Claremont McKenna College

The Effects of Experience and Familiarity on Performance in Virtual Environments

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Abstract

League of Legends[1] is one of the most played video games in the world with millions of hours played each year. I examine if both a player's experience and level of familiarity with teammates within the League of Legends virtual environment have significant relationships with individual performance. Utilizing regression analysis I have concluded that individual experience does not have a statistically significant effect on individual performance and that individual familiarity has a statistically significant negative effect on individual performance.

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1 - Introduction

An organization's leadership is frequently responsible for optimizing the completion of complex tasks, and the application of data analytics to this end allows for more informed decision making to occur. But while sales, product, and consumer analytics have become standard procedure within most professional firms, there still does not exist a source of reliable high volume data for individual and team performance analysis. The methodologies and conclusions of analysis driving current best practice are sound, but the lack of individual performance data available limits the ability of managers and leadership to construct optimal teams backed by statistically proven cause and effect relationships. In this study I navigate this obstacle by analyzing performance data gathered from virtual environments. Applying statistical analysis to teams within virtual environments creates opportunities to draw robust conclusions on what relationships exist between individual experience, familiarity, and performance. This study uses the team-based video game League of Legends as its virtual environment to produce robust and significant conclusions about individual performance.

Team-based video games share many of the same qualities as business teams assigned to complete a complex task. A given team's members can have different levels of experience, familiarity, and a myriad of individual characteristics. Team members must constantly evaluate the state of the system they are operating within, cooperate with teammates, and fulfill individual roles in the hope of achieving success. The key advantage of using virtual environments such as League of Legends is in the volume and reliability of data available for use. A standard match of League of Legends lasts between

33 minutes on average (League Math). In this period the underlying systems generate data points on the game economy, player roles, player actions, player interactions, and player decision making automatically. Depending on the infrastructure put in place by a parent organization, a new data entry could be generated at rates faster than one per second. Assuming a match lasts 33 minutes and records one data entry a second for each of the ten players in the match, 19,800 entries would be produced and recorded. In that same period of time, the analysis of a team in a business environment by traditional data collection methods such as surveying or observational recording would produce a miniscule amount of relatively questionable data. Consider then that millions of players play more than a million matches each day and the volume of data available for team composition and performance analysis usurps that of non-technological methods substantially (Riot Games). The data can then be used to optimize virtual and geolocated team[2] composition.

In this study I used Ordinary Least Squares Regressions to analyze a dataset containing a year and a half of competitive League of Legends matches for a randomly selected team. My analysis does not find a statistically significant relationship between individual experience and individual performance, but does find a statistically significant negative relationship between an individual's familiarity with team members and individual performance.

[2] Geolocated teams are teams whose members interact locally with each other in the same physical environment such as sports teams or business teams operating out of the same clubhouse or office building.

2 - Literature Review and Hypotheses

The available literature for the performance of teams in virtual environments and familiarity between members of virtual teams is an underdeveloped area of study with few conclusive findings. Geolocated team composition, performance, and familiarity studies are comparatively more developed, but lack the elements of virtuality that this study is approaching individual performance from. Both types of studies are relevant due to the schemas on virtuality and performance they provide, but as a whole are unable to provide data sufficient for unquestionably conclusive results. A natural result of this is that the literature referenced and discussed here is used to inform the construction of this study but is unable to provide a concrete statistical basis from which to build hypotheses upon. This study acknowledges the limitations of the available literature and generates from the current body of available studies an informed basis for future studies to expand upon the performance of virtual teams.

The use of statistical analysis in order to develop team compositions optimized for performance is a proven method of approach. Recent studies on the method include the Weimar and Wicker (2014) paper which discusses the value of incorporating the use of additional player statistics in optimizing team performance. Their primary discussion is focused on an underutilized relationship between player effort and team performance in professional soccer that could aid team performance optimization if introduced to player value models. Familiarity between team members is the focus of Cattani et al. (2013) who found in their study on team performance in the film industry that the more star members a team has, the worse the team performs. This performance threat is mitigated as familiarity between team members increases to the point of becoming an asset at the highest levels of familiarity. Raes et al. (2015) support this perspective with their study on group development and team learning. They found team learning behaviors are highest later in the group's development and suggest the behaviors are impacted by familiarity and group psychological safety. Familiarity as a primary factor contributing to team performance is further supported by the Mertins and Hoffeld (2014) study on the cooperation of team members. Their evidence shows that a team member's willingness to contribute is directly linked to any given team member's impression of other members' willingness to contribute. Exploring the intersection of individual ability and familiarity, Depken and Haglund (2011) examined whether increasing the average quality of team members has a nonlinear or deleterious impact on team performance. They found increasing average team member quality increases performance at a decreasing rate, citing negative peer effects as the chief reason for underperformance. Bertolotti et al. (2013) expand the analysis of team performance by analyzing the effect of multiple team membership on team performance, finding an inverse U-shaped relationship between the number of teams an individual is on and team performance. Their study also showed the use of instant messaging between team members increases performance at low levels of multiple team membership and decreases performance at high levels.

There is ample literature available on the subject of virtual teams, but the recency of virtual teams' adoption at large has resulted in little consensus about how to model, study, and evaluate virtual team performance. While the work analyzing the performance of virtual teams is limited, the body of research available on virtual teams does provide useful means for discussing differences between geolocated teams and virtual teams. By using a conceptual basis of traditional geolocated teams and controlling for the differences between them and virtual teams, a basic framework for understanding virtual teams can be reached.

Hosseini et al. (2015) developed a conceptual model detailing the degree of virtuality that measures the virtuality of a team as "to what degree deviations from face-to-face communication affect the quality of communications within the team in comparison to a face-to-face team," (p. 395). Grabher and Ibert (2013) contest this definition, and offer a competing foundation upon which to analyze virtual teams. They begin with challenging the notion of "proximity bias," or that collocation is inherently superior to a dispersed team. They provide a framing definition of what constitutes a virtual team or community, describing it as an entity where, "interaction is mainly mediated by communication tools provided by the Internet," (p. 101). Their findings support their refutation of proximity bias, noting that virtual organizations feature, "knowledge circulation [that] comes rather close to the ideal of the 'mode-2'-type of knowledge production[3] (Gibbons et al., 1994)," while having the advantage of being both hypertextual and allowing of 'reflective reframing' (p. 115-116). Looking at team performance specifically, Pinar et al. (2014) successfully apply team learning and team effectiveness scales for conventional teams to virtual teams. They find a strong relationship between team learning and team performance, stating that task-oriented team leadership and the relationships between a team leader and individual team members

[3] "In this mode the locus of knowledge collaboration shifts from the traditional institutional framework of disciplinary organized knowledge production to learning and knowledge creation in the 'context of its application'," (Grabher and Ibert, 2013, p. 115).

supports team learning and team performance. Results from an early study by Workman (2005) supports the claims of Pinar et al. regarding the effectiveness of task-oriented teams, but disagrees with the conclusion that focusing on interpersonal relationships improves virtual team performance. Workman finds that virtual teams that are means focused outperform ends focused teams, and that virtual teams with a task-oriented structure outperform teams that rely on interpersonal structures for organization.

The literature provides a basis for the expectations of a virtual team's performance. In geolocated teams where members belong to one or only a few teams, both experience and familiarity should improve the performance of the individual and team. Applying to this foundation explored concepts of virtuality, a virtual team that is means or task-oriented and focused on knowledge sharing should perform well: the effects of experience should remain positive and the effects of familiarity should remain positive but muted in a means focused environment. Using this informed foundation I have constructed two primary hypotheses for the performance of individuals in virtual environments.

H1: An individual's experience in a specific virtual environment will exhibit a positive relationship with their performance in that virtual environment.

H2: An individual's familiarity with peers or teammates in a specific virtual environment will exhibit a positive relationship with their performance in that virtual environment.

3 - Background

League of Legends is a 5v5 team-based video game owned and operated by Riot Games, a subsidiary of Chinese investment holding company Tencent. The game has an active daily user base of 7.5 million concurrent users at peak hours and 67 million unique monthly players (Riot Games). The game falls within the genre of Multiplayer Online Battle Arena (MOBA) games and is free to play: anyone who has access to a computer and makes an account can play. Players are bound to a regional server when they create an account. It is possible to play on any of the official servers from any location, but the nearest available server is typically preferred. The closer to a server's location a player is, the faster League of Legends will register the player's input commands and allow them to act. This results in a server's population of players largely reflecting the demographics of the sever's geographic region. In addition to its massive base of active players, League of Legends is also one of the world's premier electronic sports or "esports" (Fortune).[4] There are five major regions that host professional leagues and a multitude of emerging regions, with most regions having their own servers. The League of Legends competitive year lasts from January through October over the duration of two individual seasons or "splits" where regional competition takes place. In October the top teams from across the world gather to battle for the World Championship title in matches whose viewership rivals that of premier sporting events such as the MLB's World Series and NBA's Championship Series (LoL Esports). During the competitive year Riot Games makes small balance changes to the game roughly every two weeks that affect both standard

[4] Esports are organized competitive activities that occur in online or virtual environments.

play and professional leagues. After the World Championship larger experimental changes to the game are introduced for the next year of play during the “Preseason”.

The primary goal within a match of League of Legends is to destroy the enemy team’s nexus, a central structure that is located in the center of their base. During the course of the match players work to accomplish secondary objectives that increase their team’s power relative to the opposing team. These objectives include generating gold by slaying hostile units and enemy players, destroying enemy structures that defend the path to their nexus, and securing objectives around the map such as vision control or temporary increases in power. There are two primary types of matches within League of Legends; “Normal” matches that are always available and “Ranked” matches that are made available after a player has increased the level of their account to the maximum.[5] Both types of matches feature the same primary and secondary objectives. Ranked matches are subdivided into two variants: solo queue and team ranked.[6] In solo queue players are restricted to entering a competitive match alone or with a single partner and are then placed into a team with three to four randomized players. In team ranked, players must belong to a persistent team of five to ten roster members prior to entering a match. A combination of five roster members from the team then enter into a match against another team. In all Ranked matches the players choose their champions prior to the match during a drafting or “pick-ban” phase, a process where teams alternate in removing

[5] A new League of Legends account begins at level 1. Playing matches of any available type increases the level of an account. The maximum level a player can reach is 30. Player level is a system measured separately from player skill.
[6] This division and definition of Ranked is accurate for this study’s timeframe, but it should be mentioned that Riot Games has since implemented a Ranked “Dynamic Queue” and removed the variants mentioned here.

six champions from the available roster and then alternate selecting the champions which they will play. In Ranked queues players and teams each have a skill rating used for selecting opponents of the appropriate level for any given match. Winning or losing a match influences this ranking. Normal matches are not calculated into a player's competitive online ranking and do not feature a drafting phase or limitations on what combinations of players can play within the match. From here on the different Ranked queues will be referred to as the following: solo queue (solo queue with no partner), duo queue (solo queue with a partner), and team ranked.

League of Legends features a few maps upon which players may do battle, but the vast majority of matches and all professional matches are played on the "Summoner's Rift" map where two teams of five players combat one another (Figure 1). Summoner's Rift is a square map in which there are two long roads or "lanes" and one short road or "lane" reaching from the bottom left corner of the map to the opposite corner. Soon after beginning a match small computer controlled units called "minions" aligned with each team begin periodically marching down the lanes toward the enemy base. They proceed until they encounter an enemy unit or structure to attack. These minions can be slain by a player to acquire gold and are useful for destroying the opponent's structures. The space between lanes is filled by a navigable monster-infested area called the "jungle."

The two teams are composed of individual players competing from separate computers. Each player has direct control over a single character or "champion" with unique abilities and characteristics they use to fulfill one of the roles on the team. Across most levels of play, there is an accepted macro-level strategy or "metagame" for

Summoner's Rift. The established metagame dictates that one player from each team plays in the top lane, one in the jungle, and one in the middle lane. The other two players on each team play together in the bottom lane. More self-sufficient characters typically play in the jungle and "solo lanes," while characters that need assistance to reach significant levels of power team up within the remaining "duo lane." The five roles that players from each team assume within the current metagame are the following: top, jungle, mid, ad carry, and support. Each team possesses two different types of structures; "towers" and "inhibitors." Towers are defensive structures located in the lanes. Towers automatically fire upon enemy units when they come within range. Inhibitors are structures within the border of a team's base that reduce the strength of the opponent's minions. Towers are permanently destroyed within a match while destroyed inhibitors will regenerate after a few additional minutes of play.

The primary method for growing stronger in League of Legends is through purchasing items that empower your champion during gameplay. Items are an integral part of League of Legends: securing more powerful items within a match grants varied and significant advantages over an opponent. These advantages are typically strength-boosts or unique abilities for the player who purchased them. For example, the basic item "longsword" increases a player's offensive capabilities. Combining that longsword with other items and additional gold can generate better items that give additional stats or unique powers including shielding and a vampiric lifestealing effect. In order to purchase items, players must spend gold they earn while playing the match. Unique instances of gold generation are distributed to either a single player or the player’s team depending on the source and circumstances surrounding its generation. At a rudimentary level, every player generates a small amount of gold for themselves over time regardless of any actions taken. Excepting passive gold generation, players can generate gold for themselves by defeating computer controlled creatures in the lanes or jungle, by buying an item that passively increases the amount of gold generated, or by participating in a kill on an opponent’s character. Players can generate team-wide income by destroying the enemy team’s towers or by securing the killing blow on large neutral monsters. Players can also increase their power by gaining levels which grant their champion more powerful abilities. Players gain experience needed to level up by being near an enemy unit when they are slain by an ally.

Within an individual League of Legends match the standard gameplay progression begins with all players positioned within their respective bases. Players use their starting gold to purchase some basic items prior to leaving the base. Once the players have left the base, each team utilizes their unique abilities and composition to collect gold, secure objectives around the map, and combat the enemy team. Players can elect to return to their base at will provided they find the advantages of doing so preferential to those gained from exerting their presence in battle. When slain in battle players will revive at their base after a “death timer” penalty has expired. Within their base players can restore their health and spend earned gold on additional items. This ebb and flow process of combat and restoration repeats itself until the match is concluded with one team leveraging a combination of their items, unique abilities, and other acquired resources to destroy the opposing team’s nexus.

4 - Data and Empirical Methods

This study focuses on Ranked League of Legends matches played on the North American server on the Summoner's Rift map. In the course of my analysis I gathered over 11,000 data entries. Each entry represents an individual's performance and related metrics within a match they played between May 1, 2014 and January 8, 2016. My data looks at all of the matches within that timeline for a team randomly selected from a list of teams on the NA server.

I generated this data by making informational calls to the Riot Games League of Legends Application Programming Interface. This was done by developing a computer program built upon the Python programming language, SQL programming language, and the SQLAlchemy toolkit.[7] The program begins with a single player's ID and then aggregates an inclusive list of player IDs for all players who have played in Summoner's Rift Ranked matches with the input player. This process was repeated for each new player ID added to the list until an acceptable ID-volume of roughly 15,000 unique player IDs was achieved. Each of these IDs were then checked to see if the player belonged to a registered team, multiple teams, or to no teams. Each unique team and the team's members were aggregated within a SQL database. From this database of teams and team roster members a single team was randomly selected to act as the subject of the study.[8] Every Ranked match between May 1, 2014 and January 8, 2016 was gathered and stored for all roster members of the selected team.

[7] The program can be found here: https://github.com/StickmanVentures/lol-data-aggregator

[8] Initially the entire collected sample of teams was intended for use in the generation of a comprehensive sample dataset of teams and their players. The sample was restricted to a single team's data once it became apparent that the volume of data to be gathered would conflict with the Riot Games API's Terms of Service.

There are several limitations to this dataset. The first limitation is that the data only includes Ranked matches played. As discussed in the background section, players can play League of Legends both casually or competitively in Normal or Ranked queues respectively. Because Normal match experience is not incorporated within the dataset, any derived individual experience measures do not have implications beyond the Ranked League of Legends virtual environment. Experience outside of the Ranked League of Legends virtual environment is not controlled for. The second limitation is that the dataset does not include the comprehensive Ranked history of the players because Ranked matches played prior to May 01, 2014 were not captured. Players must have played Normal matches to level their account to a Ranked eligible state and are likely to have played Ranked matches prior to the first data entries of this study. This limitation can be controlled for by implementing lags upon the data which presume that the effect of the variables outside of a certain timeframe are not relevant to a present match's performance. Lags of one month and three months were selected as two durations implementable within the timeframe of the dataset. The third limitation is a lack of data on the opposing team for any given match.[9] Because there is no data on the opponents faced in a match, the fixed effects for opponent characteristics are not controlled for.

The two independent variables of interest for this study are individual experience and individual familiarity. Individual experience is measured by a variable storing the number of matches a player has played within the selected lag period length. The formula for an individual's experience is as follows:

[9] This was controlled for within the original scope of the study, but complications in the data gathering process resulted in both no opponent data and a volume of data significantly below the original volume intended.

Lag Length = One or Three months (model dependent) , i = Date of match - Lag Length

$$\text{Experience} = \sum_{i=1}^{Lag\ Length} Matches\ Played$$

Familiarity was measured in two different ways with each exposed to the one and three month lags. The first of the two measures, referred to as Familiarity 1 from this point on, is the sum of individual roster members present across all matches within the lag period. The second measure, referred to as Familiarity 2 from this point on, is the sum of matches where at least one roster member was present within the lag period.[10] The formulas for Familiarity 1 and Familiarity 2 are as follows:

Lag Length = One or Three months (model dependent), i = Date of match - Lag Length

$$\text{Familiarity 1} = \sum_{i=1}^{Lag\ Length} Number\ of\ Roster\ Members\ Present\ in\ Matches\ Played$$

Lag Length = One or Three months (model dependent), i = Date of match - Lag Length

$$\text{Familiarity 2} = \sum_{i=1}^{Lag\ Length} Matches\ Played\ with\ a\ Roster\ Member\ Present$$

There are two dependent variables of interest used to model an individual's performance in a match. The first dependent variable is the gold earned by the player

[10] Familiarity 1 will necessarily be greater than Familiarity 2 because it includes all instances of Familiarity 2 in conjunction with additional roster members on a team.

within a single match. As stated in the Background section, gold is awarded to the player for successfully performing actions that contribute to the team's victory and thusly is an appropriate individual performance measurement. The second dependent variable is the KDA ratio of the player within a match. Kills and assists by a player on an opposing player result in the enemy's brief removal from the match, while a player's death results in their removal from the match for a short duration. The KDA ratio can be thought of as the amount of time a player contributed to removing enemies from the match divided by the amount of time the player was removed from the match.[11] The KDA ratio of a player is represented by the following formula:

$$\text{KDA} = (\text{Kills} + \text{Assists}) / \text{Deaths}$$

A number of fixed effects are controlled for within the model. Individual fixed effects for the preseason, for each of the roster members on the team, and for each role within the match are all included. My analysis was performed by generating an Ordinary Least Squares regression model for each measure of familiarity and applying those models across gold earned, KDA, and both lag periods. The resulting eight models feature unique combinations of individual experience, familiarity, and one of the lag periods while controlling for fixed effects.

[11] This is an approximate conceptualization because the death timer penalty, or the amount of time a player is removed from the match upon death, grows from shorter to longer durations as the match moves on.

5 - Results

I hypothesized a positive and significant relationship between the independent variables and the dependent variables. The results of the regressions did not coincide with my hypotheses. In all models, individual experience did not have a statistically significant relationship with the dependent variable. The two measures of familiarity were statistically significant in every model, but differed in their effects for each dependent variable. In the four gold earned models, the duo queue dummy variable is not statistically significant (Tables 7-10). The team ranked dummy variable is statistically significant in all of the gold earned models with a significant negative value. The lagged familiarity measure alone is statistically significant on gold earned with a significant negative magnitude in every model at the 90 percent confidence level, and in three of the four models at the 95 percent confidence level. Familiarity interacted with the duo queue measure and team ranked measure were both not significant in these models. In the four KDA models, the duo queue dummy variable is statistically significant in the majority of models with a significant positive magnitude (Tables 11-14). The team ranked dummy variable is statistically significant in all of the KDA models with a significant positive magnitude. The lagged familiarity measures alone were not statistically significant. Familiarity interacted with duo queue and with team ranked is statistically significant in both cases with a small negative magnitude.

Across the gold earned models the constant is approximately 11,800 gold. In every model gold earned is subject to decrease by at least 1,047 gold if the match is a team ranked match. The negative effect of team ranked on gold earned is larger for the models with Familiarity 2 measures than for those with Familiarity 1 measures, with both of the Familiarity 2 models featuring losses of approximately 1,800 gold. The models using Familiarity 2 also exhibit stronger negative relationships between the standalone familiarity measure and gold earned. The difference is largest for the one month lagged comparisons: the coefficient on the One Month Familiarity 2 model is -14.861, while it is -8.857 for the One Month Familiarity 1 model. The Three Month Familiarity 2[12] and Familiarity 1 models have coefficients of -5.702 and -4.863 respectively. Across all four gold earned models the R^2 of the regressions is approximately 12 percent fit.

Across the KDA models the constant is a KDA ratio of approximately 2.6. In every model KDA is subject to increase by at least 0.646 if it is a duo queue match, and at least 3.953 if it is a team ranked match. Unlike in the gold earned models, the KDA models do not show one familiarity measure having stronger dummy variable impact than the other on the independent dummy variable measures. The KDA models do exhibit behavior similar to that in the gold earned models in the duo queue and team ranked interacted familiarity measures. While the magnitude of the impact is small, Interacted Familiarity 2 has a larger negative impact on KDA than Interacted Familiarity 1 in both lag periods. Team ranked Interacted Familiarity 2 and Interacted Familiarity 1 have coefficients of -0.148 and -0.077 for the one month model and team ranked coefficients of -0.100 and -0.038 for the three month model respectively. This behavior is consistent for duo queue Interacted Familiarity 1 and Interacted Familiarity 2 but is of varying

[12] Three Month Familiarity 2 is significant at the 90 percent confidence level.

statistical significance across the four KDA models. Across all four KDA models the R^2 of the regressions is approximately 6 percent.

The lack of impact experience has on individual performance is surprising, but several possible explanations exist for why the relationship is not statistically significant. The first is that experience is not time sensitive at the one and three month time intervals. Under this explanation, the amount of time an individual has played within the last three months does not substantially impact their gold earned or KDA. As established within the Literature Review it is highly unlikely that experience has a negligible effect on performance at all levels of experience. A potential implication of this finding is that experience in virtual environments has a logarithmic relationship with individual performance in virtual environments. If such a relationship were true, an individual's experience would exhibit a significant positive relationship with their performance up until a certain experience threshold. After a threshold amount of experience has been reached, the impact of experience on individual performance plateaus and other independent variables would begin to dominate the relationship. While it is not possible to test this explanation with this study's data, the explanation does make sense within the data's limitations. Because the investigated team had played League of Legends prior to the beginning of the collection period and possibly had played Ranked matches prior to the collection period, each player could have reached their experiential plateau prior to their first matches within the observed set if the explanation holds true. A second explanation is that skills adopted within one virtual environment are highly transferable to other virtual environments. Under this premise, experience with the League of Legends virtual environment is trumped by experience with other similar virtual environments and has a negligible effect on an individual's performance in a League of Legends match. Because this study is restricted to examining the League of Legends virtual environment, exploring this second explanation is beyond the scope of this study.

The relationship of the familiarity measures to individual performance is also surprising. I expected higher familiarity between an individual and their team roster to result in better individual performance. Contrary to my expectations, familiarity has a negative effect on performance in both the gold earned and KDA models. It is noteworthy that KDA is higher in all duo queue and team ranked matches providing everything else is held constant, but the effect of the interacted familiarity measures on KDA are still negative. This means that a team with an entirely unfamiliar roster is expected to have higher individual KDAs than a team with high familiarity between individuals and the other roster members. One possible explanation for why both gold earned and KDA decrease as familiarity increases is that the introduction of peers changes the primary objective of the individual players within the match. Players without roster members on their team are focused primarily on success and their individual performance, but the introduction of roster members into a match results in an environment where intangible social objectives such as enjoyment or team collaboration receive a higher share of individual priority. Losing focus on individual performance in favor of other objectives is a possible explanation for why individual performance suffers.

6 - Conclusion

The statistically significant finding of this study proves that the analysis of teams in virtual environments can inform our understanding of how individuals perform and teams may be optimized. The data generated from the team-based video game League of Legends yielded high volume reliable data for the analysis of individual performance.

The primary finding for players desiring to optimize their individual performance in Ranked queue types is to play without teammates they are familiar with, as familiarity had a statistically significant negative relationship with individual performance. Players should not consider their recent volume of play when seeking to optimize their performance as experience did not have a statistically significant relationship with individual performance. Organizational leadership should take into account negative effects resulting from familiarity when seeking to maximize the individual performance of their team members and take care to set consistent expectations within their teams.

Though the hypotheses of this study were not confirmed, there were significant findings within the results that future studies can expand upon. While the dataset was reliable and contained a high volume of data, there were several limitations that could be controlled for in future virtual environment data collection. Because the results of the analysis on experience were not significant, future configurations of similar studies could use the approach presented within this study on a more comprehensive dataset to draw significant conclusions about the impact of individual experience on individual performance. Future studies can also look to further develop the conclusions made here on familiarity by incorporating the data of additional teams across all levels of play.

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Data Dictionary

Dependent Variables	Description
gold_earned	The amount of gold earned by a player in the game
KDA	A player's KDA ((Kills+Assists)/Deaths) in the game

Independent Variables	Description
Dummy Variables	
duo_queue	1 if the Player has one Roster Member on their team
team_ranked	1 if the Player has more than one Roster Member on their team
jungle	1 if the Player's role is jungle
mid	1 if the Player's role is mid
bot_carry	1 if the Player's role is bot_carry
bot_support	1 if the Player's role is bot_support
is_rm_1	1 if the player is Roster Member 1
is_rm_2	1 if the player is Roster Member 2
is_rm_3	1 if the player is Roster Member 3
is_rm_4	1 if the player is Roster Member 4
is_rm_5	1 if the player is Roster Member 5
is_rm_6	1 if the player is Roster Member 6
is_rm_7	1 if the player is Roster Member 7
is_rm_8	1 if the player is Roster Member 8
is_preseason	1 if the Game is played during the Preseason
Experience Variables	
one_month_sumgames	Sum of games played within the last month
one_exp_squared	one_month_sumgames ^ 2
three_month_sumgames	Sum of games played within the last three months
three_exp_squared	three_month_sumgames ^ 2
Familiarity 1 Variables	
one_month_fcount	Sum of individual roster members present (one month lag)
one_fam_squared	one_month_fcount ^ 2
duo_fam_om	one_month_fcount interacted with duo_queue
duo_fam_squared_om	one_fam_squared interacted with duo_queue
team_ranked_fam_om	one_month_fcount interacted with team_ranked
team_ranked_fam_squared_om	one_fam_squared interacted with team_ranked
three_month_fcount	Sum of individual roster members present (three month lag)
three_fam_squared	three_month_fcount ^ 2
duo_fam_tm	three_month_fcount interacted with duo_queue
duo_fam_squared_tm	three_fam_squared interacted with duo_queue
team_ranked_fam_tm	three_month_fcount interacted with team_ranked
team_ranked_fam_squared_tm	three_fam_squared interacted with team_ranked
Familiarity 2 Variables	
one_month_rm_present_games	Sum of games with a roster member present(one month lag)
one_rm_squared	one_month_rm_present_games ^ 2
duo_rm_om	one_month_rm_present_games interacted with duo_queue
duo_rm_squared_om	one_rm_squared interacted with duo_queue
team_ranked_rm_om	one_month_rm_present_games interacted with team_ranked
team_ranked_rm_squared_om	one_rm_squared interacted with team_ranked
three_month_rm_present_games	Sum of games with a roster member present (three month lag)
three_rm_squared	threee_month_rm_present_games ^ 2
duo_rm_tm	three_month_rm_present_games interacted with duo_queue
duo_rm_squared_tm	three_rm_squared interacted with duo_queue
team_ranked_rm_tm	three_month_rm_present_games interacted with team_ranked
team_ranked_rm_squared_tm	three_rm_squared interacted with team_ranked

Tables

Table 1

Summary Statistics - Dummy Variables

Statistic	N	Mean	St. Dev.	Min	Max
duo_queue	11,215	0.10	0.31	0	1
team_ranked	11,215	0.05	0.21	0	1
jungle	11,215	0.22	0.42	0	1
mid	11,215	0.17	0.37	0	1
bot_carry	11,215	0.33	0.47	0	1
bot_support	11,215	0.14	0.35	0	1
is_rm_1	11,215	0.19	0.39	0	1
is_rm_2	11,215	0.11	0.31	0	1
is_rm_3	11,215	0.08	0.27	0	1
is_rm_4	11,215	0.05	0.21	0	1
is_rm_5	11,215	0.07	0.26	0	1
is_rm_6	11,215	0.03	0.16	0	1
is_rm_7	11,215	0.16	0.37	0	1
is_rm_8	11,215	0.20	0.40	0	1
is_preseason	11,215	0.13	0.33	0	1

Table 2

Summary Statistics - Dependent Variables and Experience

Statistic	N	Mean	St. Dev.	Min	Max
gold_earned	11,215	11,984.33	3,735.84	2,544	31,415
kda	11,215	3.95	4.00	0.00	37.00
one_month_sumgames	10,923	104.33	56.01	1	279
one_exp_squared	10,923	14,020.60	13,310.40	1	77,841
three_month_sumgames	9,864	270.84	142.78	4	579
three_exp_squared	9,864	93,739.14	82,467.83	16	335,241

Table 3

Summary Statistics - One Month Lagged Familiarity 1

Statistic	N	Mean	St. Dev.	Min	Max
one_month_fcount	10,923	24.64	37.92	0	229
one_fam_squared	10,923	2,045.38	5,220.82	0	52,441
duo_fam_om	10,923	5.66	21.71	0	210
duo_fam_squared_om	10,923	503.44	2,756.04	0	44,100
team_ranked_fam_om	10,923	3.71	20.33	0	229
team_ranked_fam_squared_om	10,923	427.17	3,143.09	0	52,441

Table 4

Summary Statistics - One Month Lagged Familiarity 2

Statistic	N	Mean	St. Dev.	Min	Max
one_month_rm_present_games	10,923	13.85	21.36	0	128
one_rm_squared	10,923	648.16	1,745.18	0	16,384
duo_rm_om	10,923	3.84	14.35	0	128
duo_rm_squared_om	10,923	220.53	1,159.94	0	16,384
team_ranked_rm_om	10,923	1.57	8.71	0	108
team_ranked_rm_squared_om	10,923	78.33	607.61	0	11,664

Table 5

Summary Statistics - Three Month Lagged Familiarity 1

Statistic	N	Mean	St. Dev.	Min	Max
three_month_fcount	9,864	66.03	97.10	0	432
three_fam_squared	9,864	13,787.72	32,653.47	0	186,624
duo_fam_tm	9,864	18.04	68.39	0	432
duo_fam_squared_tm	9,864	5,001.84	23,732.46	0	186,624
team_ranked_fam_tm	9,864	6.97	35.99	0	394
team_ranked_fam_squared_tm	9,864	1,343.60	9,004.66	0	155,236

Table 6

Summary Statistics - Three Month Lagged Familiarity 2

Statistic	N	Mean	St. Dev.	Min	Max
three_month_rm_present_games	9,864	34.29	47.88	0	236
three_rm_squared	9,864	3,468.52	8,268.77	0	55,696
duo_rm_tm	9,864	9.65	35.14	0	236
duo_rm_squared_tm	9,864	1,327.84	6,275.11	0	55,696
team_ranked_rm_tm	9,864	3.07	15.56	0	200
team_ranked_rm_squared_tm	9,864	251.57	1,608.83	0	40,000

Table 7

Gold Earned - One Month Lag, Familiarity 1

	Dependent variable: gold_earned
one_month_sumgames	-2.710
	(2.315)
one_month_fcount	-8.857***
	(3.198)
one_exp_squared	0.007
	(0.009)
one_fam_squared	0.042
	(0.025)
duo_queue	364.388
	(264.372)
team_ranked	-1,047.997**
	(459.888)
duo_fam_om	-9.502
	(8.408)
duo_fam_squared_om	0.071
	(0.052)
team_ranked_fam_om	-8.052
	(11.179)
team_ranked_fam_squared_om	0.068
	(0.056)
jungle	-211.443*
	(122.576)
mid	368.880***
	(129.305)
bot_carry	1,324.759***
	(117.382)
bot_support	-2,262.035***
	(133.893)
is_rm_1	301.536**
	(141.221)
is_rm_2	1.170
	(156.486)
is_rm_3	1,582.313***
	(186.825)
is_rm_4	42.729
	(228.926)
is_rm_5	1,065.653***
	(163.703)
is_rm_6	-274.724
	(251.552)
is_rm_7	252.932*
	(138.453)
is_rm_8	484.489***
	(129.203)
is_preseason	-279.565**
	(110.514)
Constant	11,859.880***
	(184.774)
Observations	10,923
R2	0.123
Adjusted R2	0.122
Residual Std. Error	3,502.769 (df = 10899)
F Statistic	66.708*** (df = 23; 10899)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 8

Gold Earned - One Month Lag, Familiarity 2

	Dependent variable: gold_earned		Dependent variable: gold_earned
one_month_sumgames	-2.417 (2.429)	bot_carry	1,308.295*** (117.538)
one_month_rm_present_games	-14.861*** (5.654)	bot_support	-2,270.013*** (133.894)
one_exp_squared	0.006 (0.010)	is_rm_1	329.518** (147.333)
one_rm_squared	0.101 (0.071)	is_rm_2	35.353 (156.650)
duo_queue	307.084 (298.215)	is_rm_3	1,631.552*** (186.472)
team_ranked	-1,803.271*** (452.732)	is_rm_4	50.281 (231.453)
duo_rm_om	-2.760 (14.917)	is_rm_5	1,044.939*** (163.421)
duo_rm_squared_om	0.013 (0.143)	is_rm_6	-302.458 (250.961)
team_ranked_rm_om	30.217 (24.673)	is_rm_7	225.850 (138.588)
team_ranked_rm_squared_om	-0.168 (0.257)	is_rm_8	481.134*** (129.382)
jungle	-220.534* (122.688)	is_preseason	-313.678*** (110.273)
mid	362.028*** (129.345)	Constant	11,849.590*** (186.341)

Observations	9,864
R2	0.125
Adjusted R2	0.123
Residual Std. Error	3,524.428 (df = 9840)
F Statistic	60.943*** (df = 23; 9840)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 9

Gold Earned - Three Month Lag, Familiarity 1

	Dependent variable: gold_earned
three_month_sumgames	-0.854
	(1.269)
three_month_fcount	-4.863***
	(1.543)
three_exp_squared	0.001
	(0.002)
three_fam_squared	0.010**
	(0.005)
duo_queue	136.991
	(298.282)
team_ranked	-1,357.260***
	(416.394)
duo_fam_tm	-1.200
	(4.002)
duo_fam_squared_tm	0.004
	(0.010)
team_ranked_fam_tm	-1.313
	(5.923)
team_ranked_fam_squared_tm	0.017
	(0.017)
jungle	-154.828
	(130.644)
mid	373.591***
	(141.455)
bot_carry	1,363.120***
	(125.213)
bot_support	-2,277.913***
	(143.502)
is_rm_1	506.907***
	(158.098)
is_rm_2	69.609
	(180.040)
is_rm_3	1,721.226***
	(209.301)
is_rm_4	230.370
	(250.277)
is_rm_5	1,290.537***
	(190.408)
is_rm_6	-218.126
	(272.965)
is_rm_7	329.721**
	(153.775)
is_rm_8	536.526***
	(145.630)
is_preseason	-189.893
	(152.474)
Constant	11,756.750***
	(223.590)
Observations	9,864
R2	0.125
Adjusted R2	0.123
Residual Std. Error	3,522.981 (df = 9840)
F Statistic	61.344*** (df = 23; 9840)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 10

Gold Earned - Three Month Lag, Familiarity 2

	Dependent variable: gold_earned
three_month_sumgames	-0.594 (1.226)
three_month_rm_present_games	-5.702* (3.172)
three_exp_squared	0.0001 (0.002)
three_rm_squared	0.010 (0.018)
duo_queue	-88.600 (348.111)
team_ranked	-1,826.699*** (427.647)
duo_rm_tm	5.787 (8.052)
duo_rm_squared_tm	-0.022 (0.036)
team_ranked_rm_tm	12.728 (13.854)
team_ranked_rm_squared_tm	-0.019 (0.097)
jungle	-166.037 (130.640)
mid	360.843** (141.438)
bot_carry	1,337.556*** (125.294)
bot_support	-2,304.161*** (143.513)
is_rm_1	493.307*** (171.989)
is_rm_2	157.377 (174.137)
is_rm_3	1,754.288*** (204.292)
is_rm_4	205.623 (259.290)
is_rm_5	1,251.021*** (188.726)
is_rm_6	-218.743 (270.392)
is_rm_7	268.113* (153.630)
is_rm_8	562.836*** (145.428)
is_preseason	-119.353 (139.237)
Constant	11,728.780*** (217.376)
Observations	9,864
R2	0.125
Adjusted R2	0.123
Residual Std. Error	3,524.428 (df = 9840)
F Statistic	60.943*** (df = 23; 9840)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 11

KDA - One Month Lag, Familiarity 1

	Dependent variable: kda		Dependent variable: kda
one_month_sumgames	-0.002 (0.003)	bot_carry	1.042*** (0.130)
one_month_fcount	-0.004 (0.004)	bot_support	0.848*** (0.148)
one_exp_squared	0.00001 (0.00001)	is_rm_1	0.430*** (0.156)
one_fam_squared	0.00003 (0.00003)	is_rm_2	0.253 (0.173)
duo_queue	0.864*** (0.293)	is_rm_3	3.210*** (0.207)
team_ranked	4.652*** (0.509)	is_rm_4	0.284 (0.254)
duo_fam_om	-0.024** (0.009)	is_rm_5	0.651*** (0.181)
duo_fam_squared_om	0.0001* (0.0001)	is_rm_6	1.419*** (0.279)
team_ranked_fam_om	-0.077*** (0.012)	is_rm_7	0.288* (0.153)
team_ranked_fam_squared_om	0.0003*** (0.0001)	is_rm_8	0.005 (0.143)
jungle	1.068*** (0.136)	is_preseason	-0.060 (0.122)
mid	0.548*** (0.143)	Constant	2.597*** (0.205)

Observations	10,923
R2	0.060
Adjusted R2	0.058
Residual Std. Error	3.879 (df = 10899)
F Statistic	30.327*** (df = 23; 10899)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 12

KDA - One Month Lag, Familiarity 2

	Dependent variable: kda
one_month_sumgames	-0.0002
	(0.003)
one_month_rm_present_games	-0.001
	(0.006)
one_exp_squared	0.00000
	(0.00001)
one_rm_squared	0.00001
	(0.0001)
duo_queue	0.646*
	(0.330)
team_ranked	3.953***
	(0.502)
duo_rm_om	-0.023
	(0.017)
duo_rm_squared_om	0.0002
	(0.0002)
team_ranked_rm_om	-0.148***
	(0.027)
team_ranked_rm_squared_om	0.001***
	(0.0003)
jungle	1.034***
	(0.136)
mid	0.538***
	(0.143)
bot_carry	1.045***
	(0.130)
bot_support	0.842***
	(0.148)
is_rm_1	0.386**
	(0.163)
is_rm_2	0.259
	(0.174)
is_rm_3	3.208***
	(0.207)
is_rm_4	0.337
	(0.256)
is_rm_5	0.617***
	(0.181)
is_rm_6	1.310***
	(0.278)
is_rm_7	0.267*
	(0.154)
is_rm_8	-0.004
	(0.143)
is_preseason	-0.125
	(0.122)
Constant	2.569***
	(0.206)
Observations	10,923
R2	0.058
Adjusted R2	0.056
Residual Std. Error	3.883 (df = 10899)
F Statistic	29.260*** (df = 23; 10899)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 13

KDA - Three Month Lag, Familiarity 1

	Dependent variable: kda
three_month_sumgames	-0.001
	(0.001)
three_month_fcount	0.002
	(0.002)
three_exp_squared	0.00000
	(0.00000)
three_fam_squared	-0.00001*
	(0.00001)
duo_queue	0.868***
	(0.328)
team_ranked	4.018***
	(0.458)
duo_fam_tm	-0.008*
	(0.004)
duo_fam_squared_tm	0.00001
	(0.00001)
team_ranked_fam_tm	-0.038***
	(0.007)
team_ranked_fam_squared_tm	0.0001***
	(0.00002)
jungle	1.068***
	(0.144)
mid	0.586***
	(0.156)
bot_carry	1.014***
	(0.138)
bot_support	0.830***
	(0.158)
is_rm_1	0.381**
	(0.174)
is_rm_2	0.440**
	(0.198)
is_rm_3	3.143***
	(0.230)
is_rm_4	0.203
	(0.275)
is_rm_5	0.484**
	(0.209)
is_rm_6	1.383***
	(0.300)
is_rm_7	0.323*
	(0.169)
is_rm_8	0.171
	(0.160)
is_preseason	0.230
	(0.168)
Constant	2.660***
	(0.246)
Observations	9,864
R2	0.059
Adjusted R2	0.057
Residual Std. Error	3.874 (df = 9840)
F Statistic	26.906*** (df = 23; 9840)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 14

KDA - Three Month Lag, Familiarity 2

	Dependent variable: kda
three_month_sumgames	-0.002 (0.001)
three_month_rm_present_games	0.001 (0.003)
three_exp_squared	0.00000 (0.00000)
three_rm_squared	-0.00002 (0.00002)
duo_queue	0.990*** (0.383)
team_ranked	4.273*** (0.470)
duo_rm_tm	-0.017* (0.009)
duo_rm_squared_tm	0.0001 (0.00004)
team_ranked_rm_tm	-0.100*** (0.015)
team_ranked_rm_squared_tm	0.001*** (0.0001)
jungle	1.053*** (0.144)
mid	0.593*** (0.155)
bot_carry	1.031*** (0.138)
bot_support	0.840*** (0.158)
is_rm_1	0.464** (0.189)
is_rm_2	0.358* (0.191)
is_rm_3	3.068*** (0.225)
is_rm_4	0.339 (0.285)
is_rm_5	0.440** (0.207)
is_rm_6	1.262*** (0.297)
is_rm_7	0.310* (0.169)
is_rm_8	0.154 (0.160)
is_preseason	0.144 (0.153)
Constant	2.762*** (0.239)
Observations	9,864
R2	0.060
Adjusted R2	0.057
Residual Std. Error	3.873 (df = 9840)
F Statistic	27.146*** (df = 23; 9840)
Note:	*p<0.1; **p<0.05; ***p<0.01

Figures

Figure 1

Summoner's Rift Map