and “My experience playing !Osu and how it improved my league in order to climb the ladder”, in addition to the threads quoted above.

5.6. Self-Tracking and Self-Experimentation
Currently, LoL players have some interest in experimenting with their play, usually with the goal of improving at the game. I applied codes to twelve posts, marking them as “self-tracking” posts, with four handling long-term tracking, two handling extended play sessions, and six regarding champion specialization. One item that comes up regularly is playing one champion to improve at just that champion, and that mastery of that champion will translate into improvements in ranking. Beyond that, some players try to do 24-hour long play sessions to compact weeks worth of play into a day in order to see trends more easily. Finally, self-tracking is a very common theme. There does not appear to be any application which allows players to track their own progress (short of a few unsophisticated tools on the web) so players must build

Figure 4. One player’s graph of their elo over almost 100 games.
up their own models. Players tend to track the same set of statistics (win rate, champion played, notes) with a few items variant between them (physical state, k/d/a, ways to improve). Players also tend to have a tough time sticking with self-tracking, regularly stopping within ten to twenty games. However, there are also success stories of players tracking over 100 games at a time, using detailed infrastructures, and usually relying on spreadsheets to maintain their data.

5.7. The Social Side of Tracking
While users would infrequently post on self-tracking and self-experimentation, there was a high proclivity among users to either follow others’ self-tracking and request follow-ups, or to adopt their own survey based off of others’ initiatives. In response to Umashi’s “Specialization Experiment – Week One Update” thread, Zheusey comments, “Was just wondering where this had gone yesterday – thanks Umashi.” Bikt also comments, “In what way are you going to inform community about the results?” on another such thread, joined by ibasawstealth who comments, “Keep us updated on the experiment. Thanks for helping out the community.”

It seems that there is some high threshold (or low willingness to begin) to begin experimentation, but once some initial work is done, many other community members are willing to join. On the thread “I’m doing an experiment to see if I can make my 1400 elo friend a better player in two weeks.” by Umashi, Dacolt comments, “As a person stuck in a lowish elo in nearly the EXACT same situation, I, too, will perform this experiment…”, and Bomboloero also comments, “I’ll do the experiment too, except I’m using Kennen instead of Nidalee. To track my progress I have made an Excel document…”. It is likely that setting up the initial tracking framework is mentally rigorous enough to turn users away – or perhaps self-tracking is rampant on the individual level, but sharing the results of that is difficult. I am inclined to think it is the former due to the community response to sharing self-tracking.

6. Research Pivot
Following the forum analysis, I determined that reaction times, while a portion of what the community cared about, were not such a clear issue that they should be addressed. Few people mentioned external factors to reaction time, indicating a lack of interest or awareness on the issue. The issue which surfaced as a more actionable area was the community’s self-improvement habits as a whole. Given the less than ideal methods of self-tracking which exist in the status quo, as well as the difficulty that exists in analyzing one’s own games, self-improvement is a difficult task that could be expedited by a toolset to help players think about and act on their gameplay.

7. Framework
The first step in aiding players was to construct a framework for them to discuss their gameplay. Given the problems discussed above, giving players a way to break down their strengths and weaknesses to find actionable ways of improving themselves. To do this, I constructed a framework, highlighting what I detail as the “five facets of skill”. This framework is intended to give players a new language to discuss and classify their gameplay. While this framework was built off an analysis of the League of Legends community, it is generic enough to be extendable to other competitive video games.
7.1. **Game Knowledge**, is the first facet of the framework, and describes falsifiable facts about the game. Game Knowledge is hardcoded into the game, and defines a particular knowledge base, such as attack and damage values, and how underlying calculations function. This ranges from broad facts, such as the objective of the game and what the controls are, to more minute details, such as in-game timers and gold costs of various items. An example of this is knowing that the Flash summoner spell, an in-game ability accessible to all players which instantaneously teleports the champion a short distance, can be used once every 300 seconds.

7.2. **Game Theory** is the second facet of the framework, which takes the lessons from Game Knowledge and crafts them into optimal sets of actions in general. Game Theory informs things like itemization paths and ways to build a team composition. This overlaps heavily with what the community refers to as “theorycrafting”, where players examine what can be done in the game, and propose different approaches to the game, or different ways of thinking. An in-game example of this is knowing that using Flash to dodge another champion’s ability is more optimal than using Flash to travel between two points faster.

7.3. **Strategy** is a contextualization of Game Theory, and an application of the prior facet into the game. Strategy is the set of macro-level actions which a player or team would desire to take given the status of the game. Strategy encompasses skills like shotcalling, adapting in-game item builds, and in general, determining which optimal strategies apply to the situation. An in-game example of this is knowing when to hold Flash versus use it, in a situation where using it would be optimal in a vacuum. For example, opting to die instead of using Flash to save yourself since you predict that a more important time to use Flash will occur in the next two minutes.

7.4. **Presence** is a micro-level facet, compared to the macro-level scope of the facets before it. It is knowing how to execute a strategy, and is much more in-the-moment. It is recognizing when and how to act, and the ability to plan out a series of actions in advance. In comparison with strategy, Presence details micro-level actions to take, such as knowing when to trade in lane, or teamfight mid and late-game. An in-game example of Presence is seeing an enemy champion moving towards you, and deciding to Flash away to a particular location as soon as that champion uses a particular ability.

7.5. **Mechanics** is the ability to execute on presence. It takes into account reaction time, accuracy of mouse movements, consistency of movements, and general ability to interface with the hardware to manipulate the game to match the actions outlined by presence. Using the prior situation, Mechanics is the raw ability to move your mouse and click the related key to use Flash in a fast enough and accurate enough manner such that you are not hit with by an enemy ability.

8. **Utilizing the Framework**
While the framework is meant to be a general tool for players to use in the context of their games, it can be used in a directed manner in order to inform a process which can better guide player improvement. Beyond simply adding the facets to their language, players can take short, arbitrary clips from their gameplay, and analyze those clips with regards to the various facets. Through a self-study, I found I could remember exact situations within gameplay and my thoughts during those moments one or two days after they occurred, as long as I had the replay to jog my memory. This indicates the propensity for players to review their games, even after some time has elapsed since the exact moment when something occurred, and use those reviews in a constructive, directed manner.
9. Experimental Design
In order to evaluate the usefulness of this framework in its intended context, I designed an experiment to assess the viability of the framework in improving a player’s self-analysis. The study was run over 12 participants over the course of a week. After the studies were run, before analyzing data, I devised a few hypotheses over the data, which I analyze below.

9.1. Early Stages
The first stage of experimentation was evaluating the framework myself. I used the framework over several of my own games, and learned two important lessons while matching data in the framework. First was that deaths were a good focal point for this research. It provided a concrete set of events in game to analyze, and also was a type of event which one could concretely provide analysis about what happened and what could have gone better. Second, I learned that I could recall games 24 to 48 hours after they occurred, which was important in opening up pathways for experimentation. I also discovered that a limitation of the framework was that while it facilitated desire to improve at the game, it was not a prescriptive method, so players uninterested in applying themselves to introspection would likely gain little from this framework.

9.2. Participant Experimentation
In order to test this framework, I conducted a between-subjects analysis over 12 participants. These participants were split into control and experimental conditions. Both groups were asked to play League of Legends and save their recordings, then come in the next day to analyze their gameplay. Participants were asked to answer two questions for each time they died in one of their games – first, “what caused the death?” and second, “what could you have done better?” Questions were left open-ended to observe what the player thought they should write there, if anything. While the control group was only told that we would be looking at their response, the experimental group was also provided the framework as something helpful for answering those questions.

In population selection, I surveyed approximately 80 submissions from the League of Legends student organization, the Union of Purple Caster Minions. I invited respondents who indicated that they played ranked queues at least a few times a week, primarily played Summoner’s Rift, played on a Windows 7, 8 or 10 computer, and who had never banned or restricted from gameplay. I also took note of the in-game ranking of the invitees, and made sure to evenly distribute the rankings between the two experimental groups.

I chose players who played ranked queues regularly and who primarily played on Summoner’s Rift so that participants would be familiar with the format when I asked them to play ranked games prior to coming in. I focused on ranked games so that players would be more likely to be playing to win, as opposed to potentially confounding reasons, such as experimentation, or to have fun with friends.
not that any of those three are mutually exclusive. The technical requirement of the most reliable replay systems meant that I recruited participants who used compatible operating systems. Finally, I opted out of choosing players with bans, ranked bans, or chat bans, as the former two would prevent them from completing the study, and the final one could get in the way of optimal gameplay. In addition, players with a history of these bans or restrictions tend to have issues with delivering analysis constructively, which would add another variable to my analysis.

I set out to observe a few key areas of analysis. Primary focuses were the number of reasons that players gave per response, as well as the diversity of reasons per response. We can also look at the depth of analysis, how far back analysis goes (referring to events which were seconds versus minutes old) and how constructive analysis is, looking to the number of actionable items per response. Of secondary concern are how player-focused the responses are, when actionable items occur (focused in the first or the second question), and how many edits are made in the final stage of the study. From an initial glance, it appears that there is some correlation between in-game rank and the helpfulness of the analysis, but that still is to be determined.

9.3. Experimental Hypotheses
After conducting these experiments and prior to analyzing my results, I formulated a pair of hypotheses to focus my analysis of the data.

- The “five facets of skill” framework facilitates player self-analysis, as indicated by a greater number and diversity of reasons and actionable items provided per death.
- The “five facets of skill” framework is employed more effectively by players with higher ranking, as indicated by larger increases in analysis between players with higher ranks.

10. Experimental Findings
10.1. Metrics
I measured participant responses with several quantitative analyses. The first three metrics were observed from the first form, and the last three metrics were derived from the second form.

- Form 1 reasons – the number of reasons given among all deaths
- Form 1 personal identifiers – the number of reasons among all deaths which focused on the individual, as opposed to themselves or the enemy team
- Form 1 unique personal reasons – the number of unique reasons given among all deaths
- Form 2 action items – the number of actionable means of improvement among all deaths
- Form 2 personal action items – the number of action items centered on the player among all deaths, as opposed to critiques of their team
- Form 2 unique action items – the number of unique actionable items

I grouped these metrics by control or experimental as well as by ranking in a secondary analysis.
10.2. Findings

After conducting this analysis, I created a summary table of results, computing absolute totals, and more meaningfully, per-death averages. There was noticeable variation between death totals, especially in the ranked analysis, so the per-death metrics are the meaningful results here. Overall, it appears that the inclusion of the framework inspired players to be more analytical about their gameplay, but that ranking had little effect on a player’s ability to analyze data. We observe that all metric averages increase between the control and experimental groups, but that there is no clear pattern between the ranks.

### Overall Trends

Looking at the first two rows of the findings table, we find that players give an average of 2.35 reasons per death, with 1.54 of those reasons targeted at themselves. Further, about two-thirds of those reasons are unique. What this means is that players are good at identifying a varied set of reasons which influenced their death, and spend about 60% of their time focusing on their own play, with the other 40% identifying enemy and ally actions. Beyond that, players identify 1.8 action items per death, with 1.78 of those targeted at themselves, and 1.14 of those being unique. Players are good at identifying at least one area for improvement for each death, and generally keep them focused on themselves. However, there are recurring trends in these analyses, revealing that each player might have underlying fundamental problems, rather than a set of unrelated issues.

### Experimental versus Control

Looking specifically at the experimental versus control group data, it seems that there was some positive effect afforded by the introduction of the framework. On form 1, participants provide roughly 30% more reasons for their death, though only one-third of those are focused on themselves. The more notable change is that players begin to identify a larger set of unique reasons for their deaths, with unique reasons increasing by half. On form 2, the results are much more striking, with overall and personal reasons increasing by 50% each, and unique reasons per death almost doubling. This signals (without deeper analysis) that the framework might make players think more deeply about their gameplay, analyzing a broader range of items. This would seem to be consistent with the notion that expanding a player’s language regarding skill would give them additional lines of analysis.

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Figure 7. A summary of the metrics from the study.

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<tr>
<th></th>
<th>Player</th>
<th>Condition</th>
<th>Rank</th>
<th>Role(s) Played</th>
<th>Deaths</th>
<th>F1 Reasons</th>
<th>F1 Identifiers</th>
<th>F1 Uniques</th>
<th>F2 Action</th>
<th>F2 Identifiers</th>
<th>F2 Unique</th>
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10.5. Ladder Rankings

The most notable statistic here is the decline in deaths per rank, with lower ranked players, silver players, dying 50% more often than the diamond ranked players. It is important to remember here, however, that each category has only two to three data points. Interestingly, the players who analyze their games the deepest are at the gold and diamond levels, with silver and platinum being more closely correlated. This would indicate, short of some link between gold and diamond rankings, that there is little correlation between rank and framework efficacy. One might speculate that there is some weak relationship, given that silver is noticeably below any of the other higher ranks.

10.6. Statistical Significance

In addition to the mean analysis, I performed a least-means multiple regression of the results, encoding the control versus experimental groups as $[0, 1]$, and ranking as a number corresponding to the overall ranks, increasing as rank increased. I report the associated p-values in Figure 8. The first column of p-values corresponds to the experimental groupings, holding rank constant, and the second column is a linear regression on ranking, holding the groupings constant. Finally, the third column of p-values is a multiple regression taking both into account. The majority of the reported p-values were well above the 0.05 mark, but two p-values, both for the form 2 unique actionable items metric, were close to the 0.05 mark. This indicates that for the most part, our results indicate that the framework could be a useful contribution in improving player analysis, but that there is also a significant impact on the diversity of constructive suggestions that players provide in their analysis when provided with the framework. The slope of the curve drawn for the experimental groupings for these columns was 0.69 and 0.60, respectively.

<table>
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<th>M</th>
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<td>Condition</td>
<td>Ranking</td>
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<td>0.0496</td>
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</table>

Figure 8. P-values for experimental variables

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3 Bronze 5, for instance, was 1, Bronze 4 was 2, up to Challenger, which was encoded as 27.
10.7. Experimental Conclusions
Having analyzed the data from the experiments, we find that the framework has potential to facilitate player analysis, but in general the data is insufficient to make any strong claims. We can say with high confidence though, that the framework does help elicit a greater diversity of responses from players. Additionally, we do not have sufficient evidence to uphold the notion that a player’s existing skill or ranking plays a meaningful role in adding to the benefits of using the framework. In general, there is not enough data, or a clear enough trend, to correlate rankings with any sort of increased helpfulness of the framework.

11. Discussion
11.1. Confounding Factors
The study, while changing only one condition between the two groups, might not necessarily be indicative of the usefulness of the framework and language. There is the chance that the additional level of analysis was afforded by additional time spent with thinking about skill before entering the primary analysis, or that the presentation of the framework overemphasized its usefulness. In either case, the framework would still then be helpful, though as a catalyst for getting players to think more about their skill, rather than being the primary vehicle through which players might think.

One small confounding factor was the inclusion of futile deaths – notably, deaths within the last one to two minutes of the game. During these times, regardless of if players are winning or losing, there is a high chance that they will die regardless of what they do (if losing) since the enemy team is usually very powerful by that point, or commit suicidal actions (in either condition), perceiving their death as having no impact on the game at that point. This is not always true, and since some deaths at those points can be avoided due to better play and can impact the outcome of the game, I included those data points.

In future iterations of this study, I would revisit the wording I used within the experimental condition. I provided the framework as “something other participants have found helpful”, and that the participant should “feel free to use”. This added an additional factor to the study of both the attractiveness of the framework for use as well as its raw facilitative ability. In the future, I would ask participants directly to utilize the framework in their analysis to remove that first factor and thus be better able to identify the causes for the results.

Additionally, I would better regulate the number of deaths analyzed to a flat number, not asking participants to analyze data beyond that point. I suspect that in some cases, having to analyze up to double the number of instances as another participant may have fatigued participants, causing them to provide less detailed analysis overall. I did not perceive sessions to take significantly longer in instances where players had many deaths, so this certainly may have affected player analysis.

11.2. Quantitative Aid
While the framework itself is very qualitative, it would be easily translatable to support a quantitative framework in the context of helping players. Players could be asked to not only rate their own gameplay in terms of what they could have done better or worse, but also to rate themselves in each category holistically, on a scale of 1 to 10, for instance. This would allow players to track their own rating of themselves over time, and see a visible means of improvement. Another possible method might be to highlight recurring trends of actionable items as a checklist, and check them off as their occurrence rates drop off. Regardless, in either scenario, the effectiveness of the framework is only
as effective as the user’s ability to critique themselves, as players who fall subject to Dunning-Kruger⁴ effects are unlikely to provide themselves with as much useful analysis in any setup. However, facilitating those players’ improvement is not the focus of this framework; it only aims to aid those players who are already motivated to improve themselves and can be critical of their own play. The fact that that a quantitative analysis will not be normalized has little issue since these analyses are meant for the individual only, as opposed to population rankings, where some other metrics would need to be put in place.

12. Conclusion
12.1. Takeaways
At the end of this research, I have taken away three primary lessons from the work I have done this year. First, that League of Legends players are highly motivated to improve, but do not have all the tools to do so effectively. Second, that League of Legends players have difficulty constructively discussing gameplay with the current language of skill that they utilize. Finally, that we can develop a framework that positively impacts player improvement within League of Legends. This is not to take away from all of the research methods and important academic considerations that I have personally learned, but rather to focus on the meaningful contributions of this research.

12.2. Future Work
With the experimental findings above, the next steps are twofold. Understanding the value of the framework could be further pursued with a more controlled study to provide data for an academic paper, but at the same time, a physical tool could also be built out (also able to inform an academic paper) to both provide players with this additional means of self-improvement, and also as a means to collect data en masse. The second path would almost certainly be the more rigorous one, but would afford me populations and scaling beyond what would be feasible with in-person interviews.

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⁴ From Wikipedia, “The Dunning–Kruger effect is a cognitive bias wherein unskilled individuals suffer from illusory superiority, mistakenly assessing their ability to be much higher than is accurate.”
Citations


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