Universidad de Alcalá
COMISIÓN DE ESTUDIOS OFICIALES DE POSGRADO Y DOCTORADO

ACTA DE EVALUACIÓN DE LA TESIS DOCTORAL

Año académico 2018/19

DOCTORANDO: **MORA CANTALLOPS, MARÇAL**
D.N.I./PASAPORTE: ******9911P**

PROGRAMA DE DOCTORADO: **D430-COMUNICACIÓN, INFORMACIÓN Y TENCNOLOGÍA EN LA SOCIEDAD EN RED**
DPTO. COORDINADOR DEL PROGRAMA: **CIENCIAS DE LA COMPUTACIÓN**
TITULACIÓN DE DOCTOR EN: **DOCTOR/A POR LA UNIVERSIDAD DE ALCALÁ**

En el día de hoy 20/11/18, reunido el tribunal de evaluación nombrado por la Comisión de Estudios Oficiales de Posgrado y Doctorado de la Universidad y constituido por los miembros que suscriben la presente Acta, el aspirante defendió su Tesis Doctoral, elaborada bajo la dirección de **MIGUEL ÁNGEL SICILIA URBÁN.**

Sobre el siguiente tema: *EXPLORING PLAYER EXPERIENCE AND SOCIAL NETWORKS IN MOBA GAMES: THE CASE OF LEAGUE OF LEGENDS*

Finalizada la defensa y discusión de la tesis, el tribunal acordó otorgar la CALIFICACIÓN GLOBAL[1] de (**no apto, aprobado, notable y sobresaliente**): SOBRESALIENTE

Alcalá de Henares, 20 de Noviembre de 2018

EL PRESIDENTE
Fdo.: Juan Manuel Dodero

EL SECRETARIO
Fdo.: Salvador Sánchez

EL VOCAL
Fdo.: Jordi Conesa

Con fecha 17 de diciembre de 2018 la Comisión Delegada de la Comisión de Estudios Oficiales de Posgrado, a la vista de los votos emitidos de manera anónima por el tribunal que ha juzgado la tesis, resuelve:

- [x] Conceder la Mención de "Cum Laude"
- [ ] No conceder la Mención de "Cum Laude"

La Secretaria de la Comisión Delegada

FIRMA DEL ALUMNO,

Fdo.: Marçal Mora

[1] La calificación podrá ser "no apto" "aprobado" "notable" y "sobresaliente". El tribunal podrá otorgar la mención de "cum laude" si la calificación global es de sobresaliente y se emite en tal sentido el voto secreto positivo por unanimidad.

INCIDENCIAS / OBSERVACIONES:

Universidad de Alcalá
COMISIÓN DE ESTUDIOS OFICIALES
DE POSGRADO Y DOCTORADO

En aplicación del art. 14.7 del RD. 99/2011 y el art. 14 del Reglamento de Elaboración, Autorización y Defensa de la Tesis Doctoral, la Comisión Delegada de la Comisión de Estudios Oficiales de Posgrado y Doctorado, en sesión pública de fecha 17 de diciembre, procedió al escrutinio de los votos emitidos por los miembros del tribunal de la tesis defendida por *MORA CANTALLOPS, MARÇAL*, el día 20 de noviembre de 2018, titulada *EXPLORING PLAYER EXPERIENCE AND SOCIAL NETWORKS IN MOBA GAMES: THE CASE OF LEAGUE OF LEGENDS*, para determinar, si a la misma, se le concede la mención "cum laude", arrojando como resultado el voto favorable de todos los miembros del tribunal.

Por lo tanto, la Comisión de Estudios Oficiales de Posgrado **resuelve otorgar** a dicha tesis la

MENCIÓN "CUM LAUDE"

Alcalá de Henares, 18 de diciembre de 2018
EL VICERRECTOR DE INVESTIGACIÓN Y TRANSFERENCIA

UNIVERSIDAD DE ALCALÁ · VICERRECTORADO DE INVESTIGACIÓN Y TRANSFERENCIA

F. Javier de la Mata

F. Javier de la Mata de la Mata

Copia por e-mail a:
Doctorando: MORA CANTALLOPS, MARÇAL
Secretario del Tribunal
Director de Tesis: MIGUEL ÁNGEL SICILIA URBÁN

Universidad de Alcalá

ESCUELA DE DOCTORADO
Servicio de Estudios Oficiales de Posgrado

DILIGENCIA DE DEPÓSITO DE TESIS.

Comprobado que el expediente académico de D./Dª Marçal Mora Cantallops reúne los requisitos exigidos para la presentación de la Tesis, de acuerdo a la normativa vigente, y habiendo presentado la misma en formato: ☒ soporte electrónico ☐ impreso en papel, para el depósito de la misma, en el Servicio de Estudios Oficiales de Posgrado, con el nº de páginas: 192 se procede, con fecha de hoy a registrar el depósito de la tesis.

Alcalá de Henares a 13 de septiembre de 2018

Purificación Reviejo

Fdo. El Funcionario

MARÇAL MORA-CANTALLOPS

EXPLORING PLAYER EXPERIENCE AND SOCIAL NETWORKS IN MOBA GAMES: THE CASE OF LEAGUE OF LEGENDS

Dr. D. Miguel Ángel Sicilia Urbán, Profesor Catedrático de Universidad del Área de Lenguajes y Sistemas Informáticos del Departamento de Ciencias de la Computación de la Universidad de Alcalá, en calidad de Coordinador de la Comisión Académica del Programa de Doctorado en comunicación, información y tecnología de la sociedad en red, así como director de la Tesis en cuestión,

CERTIFICO: Que una vez concluido el trabajo de Tesis Doctoral titulada "Exploring player experience and social networks in MOBA Games: The case of League of Legends" realizada por D. Marçal Mora Cantallops y dirigida por el Dr. D. Miguel Ángel Sicilia Urbán, dicho trabajo tiene suficientes méritos teóricos, contrastados adecuadamente mediante validaciones experimentales y que son altamente novedosos. Por todo ello se considera que reúne los requisitos para su presentación y defensa pública.

Y para que conste, firma la presente en Alcalá de Henares, a 12 de septiembre de 2018.

El director de la Tesis

Fdo. Dr. Miguel Ángel Sicilia Urbán

DOCTORADO EN COMUNICACIÓN, INFORMACIÓN Y TECNOLOGÍA DE LA SOCIEDAD EN RED

EXPLORING PLAYER EXPERIENCE AND SOCIAL NETWORKS IN MOBA GAMES: THE CASE OF LEAGUE OF LEGENDS

MARÇAL MORA-CANTALLOPS

Director: Dr. Miguel Ángel Sicilia

Alcalá de Henares, September 2018

A true master is an eternal student.

— Master Yi, *League of Legends* Champion

“Explain to him that we don’t do things, Stibbons,” said the Lecturer in Recent Runes. “We are academics.”

— Lecturer in Recent Runes, in *A Collegiate Casting-Out of Devilish Devices*, a Discworld short story by Terry Pratchett

ABSTRACT

In spite of the popularity of Multiplayer Online Battle Arena (MOBA) games such as *League of Legends* (LoL), both the Player Experience (PE) and the structure of the social networks that arise in this relatively new genre remain largely unexplored. As players spend increasingly more time playing online competitive games, the positive and negative impacts of doing so become relevant; it is, therefore, important to understand how PE is structured to systematically address mechanisms that elicit a response from the players. This work begins by obtaining and characterizing a sample of *League of Legends* players and proceeds to use the resulting variables and structural social relationships as inputs to explore their links to PE. In the end, PE is pivotal to engage players and, therefore, it is key to the success of any digital game. Our results show, among other findings, how *League of Legends* players perceive the game as "fair" for their competence level for all ranks, while their relatedness towards teammates is affected by their social structure. Empathy and negative feelings, however, seem to be unaffected by team composition. Knowledge about PE in *League of Legends* can not only be employed to improve LoL or MOBA games, but also to develop better and more engaging games while improving their quality. As online competitive gaming is quickly becoming one of the largest collective human activities globally, PE research also becomes crucial.

RESUMEN

A pesar de la popularidad de los juegos de arena de combate multijugador en línea (MOBA en inglés) como *League of Legends* (LoL), tanto la experiencia de jugador (PE) que proporciona este género relativamente reciente como las redes sociales que se generan a su alrededor siguen, en gran medida, inexplorados. Con el incremento del tiempo que los jugadores dedican a este tipo de juegos competitivos en línea, los impactos positivos y negativos de hacerlo cobran relevancia; es, por lo tanto, importante entender cómo se estructura dicha experiencia para abordar de forma sistemática los mecanismos que desencadenan respuestas de los jugadores. El presente trabajo empieza obteniendo y caracterizando una muestra de jugadores de *League of Legends* y sigue con el uso de las variables resultantes y de la estructura de las relaciones sociales como entradas para explorar su relación con la experiencia de los jugadores. Al fin y al cabo, la PE es básica para involucrar al jugador y, por lo tanto, es clave para el éxito de cualquier juego digital. Los resultados muestran, entre otros, cómo los jugadores de *League of Legends* perciben el juego como "justo"para su nivel de competencia en cualquier rango, mientras que su afinidad respecto a los compañeros se ve afectada por la estructura social. La empatía y los sentimientos negativos, no obstante, no parecen verse afectados por la composición del equipo. Entender la experiencia del jugador en *League of Legends* puede no tan sólo ser útil para mejorar el propio LoL o los juegos de tipo MOBA, sino también para desarrollar juegos

más inmersivos a la vez que se mejora su calidad. A medida que los juegos competitivos online se convierten rápidamente en una de las mayores actividades colectivas humanas a nivel global, la investigación sobre la experiencia del jugador adquiere también una importancia crucial.

PUBLICATIONS

Some ideas and figures have appeared previously in this list of publications

Mora-Cantallops, M. (2017). Análisis de usos de YouTube en la comunidad española de League of Legends. In D. Aranda, J. Sánchez-Navarro, & A. J. Planells (Eds.), *Game & Play: La cultura del juego digital* (pp. 11–22). Ediciones Egregius.

Mora-Cantallops, M., & Sicilia, M.-Á. (2016). Motivations to read and learn in videogame lore. In *Proceedings of the Fourth International Conference on Technological Ecosystems for Enhancing Multiculturality - TEEM '16* (pp. 585–591). doi:10.1145/3012430.3012578

Mora-Cantallops, M., & Sicilia, M.-Á. (2018a). Exploring Player Experience in Ranked League of Legends. *Behaviour & Information Technology*. doi:10.1080/0144929X.2018.1492631

Mora-Cantallops, M., & Sicilia, M.-Á. (2018b). MOBA games: A literature review. *Entertainment Computing*, *26*, 128–138. doi:10.1016/j.entcom.2018.02.005

Mora-Cantallops, M., & Sicilia, M.-Á. (2018c). Player-centric networks in League of Legends. *Social Networks*, *55*, 149–159. doi:10.1016/j.socnet.2018.06.002

We have seen that computer programming is an art,
because it applies accumulated knowledge to the world,
because it requires skill and ingenuity, and especially
because it produces objects of beauty.

— Donald E. Knuth (Knuth, 1974)

ACKNOWLEDGMENTS

I'd like to start by thanking my supervisor and director, Miguel Ángel, for his straightforward communication and pragmatism in this process, his constant support and admirable vision. This is his thesis as much as it is mine; without that first coffee in Alcalá I might have never even played *League of Legends*. But here I am, three years later, building a thesis around that game. I'd like to extend this gratitude to Elena, to Salva, and to the rest of the Computer Science department in the University.

This work wouldn't have existed without the help of the Sergi Mesonero from the LVP (Liga de Videojuegos Profesional), who made the survey possible and allowed me to retrieve valuable data for this study; my recognition also to Míriam, who insisted many times to get as many answers as possible.

I can't forget the support and mentorship that I received from two good friends: Dr. Anton Planells and Dr. Víctor Navarro-Remesal. Both have been (and still are) my reference Game Studies academics. Thanks to them for accepting me in their projects and lines of thought, and to Víctor for counting on me for his Museums of Failure. There is still much work to do.

Thanks to all my ex-colleagues in P & G and Coty, who made this transition easier. Special mention to Valentin, Ana and Joxemari for these years of conversation (or therapy, I could say).

Although I would like to thank all my friends (you know who you are), there are also special thanks to Ricardo, who could have been my second brother; meeting you is the reason why moving to Madrid was worthwhile. My acknowledgement to the rest of the retrogaming family too; Bruno, Marcos, Antonio, those hamburgers (and laughs) kept me alive.

I'd finally like to thank my family in general but specially my parents, always supportive. To my brother, a real doctor, and Olvido. To my grandmother Lola and my uncle Jordi, always tracking my progress. To Kuma and Brownie, who accompanied me in this voyage, laying beside my chair unconditionally. There is only one thing better than a dog: two.

This would have been impossible without my wife and vital reference point, Cristina, who showed me the way. There are no words to express my eternal gratitude, but I have all the time to show what I mean. I'm glad I met you.

Thanks, everyone, you made me a better person.

CONTENTS

I CONTEXT

1 INTRODUCTION 3

2 PROBLEM STATEMENT AND OBJECTIVES 9

2.1 Main objective 9

2.2 Partial objectives 10

3 BACKGROUND 11

3.1 Brief History of the Multiplayer Online Battle Arena 13

3.2 Previous work 15

3.2.1 Modelling and Prediction 15

3.2.2 Behaviour and Motivation 17

3.2.3 Community and Competition 22

3.2.4 Teams and Collaboration 22

3.2.5 Gender and cultural studies 23

3.3 League of Legends 24

3.3.1 Teams 25

3.3.2 Rank 27

3.3.3 Game Phases 28

3.3.4 Patching 30

3.3.5 API 30

3.4 Player Experience 31

3.5 Social Networks 36

II METHODS AND RESULTS

4 DATA COLLECTION AND METHODS 43

4.1 Player Sample 43

4.2 Survey 44

4.2.1 Demographics 45
4.2.2 Practices 45
4.2.3 PENS 46
4.2.4 SPGQ 47
4.2.5 Additional information 47
4.3 League of Legends API 48
4.3.1 AccountID 48
4.3.2 Matchlist 49
4.3.3 Match Details 51
4.4 Social Network Analysis 52
4.4.1 Ego networks 52
4.4.2 Network generation 53
4.4.3 Indicators 55
4.4.4 Clustering 60
5 RESULTS 63
5.1 Player-centric networks 63
5.1.1 Variables 64
5.1.2 Bivariate correlation 65
5.1.3 Clustering process 66
5.1.4 Final model 67
5.1.5 Cluster analysis 69
5.2 Player social habits and rank 75
5.3 Player survey 77
5.3.1 Demographics 77
5.3.2 Player Rank 78
5.3.3 Seniority 79
5.3.4 Play preference 81
5.3.5 Communication 82
5.3.6 Role 83
5.3.7 Champion selection 84

5.3.8 Adaptation 86
5.3.9 In-game purchases 87
5.3.10 Viewership 88
5.4 Player experience 89
5.4.1 Reliability 90
5.4.2 Dimensions 90
5.4.3 PE and skill level 91
5.4.4 Team formation effect in PE 94
5.4.5 Roles in PE 97
5.4.6 Economy and PE 97
5.4.7 Gendered Play Experience 101
6 DISCUSSION 105
6.1 Partial objectives 105
6.1.1 Literature review 105
6.1.2 Player sample 110
6.1.3 Player information extraction 110
6.1.4 Systematic classification of player social behaviour 111
6.1.5 Player perception 112
6.2 Player experience in League of Legends 113
III CLOSING REMARKS
7 CONCLUSION 119
7.1 Social playing typologies 119
7.2 Player survey 121
7.3 Player experience 123
8 LIMITATIONS AND FUTURE WORK 129
IV APPENDIX
A SURVEY 135

BIBLIOGRAPHY 157

LIST OF FIGURES

Figure 1.1 League of Legends All-Star event (2016) in Palau Sant Jordi, Barcelona. Source: www.elperiodico.cat 7

Figure 3.1 Typical MOBA map (with labelled lanes) for illustrative purposes. Original PNG version by Raizin, SVG rework by Sameboat. 26

Figure 4.1 Network generation. (a) Ego with a single team (b) Alter network from (a) after ego removal (c) Ego after two matches with complete different players (d) Alter network from (c) after ego removal . . . 55

Figure 5.1 Bivariate correlations between variables of interest 66

Figure 5.2 Number of clusters derived from affiliation propagation versus shared preference (all indicators included). 67

Figure 5.3 Graphical representation of clusters resulting from the affiliation propagation algorithm with preference -45 and all indicators included. This is only a 2D slice of a 7 dimension space for illustration purposes. 68

Figure 5.4	Number of clusters derived from affiliation propagation versus shared preference (best three indicators only).	69
Figure 5.5	Graphical representation of clusters resulting from the affiliation propagation algorithm with preference -30 and restricted to the best three indicators. This is a 2D slice of the 3D space.	70
Figure 5.6	3D representation of the resulting clusters. Note that figure 5.5 is the 2D view from above.	71
Figure 5.7	Violin plots for total games, modularity, components and largest component proportion per cluster.	72
Figure 5.8	Graphical representation of sample player-centric networks.	73
Figure 5.9	Rank distribution per cluster. C1 has less high ranked players than other clusters. C3 and C4 are disproportionally higher ranked.	75
Figure 5.10	Rank Tier and Total Number of Ranked Wins	81
Figure 5.11	Champion select screen, with team roles illustrated at the centre	84
Figure 5.12	Analysis of five key franchises. Source: Newzoo (Pannekeet, 2017)	89
Figure 5.13	PE in League of Legends per Rank tier	93
Figure 5.14	PE in League of Legends per Rank tier	94
Figure 5.15	PE in League of Legends per expense level	100
Figure 5.16	PE in League of Legends by gender	104

LIST OF TABLES

Table 1.1 Top free-to-play PC games by revenue, 2017 4
Table 1.2 Top eSports games by viewership, 2017 . 5
Table 4.1 Result of the summoner API call 49
Table 4.2 Result of the matchlist API call 50
Table 4.3 Content of the MatchReferenceDto list . 50
Table 4.4 Result of the match API call 51
Table 5.1 Distribution of the numeric variables in the dataset (I) 64
Table 5.2 Distribution of the numeric variables in the dataset (II) 65
Table 5.3 Indicators extracted from sample player-centric networks 72
Table 5.4 Age demographics 78
Table 5.5 Sample size per tier in the survey 79
Table 5.6 Number of ranked matches played by players 80
Table 5.7 Play preference among players and clustering 81
Table 5.8 Number of ranked matches played by players 83
Table 5.9 Role distribution in sample 85
Table 5.10 Champion selection owned by players . 85
Table 5.11 Player adaptation to changes 87
Table 5.12 Purchase frequency 87
Table 5.13 Player expense per purchase 88

Table 5.14 PENS results for rank 92
Table 5.15 SPGQ results for rank 94
Table 5.16 PENS results by cluster 96
Table 5.17 SPGQ results by cluster 96
Table 5.18 PENS results by role 98
Table 5.19 SPGQ results by role 98
Table 5.20 PENS results by expense 99
Table 5.21 SPGQ results by expense 100
Table 5.22 Gender-Rank frequency table 102
Table 5.23 Gender-Role frequency table 102
Table 5.24 Mann-Whitney U test on PENS dimensions depending on gender 103
Table 5.25 Mann-Whitney U test on SPGQ dimensions depending on gender 103

LISTINGS

Listing 4.1 Get a summoner by summoner name . . 48
Listing 4.2 Get the summoner's matchlist 49
Listing 4.3 Get the details on a particular match . . 51

ACRONYMS

API Application Programming Interface

ASW Average Silhouette Width

DOTA Defense of the Ancients

FPS First Person Shooter

GEQ Game Experience Questionnaire

LoL League of Legends

LVP Liga de Videojuegos Profesional

MMOG Massively Multiplayer Online Game

MMORPG Massively Multiplayer Online Role-Playing Game

MOBA Multiplayer Online Battle Arena

MUD Multi-User Dungeon

PE Player Experience

PENS Player Experience of Need Satisfaction

RPG Role-Playing Game

RTS Real-Time Strategy

SDT Self-Determination Theory

SNA Social Network Analysis

SPGQ Social Presence in Gaming Questionnaire

UX User Experience

WoW World of Warcraft

Part I

CONTEXT

1 INTRODUCTION

Over the last few decades, video games have grown until becoming one of the main entertainment mediums in our society. Video games are becoming progressively more engrained into individuals' everyday life "due to the fact that they are pleasurable, social, pastime activity" (Walker, 2017). As Kuss and Griffiths (2012, p.279) explain, electronic games connect likeminded people, thereby fostering sociocultural protocols and behaviours that are associated with gameplay. These psychological impacts on behaviour are the ones that brought the most interest around video games within the scientific community (Lemmens, Valkenburg, & Peter, 2009).

To date, however, competitive gaming (and, specifically, online competitive gaming) "has not been widely researched or recognised in the scientific and professional literature on video games" (Griffiths, 2017). Online competitive gaming comprises players who compete either individually or within teams against other players over a network, in organised tournaments (either paid or unpaid) or in their homes.

According to Superdata's 2017 report on digital games and interactive media, free to play games represent 69% of the PC games market (valued at 33 billion dollars) (Superdata, 2017). Although 56% of the free to play revenue comes from RPG and FPS, Multiplayer Online Battle Arenas (MOBAs) bookend the top five in the ranking, with *League of Legends* in the first position

RANK	TITLE	GENRE	PUBLISHER	REVENUE
1	League of Legends	MOBA	Riot Games Tencent	$2,1B
2	Dungeon Fighter Online	RPG	Nexon Tencent	$1,6B
3	CROSSFIRE	Shooter	Smilegate Tencent	$1,4B
4	World of Tanks	Shooter	Wargaming	$471M
5	Dota 2	MOBA	Valve Corporation	$406M

Table 1.1: Top free-to-play PC games by revenue, 2017 Superdata

RANK	TITLE	PUBLISHER	REVENUE
1	League of Legends	Riot Games Tencent	157M
2	PUBG	Bluehole	102M
3	Hearthstone	Activision Blizzard	83M
4	Dota 2	Valve Corporation	65M
5	Overwatch	Activision Blizzard	63M

Table 1.2: Top esports games by viewership, 2017 Superdata

(2,1 billion dollars in revenue) and DOTA 2 in the fifth (at a distant 406 million dollars).

Gaming is the second most popular content category on YouTube (Superdata, 2017) but Twitch captures more revenue (54% of share). This shows in the *eSport* market, that experimented a 10% growth in 2017. The most popular games helped *eSports* reach 258 million unique viewers; *League of Legends* is the undisputed number one, with 157 million unique viewers worldwide. According to the same report, “games that lead their genres in monthly active users like *League of Legends* and *Overwatch* have an edge when it comes to growing a robust esports audience.”

Despite these figures and the forecasted growth, little empirical activity has catalogued these activities. And yet, a full media ecosystem is growing around these games; online competitive gaming is now streamed over the Internet, followed by millions of fans (many of whom are also players) and selling out traditional sports venues (such as basketball stadiums). Cash prizes are also common and, for a few selected professional players, it has become a full-time job. The level of skill and adaptation required from these players is, probably, unprecedented in team sports.

A few academic studies are already pointing out how competitive and collaborative games can promote social behaviour and develop new skills in the players (if used properly). Studies have also suggested that video games can provide an enriched medium for strategic problem-solving, although it might be even possible that these effects have different intensity across the player base (being more extreme in professional players versus casual ones).

MOBA Player Experience (PE), however, has been identified as being "highly frustrating and challenging, and cultivating less autonomy than other genres" (Johnson & Wyeth, 2015). MOBA players identify competition, mastery and teamwork as the essential aspects of the genre; factors that contribute to an intense ludic and social experience. Mastery and teamwork are intertwined as, in *League of Legends*, players not only need to have a good command of their chosen characters but they also need to understand how these characters complement each other in a team (Kim, Keegan, Park, & Oh, 2016).

Competitive gaming, as video game playing in general, has positive aspects and negative ones, so it's an important area to evaluate its psychological effects onto players. On top, MOBA games seem to provide a fundamentally distinct PE than other genres (Johnson & Wyeth, 2015) and, yet, they lead the rankings in number of players, revenue and viewers. Thus, it becomes relevant to explore the PE of MOBA (and, specifically, *League of Legends*) players.

Figure 1.1: League of Legends All-Star event (2016) in Palau Sant Jordi, Barcelona. Source: www.elperiodico.cat

The social networks that arise in competitive gaming contexts play a fundamental role in this experience. MOBA games are designed with the player at the centre, as for these "persistent games" (or games offered as a service) building and maintaining communities is a crucial aspect to their success. Social networks inside and outside multiplayer games have been mentioned in "numerous studies across ethnography and social science" but "substantially less attention has been given to the quantitative analysis of social networks in games, notably at large scale" (Pirker, Rattinger, Drachen, & Sifa, 2018). According to Pirker et al. (2018), this means that there is a gap in understanding social networks for games outside Massively Multiplayer Online Games (MMOGs) and virtual worlds, including *eSports* and major commercial titles (or both at the same time). It becomes also relevant, thus, to investigate the relationship between the structure of such networks and the PE derived from playing MOBA games.

In the next chapter (Chapter 2) the research objectives will be presented. The context will be then completed with a background review in Chapter 3. Methods will be explained in Chapter 4 before continuing with the analysis of results in Chapter 5 and the posterior discussion in Chapter 6. The closing remarks will include both a conclusion (Chapter 7) and an acknowledgement of the limitations of the present work and the lines for future research in Chapter 8.

2

PROBLEM STATEMENT AND OBJECTIVES

Online competitive gaming has become one of the largest collective human activities globally and understanding motivations and social interaction is still not fully achieved. To advance in the state of the question, this work aims to explore the PE in *League of Legends* as a particular case of the MOBA game genre. The purpose is to understand whether player attributes (skill, social behaviour, demographics, economic factors) have an influence on the player's PE and social presence.

Some of this indicators, however, are not straightforward to obtain. Social behaviour in particular can be asked in a survey but responses are often biased and altered by the respondents. Thus, before exploring PE, a systematic classification of online competitive players based in structural network criteria will be proposed; as data will be extracted directly from the game, it will be virtually unbiased. The resulting classification will be then used as one of the indicators. Therefore:

2.1 MAIN OBJECTIVE

- To explore PE in *League of Legends* as a function of (a) its players' attributes and (b) the structure of their competitive social network.

2.2 PARTIAL OBJECTIVES

- To review the previous work on MOBA games.
- To develop a basis for a systematic classification of player-centric networks in competitive online games based on structural network criteria.
- To compare the players' perceptions against the systematic results extracted from the game.

3

BACKGROUND

Massively multiplayer online games (often abbreviated as MMOG or even MMO) are online games with large numbers of players playing on the same server. Their player bases range from thousands to millions and many of them feature persistent open worlds. The most explored MMOGs among researchers are in the category of Massively Multiplayer Online Role-Playing Games (MMORPGs). Games such as World of Warcraft (WoW) can be linked with the much older Multi-User Dungeon (MUD) text-based games, as they fill a similar niche in the gaming world and, at least to some players, provide a fully social experience (Mortensen, 2006).

In spite of the emergence of studies focused on MMORPGs in the last decade, few studies have approached MMOGs from other genres or subgenres such as MOBA games. In a few words, MOBA games are a subgenre of real-time strategy games in which two teams, typically consisting of five players each, compete against each other with each player controlling a single character. Contrary to real-time strategy games, there is no unit or building construction in a MOBA game, so much of the strategy revolves around individual character development and cooperative team play in combat (Yang, Harrison, & Roberts, 2014).

The most played PC game is a MOBA game: League of Legends (LoL)[1]. And within the MOBA game genre, LoL is the undisputed leader; in 2016, the statistics portal *Statista* estimated its market share at 66,3%, more than five times higher than the closest competitor, DOTA 2 (14%)[2]. It could be argued, thus, that LoL is not any other MOBA game but the MOBA game par excellence; examining LoL could be put on the same level as analysing the whole MOBA genre.

Despite its vast enthusiast community and influence on contemporary game designers, MOBA games remain under-explored by academics, as existing studies acknowledge (Ferrari, 2013). Few games, however, exhibit a greater need for socially-aware services than this relatively new genre (Iosup, van de Bovenkamp, Shen, Lu Jia, & Kuipers, 2014), as it brings new ways of collaboration and competition on the table, gender and cultural challenges and even new social networks which need to deal with the inherent toxic behaviour that arises in these contexts. MOBA games such as *League of Legends* provide the same opportunity as other MMOGs: namely the scale (*League of Legends* is one of the most played online games globally), data (which is recorded in its servers and accessible using an API) and relevancy (McDonald, 2017). *eSports* are a related (and relevant) phenomenon. Taylor (2012) conducted extensive ethnographic research in this regard, while Trepte, Reinecke, and Juechems (2012) used an *eSports* portal to recruit online participants for their work on how offline factors impact online social capital, thus recognizing the relevance of online gam-

1 https://newzoo.com/insights/rankings/top-20-core-pc-games/, accessed July 1st, 2018

2 https://www.statista.com/statistics/525976/market-share-moba-games-worldwide/

ing for research, now that "online gaming has become a major leisure time activity". Carrillo Vera (2015) claims that the impact achieved by *League of Legends* calls for academic and scientific analysis from a range of disciplines, including sociology, economy or communication; taking into account the amounts of data generated every day, however, computer science should also play an important role. This consideration is echoed by Mora-Cantallops and Sicilia (2018), who identified a research opportunity behind MOBA games as a whole, while asking for "future research to include innovative approaches that combine the traditional and common surveys and interviews with data and computer science techniques."

This background is structured as follows: after a brief history of the MOBA genre, a review of the literature and research on MOBA games will follow. LoL will then be introduced and detailed, as a few terms that will be used over this work need to be understood within the game context and dynamics. Previous and related works on PE and Social Network Analysis (SNA) will close this background chapter.

3.1 BRIEF HISTORY OF THE MULTIPLAYER ONLINE BATTLE ARENA

Although MOBA games have become very popular in the recent years, everything started from a small and niche fan-made custom map for Blizzard's Real-Time Strategy (RTS) game *StarCraft*, Aeon of Strife (AoS), back in 1998, by a modder called Aeon64. While AoS set the basics, it wasn't until Defense of the Ancients (DOTA) when the MOBA genre was born as it is known today. DOTA was another custom map by a modder

A modder is an individual who deliberately modifies games to his advantage or for fun called Eul for another Blizzard game, *Warcraft III*. It didn't take long until other players started with their own modifications, adding heroes or items. Steve Feak "Guinsoo" combined elements from selected variations of DOTA to create a version called *DOTA Allstars*, which quickly became the most popular version of the game. Feak left *DOTA Allstars* in the hands of another modder, IceFrog. Under IceFrog's management, the game became more balanced and increasingly popular. In spite of this, *DOTA Allstars* still required *Warcraft III* to run. With its player base growing up day by day, everything was ready for a wide release.

An early commercial MOBA release was 2009's *Demigod*, which didn't catch on, mainly because it was competing with DOTA, which was freely distributed instead. Later that year, LoL was launched by Riot Games, with Steve Feak in their team, and with a completely different business model: it was free to play. Anyone could download it and play with a rotating selection of heroes and some limitations – and additional content could be purchased in-game. The business model worked and Riot was able to capitalize on that, becoming the market leader by far.

In 2009, developer Valve hired IceFrog to work on DOTA 2, a standalone successor to the original DOTA. Much more faithful to the original *Warcraft III* map, DOTA 2 was released in 2013 through Valve's STEAM digital store and it is the second most popular MOBA game and the most played game on STEAM (according to their website[3]).

However, LoL and DOTA are not the only competitors: a myriad of other titles such as Smite - 2014 - Heroes of Newerth -

3 http://www.dota2.com/play/, accessed July 1st, 2018

2010 - and Heroes of the Storm - 2015 -, the recent entry from Blizzard itself, followed suit and were also played by millions of players, although far from the numbers of the two MOBA leaders.

3.2 PREVIOUS WORK

As part of this thesis, a complete literature review of the previous work on MOBA games was conducted (Mora-Cantallops & Sicilia, 2018). The result was the identification of the following topics of MOBA related research, which are going to be developed over the next subsections:

- Modelling and Prediction
- Behaviour and Motivation
- Community and Competition
- Teams and Collaboration
- Gender and cultural studies

3.2.1 *Modelling and Prediction*

One of the main lines in research on MOBA games aims to understand how to predict the outcome of games and what are the best tactics and strategies to use. Some of them focus in strategy (so, trying to achieve the more general goal of determining the best way to spend resources) and others in tactics (trying to model how individual units should be used and how combats can be won).

In Yang et al. (2014), combat is modelled using sequences of graphs and patterns are extracted that are predictive of successful outcomes (both of combat and of the entire game) with 80% accuracy.

In Rioult, Métivier, Helleu, Scelles, and Durand (2014), an exercise of prediction using topological measures on the team – area of the polygon described by the players, inertia, diameter or distance to the base – is conducted, highlighting its potential for a strategic analysis of team play. Work by Drachen et al. (2015) points in the same direction but making use of spatio-temporal behaviours of the team. It also brings an additional and relevant variable to the mix: skill level. On the other hand, Batsford (2014) leaves players aside and aims to calculate an optimal jungling route in DOTA 2 using various algorithms and looking at the experience obtained over time. It is a different approach that fits into the same idea as the previous works: what should players do to play optimally in a match?

More recently, Li et al. (2016) presented a visual analytics system aimed to find key events and game parameters that might result in snowballing or comebacks in MOBA games. Xia, Wang, and Zhou (2017), on the other hand, claim that "how to win such games is a problem worth exploring" and thus proposed a set of evaluation indicators for testing gameplay in DOTA 2. Results show how, at least in professional environments, tactical awareness is more important than operational skills.

In their related studies, Z. Chen, Nguyen, et al. (2018) and Z. Chen, Xu, Nguyen, Sun, and Seif El-Nasr (2018) analysed avatar selection and their synergies, and noticed that "due to intricate design and complex interactions between game avatars, through understanding of their relationships is not a trivial task". A model was proposed based on an evaluation of three popular MOBAs.

Models and machine learning algorithms are also being applied to MOBA games. Do, Silva, and Chaimowicz (2017) obtained promising results on the development of an intelligent agent to play alongside (or against) human players. Eggert, Herrlich, Smeddinck, and Malaka (2015), on the other hand, applied supervised machine learning to classify player behaviour according to DOTA 2 commonly accepted roles. Sapienza, Goyal, and Ferrara (2018) applied deep neural networks to obtain optimal team compositions, while Woolley and Malone (2017) combined multiple techniques to obtain a value of collective intelligence for a group and predict their performance, also showing how "tacit coordination in this setting plays a larger role than verbal communication".

3.2.2 *Behaviour and Motivation*

Things get diverse when analysing what is the most discussed topic (Mora-Cantallops & Sicilia, 2018). How do players behave and what motivates them to play (or leave)? Four subcategories have been identified.

TOXIC BEHAVIOUR Due to the amount of players and young people in MOBA games, toxic behaviour stands out as the main worry among scientists. Even developers (such as LoL developer Riot) are focused on fighting against toxic behaviour, with dedicated teams of staff (McWhertor, 2012). In Kou and Gui (2014), Kou and Nardi (2013), the effort of Riot Games to deal with it is first discussed via an ethnographic study on anti-social behaviour and the Tribunal system is presented, followed in the second paper with an investigation on the hybrid governance system that evolves within the ambiguity of LoL's rules. The Tribunal was a system introduced in May 2011 by Riot Games to manage player behaviour and to address the problem of toxicity, also analyzed by Johansson, Verhagen, and Kou (2015).

An article by Kwak, Blackburn, and Han (2015) goes a step beyond and explores toxic behaviour across different cultures (EU, NA, Korea) while trying to connect it with several compelling theories from sociology and psychology. On top, it explores how group setting – in-group favouritism and out-group hostility – impacts on reporting other players that engage in undesired behaviours.

Last, Shores, He, Swanenburg, Kraut, and Riedl (2014) examine deviance and develop a metric, toxicity index, to identify toxic players, while looking at the effects that interacting with them has on retention. Relationships between toxicity and role, playing experience or number of friends in a team are also covered in an attempt to understand what variables are indicative of deviance.

ADDICTION Addiction to games is an increasing concern and MOBA games are no exception. For Nuyens et al. (2016), "empirical studies focusing on the use and abuse of MOBA games are still very limited, particularly regarding impulsivity, which is an indicator of addictive states but has not yet been explored in MOBA games". Their results showed links between impulsivity-related constructs and signs of excessive MOBA game involvement and highlighted potential concerns about the addictive nature of MOBAs. Triberti et al. (2018) tested the relationship between average time spent playing and a few other variables with IGD (Internet Gaming Disorder) and found a few interesting conclusions related to the use of youngsters' spare time.

Loot boxes are also receiving attention due to their 'slot machine' mechanics. Ripamonti et al. (2018) sustain that the loot box system influences players' behaviour and tackle the issue with a simulative study (with Agent-Based Model techniques) of the effects of different systems in heterogenous player bases.

PLAYER EXPERIENCE Focusing on the PE over different video game genres, Johnson and Wyeth (2015) found that MOBA games stand out as offering the most distinct PE, complementing their research with six interviews to MOBA players. Although a limited sample, it provides important initial understanding of the unique nature of the PE in MOBA games.

In Kahn et al. (2015), a large scale survey was conducted in North American servers for LoL, in order to classify player motivations, and six buckets were identified, extending previous scales and linking motivation type to in-game behaviours.

Between player experience and motivation to play, an online competitive video game critical issue appears: matchmaking. Especially critical in MOBA games, as it impacts in balance, fairness and retention, Véron, Marin, and Monnet (2013) conducted a deep analysis on millions of game sessions to understand the weaknesses of LoL's matchmaking system and proposed new courses of action to improve it. Likewise, Myślak and Deja (2015) showed how LoL's current matchmaking system is built on a base of conditions that do not hold true in the presence of empirical data and proposed a new ranking system that would potentially improve user experience. Pramono, Renalda, Kristiadi, Warnars, and Kusakunniran (2018) understood that "a close and tight match is what make [sic] MOBA fun to play and increase its user satisfaction," and identified problematic factors for an appropriate matchmaking: high latency, toxic players and inexperienced players in a particular role, proposing new variables to be taken into account. This follows the same idea as seen in Suznjevic, Matijasevic, and Konfic (2015), who proposed to adapt the rating algorithm to the application context and Shim, Kim, and Kim (2014), who used PageRank based Evidence Accumulation to "detect bad players showing abnormal plays or appearances in games with embedded malicious intentions".

While fairness might seem a key factor for MOBA games, Wu, Xiong, and Iida (2016) showed how although the ban and pick system and character and map balance are important factors, they seem to be less essential than they are in other games such as board games or sports.

In their work, Silva, Do, Silva, and Chaimowicz (2017) developed a mechanism to dynamically balance the difficulty in MOBA games, but noted that, for users, "the player's expertise has a greater influence on the perception of the difficulty level and dynamic adaptation".

PLAYER CHURN Almost as important as understanding toxic behaviour, player churn is a relevant problem for MOBA games. When players leave a game early (mostly because they feel frustrated) it impacts the rest of the team's player experience. In Edge (2013), a model for how a player frustration builds in response to relative control over the game's outcome was built, based on new motivation theory ideas, aiming to predict churning.

More recently, Daneels, van Rooij, Koeman, and Van Looy (2017) explored retention in free to play games, understanding its vital importance and social relevance. Overall, motivations to start playing have been more studied than cessation behaviour. Their results indicate that cessation is related to the discontinuation of the initial motivations, contextual elements, game related elements, negative experiences and, even, physiological reasons.

LEADERSHIP STYLE How does the two worlds of computer games and reality bridge together to impact human lives? How does having two parallel worlds effect the development of an individual's characteristics? The urge to discover such profound relationships changing our society today is the motivation behind the paper by Nuangjumnonga and Mitomo (2012), as it aims to examine the correlation that exists between character roles in games and leadership in everyday life. Using a survey, the relationship between the respondent's leadership style (authoritarian, democratic or laissez-faire) and game role (carry, support or ganker) is explored. Although outdated versus current metagame – roles have evolved –, their study shows how MOBA games can also be a useful tool to bring together the world of video games and the real World, as well as to measure their impact on human lives.

3.2.3 *Community and Competition*

The metagame involves everything about the game outside the game which shapes the way the game is played

One of the most unique aspects of MOBA games is the so-called metagame, which is of vital importance for understanding the game. Donaldson (2015) analyses play in *League of Legends* through a binary model of expertise (mechanical and metagame), combining the in-game and the out-game practices that could lead to competitive success.

MOBA may represent the first videogame genre co-created entirely by a play community (Ferrari, 2013). And because of that, Ferrari looks back to how MOBA games in general and *League of Legends* in particular reflect the "rhetoric of the imaginary" in play theory applied to popular game design, from a handful modders to the mainstream public.

3.2.4 *Teams and Collaboration*

MOBA games have a particular aspect that is potentially fascinating: temporary teams are formed by complete strangers to fulfil relatively complex tasks in a short time. (Kou & Gui, 2014) conducted an ethnographic study via semi-structured interviews that aimed to answer how players interacted and collaborated with their teammates in temporary teams.

On the other hand, two complimentary works: Pobiedina, Neidhardt, Del Carmen Calatrava Moreno, Grad-Gyenge, and Werthner (2013) worked towards under-standing how an effective team could be formed and, to that interest, ran a statistical approach to identify factors that were related to the chance of a team to win a match. Afterwards, Pobiedina, Neidhardt, Moreno, and Werthner (2013) ranked these factors according to their influence on team success.

3.2.5 *Gender and cultural studies*

Since videogames became of interest to researchers, gender, violence and cultural studies have been linked to them. Since the early days, violence and videogames have always been in the public agenda and gender studies took the baton in the recent years.

Ratan, Taylor, Hogan, Kennedy, and Williams (2015) combined the results of a qualitative study with a quantitative complement. They examined the barriers that female players experience and, while extensive, they also acknowledge that it only represents one first step in that direction and more research is required. Only two female players (of quite similar demographics) took part in the qualitative interviews, a factor that could be seen as a threat to internal validity.

Gao and Shih (2018) acknowledge "that female players participate less in competitive games than male players". However, they note that "there are more female players are than male players in King of Glory (KoG)". Thus, their analysis is focused on understanding how the platform where the game is played impacts on its audience.

KoG is one of the most popular mobile MOBAs in China

On the cultural side, a unique article by Heidbrink, Knoll, and Wysocki (2015) was found; it gives a practical and basic introduction into methods applicable for researching different aspects and occurrences of religion in digital games, gamers and the practice of digital gaming, illustrated via a case study of the MOBA game *Smite* – with a religious themed background -, in the only reference that uses that particular game as a subject of study.

Although often found in video game-related research, no studies that focus on violence in MOBA games were found.

3.3 LEAGUE OF LEGENDS

League of Legends is a multiplayer online battle arena game that follows a freemium model, but where the in-game transactions do little to impact a player's performance or ability. Players are identified using a *Summoner* name (their nickname in the game) and are classified inside the game according to their proven skill (Rank). As of June 2018, there are 141 *Champions* (player characters) available to choose, each with a different set of abilities and different base statistics. Each *Champion* is arguably better suited for a particular playing position. Over the years, these positions have evolved and are currently set according to the lanes: one "top", one "mid" and one "bot", with a "jungler" gathering the resources in the jungle between lanes and a "support" which would, in theory, have some degree of freedom to provide utility to the team but it is usually linked to the "bot" player/position. During the game, each player earns gold from multiple sources and can use it to purchase multiple items that have the power to enhance the *Champion*. The combination of a *Champion* and the chosen items is called a "build".

New Champions are added to the roster several times a year, but older Champions are also often revisited to improve their gameplay and visuals to modern standards

Riot Games uses a Free-to-Play model for *League of Legends*; this means that the game can be downloaded and played for free but some content needs to be paid for, using either real currency (which is previously used to purchase "Riot Points") or in-game currency (in this case, named “Influence Points”) which is obtained in various amounts at the end of each match. *Champions* (the player in-game avatars) can be purchased using both types of currency but skins (appearances that can be applied to customize a particular *Champion*) can only be purchased using real-world money. In any case, it is important to notice that skins are only eye candy, gimmicks that change the looks of the player-controlled character and/or his abilities, therefore not directly impacting gameplay (Mora-Cantallops & Sicilia, 2016).

3.3.1 *Teams*

In *League of Legends*, teams are composed by five human players each, but these five players can be joined in multiple different combinations, from “solo” (which means that the player enters the queue alone and the matchmaking system finds the rest of the team to play with) to a full team composition. Furthermore, each player takes a role in the team. Current matchmaking system allows players to express their preferences and then assigns them to a role, which also has an effect on the range of avatar characters (or *Champions*) that the player will choose, as some are better suited for one role than others depending on the meta-game at the time (Donaldson, 2015). Role definitions have evolved from season to season, but stabilized at five main roles. Three players control the lanes (Top, Mid and Bottom) while Support provides utility to the team (spending most of the game paired with Bottom) and Jungle makes use of the resources in-between lanes (see figure 3.1). Players can also choose to “Fill”, which means that they will take any free role. *League of Legends* is a team game; all five roles are relevant. Support in particular is often in charge of controlling the flow of the match and map vision. As critical as it might be, Support players obtain "lower visibility and satisfaction" for their achievements, as discussed by Riot, the developer, itself . By contrast, damage dealers often "get great celebrations of their skilled play"[4].

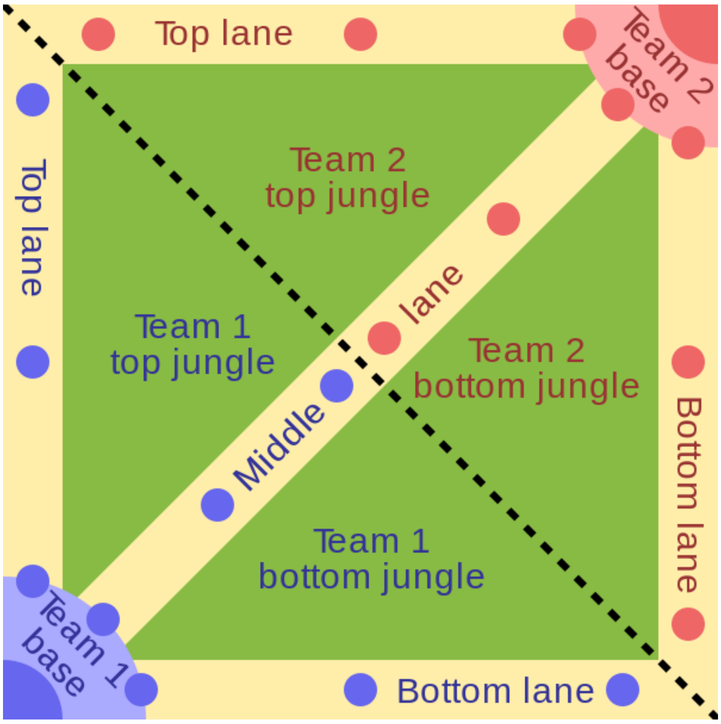

Figure 3.1: Typical MOBA map (with labelled lanes) for illustrative purposes. Original PNG version by Raizin, SVG rework by Sameboat.

Most of the strategy in the game revolves around one single element: gold, which can be obtained from multiple sources. *Creeps* or *minions* are non playable characters that appear periodically in waves for each team. Last-hitting an opponent minion (therefore, killing it) grants gold to the killer. Maximizing

4 https://na.leagueoflegends.com/en/news/champions-skins/free-rotation/some-thoughts-support, accessed July 1st, 2018

creep score (CS) requires intense focus, timing, and input mastery and is the most basic (and difficult) goal. Killing other players is another important source of gold, but, unlike *minions*, not only the last hitting player gets gold. All teammates that contribute to the kill by doing some damage get an "assist" and a smaller amount of gold. When a player is killed, it re-spawns in a variable amount of time: the later in the game, the longest it takes. For individual players, KDA (Kill-Death-Assist) ratio is often used as a performance indicator, adding kills and assists and dividing by deaths. Other sources of gold include neutral objectives and turrets. But, why do players need gold? They need it to buy and upgrade their items, which empower their *Champions*. Better itemization is key to success, as it is to get your items before the opponent does (leading to unbalanced periods in favour of the leading team called "power spikes").

Thus, the key to League of Legends is to be more efficient than the opponent team in obtaining resources from the map and using this advantage to destroy the enemy base (or nexus)

3.3.2 *Rank*

In *League of Legends*, players are ranked accordingly to their skill level. There are seven tiers in the so called "ladder", in increasing order of skill: Bronze, Silver, Gold, Platinum, Diamond, Master and Challenger. After a few placement matches, players get placed in competition categories (League tiers), and subcategorized into Divisions. The main objective becomes then to climb the ladder by continuously winning matches. Behind this ranking (and using an undisclosed calculation in the case of *League of Legends*) there is an Elo rating system similar to the one originally used for chess players. In short, it is assumed that a player's performance has a normal variation among games; the mean of that distribution is the Elo rating, which is determined by the win/loss statistics. Therefore, a player with a high Elo performs, in average, better than a player with a lower Elo. This is important as, once players are ranked accordingly, it's much easier to set "fair" matches between players of a similar skill level, which is crucial for a good PE (Véron et al., 2013).

Rank distribution changes over the season and can be different depending on the region, but in general, Silver is the most populated division followed by Bronze and Gold. All three account for 90% of the players, while the top 10% are Platinum or above and only 2% are Diamond or above. Less than 0.1% players are in Master or Challenger; this last one, actually, is limited to 200 players.

3.3.3 *Game Phases*

A typical *League of Legends* can be divided in five main phases (Ferrari, 2013), summarized as follows:

1. **Draft phase**: where players pick the *Champions* they will play. During this phase, bans are issued (*Champions* that will be removed from selection) and each team asymmetrically chooses its composition.

2. **Opening phase**: a brief 75 seconds phase where players appear in the *Summoner's Rift* (the playing field) and position themselves while minions appear. Some skirmishes between players might happen, but they are usually non-fatal, as power is still low.

3. **Laning phase**: in this phase, teams separate across lanes as per their roles. Each lane has one *Champion* guarding

the first turret from the opposing *Champions* and *minions* except the bottom one, which has a support player whose objective is often not to farm gold but to facilitate kills to his partner and to provide vision. The fifth player, the jungler, attack the neutral monster camps inside their jungles, establishing a route for maximizing their gold farming and providing optional support for lanes. This support often comes in form of "ganks", that basically consist of attempts to assist the lane player in killing his or her opponent. While in lane, the primary objective is to accumulate creep score.

4. **Teamfight phase**: laning phase ends when turrets start to fall, lanes become longer and the leading team has more time to move around the map without losing efficiency. This movement is aimed at securing vision over the map and control over the bigger objectives (dragons and *Baron Nashor*), neutral powerful monsters that, when killed, provide further utility to the team to get closer to the opponent's nexus, the final objective. During these phase, fights become team-based, so coordination is crucial.

5. **Endgame phase**: the final objective of teamfights is to kill as many opponents as possible; as re-spawn times get longer towards the end of the game, a good teamfight near the end guarantees numeric superiority that is often the main driver to end the game. The game ends when one team gains access to the opponent's base and destroys its nexus.

Phases are way more complex and intricate from a strategy point of view, but this is meant as an introduction to the game.

3.3.4 *Patching*

To introduce new features in the game while keeping the balance, Riot Games releases compulsory patches, usually bi-weekly. Every two weeks, the game is updated with changes to items, *Champions* and abilities. Details about what changes are published in detail in their website[5]. Riot implements changes to the game either to balance items or *Champions* that have become dominant or to encourage the use of forgotten *Champions*. Patches are also used to introduce new *Champions* to the game and aesthetic modifications. Most of the metagame revolves around these patches and how players adapt to them (Donaldson, 2015).

In their project about the influence of the 2008 global economic crisis in video games, Pérez-Latorre, Oliva, and Besalú (2017) related the emphasis in *resilience* after the crisis with the success of free to play games such as *League of Legends*, as the player becomes hyper-flexible and must constantly adapt to changing rules and mechanics; the challenge is one of a constant learning. According to them, the free to play trend converges with the flexibility of labour and the *precariat*.

3.3.5 *API*

It is also relevant to note how *League of Legends* developer Riot Games provides players with free access to its Application

5 https://na.leagueoflegends.com/en/news/game-updates/patch

Programming Interface (API), a set of tools that can be used to extract player and game data for further research. In this study, the API will be used to retrieve historical professional match data.

Some of the available queries[6] (that are going to be used to extract player information) are:

- **Summoner (by name)**: returns a *Summoner* object containing the playerID from a *summoner* name.
- **Matchlist**: returns a list of matches played by a playerID.
- **Match**: returns all the available information about a single match.

3.4 PLAYER EXPERIENCE

As players spend increasingly more time playing MOBA games such as *League of Legends*, attention is turning on the possible positive and negative impacts of doing so. "The uniqueness of gaming experience is one important reason for the success of digital games in general [...] therefore, it is important to know how player experience is structured to systematically address mechanisms that elicit player experience" (Wiemeyer, Nacke, Moser, et al., 2016). King, Delfabbro, and Griffiths (2010, 2011) have argued that multiple structural characteristics of video games may influence player behaviour and that when studying the effects of gaming, researchers need to take into account game features and genres. Relationships between game genre,

6 The full API documentation can be found at https://developer.riotgames.com/api-methods/

personality and gaming experience were also found by Johnson, Wyeth, Sweetser, and Gardner (2012).

It is important, however, to distinguish User Experience (UX) from PE. As Lazzaro (2008) argues, UX is the experience of use (so, it looks at what prevents the ability to play) while PE is the experience of play (so it looks at what prevents the player from having fun). One could debate, however, whether fun is a requirement in a game, so it might be more accurate to say that PE looks at what prevents the player from being engaged. To understand why *League of Legends* player base keeps growing nine years after its release is essential to analyse its unique PE (Johnson & Wyeth, 2015) in detail, and look not only at the differences across genres but also at the internal differences among MOBA players.

Since interest in UX (later shifted to PE) started to grow, numerous different concepts have been used (or proposed) to describe it (Brown & Cairns, 2004; de Kort et al., 2007; McMahan, 2003; Nakatsu, Rauterberg, & Vorderer, 2005; Sweetser & Wyeth, 2005). However, there is a degree of overlap among the concepts and, as a consequence, numerous challenges to understanding and actually measuring them (Takatalo, Häkkinen, Kaistinen, & Nyman, 2010).

Over time, multiple psychological models have been developed, trying to explain the structure of PE and the factors that contribute to it. A few models (e.g. SDT [Ryan and Deci, 2000], ARCS [Keller, 2010], Flow [Nakamura and Csikszentmihalyi, 2014]) have a wider range of applications than gaming, while others (e.g. GameFlow [Sweetser and Wyeth, 2005], FUGA [Poels, de Kort, and IJsselsteijn, 2008], CEGE [Calvillo-Gámez, Cairns, and Cox, 2015]) have been developed specifically for the game do-main. The Player Experience of Need Satisfaction (PENS), cited in Wiemeyer et al. (2016, p.247-248) as one of the most influential approaches, will be used in this study. It is based in the Self-Determination Theory (SDT), as proposed by Ryan and Deci (2000) and extended by Ryan, Rigby, and Przybylski (2006) (see also Przybylski, Rigby, & Ryan, 2010) to the Player Experience of Need Satisfaction (PENS).

While models aim to explain player experience, scales and surveys are methods developed to measure it. Two recent examples of these are the Play Experience Scale (Pavlas, Jentsch, Salas, Fiore, & Sims, 2012) and the Game User Experience Satisfaction Scale (GUESS), by Phan, Keebler, and Chaparro (2016), but the most widely used questionnaires are the Immersive Experience Questionnaire (IEQ) (Jennett et al., 2008) and the Game Experience Questionnaire (GEQ) (Brockmyer et al., 2009). Together with the PENS model, these are considered the three dominant tools in gaming research (Denisova, Nordin, & Cairns, 2016). The PENS questionnaire has been validated already in multiple studies across several fields, as PENS can be applied to a wide array of situations: a few examples are Serious Games (Gerling et al., 2014), Personality vs Motivation in Video Games (Johnson & Gardner, 2010) and even how control devices impact on the PE (McEwan, Johnson, Wyeth, & Blackler, 2012).

Although GEQ was eventually discarded in favour of PENS, de Kort et al. (2007) noticed the relevance of social context in digital gaming and developed an additional scale called Social Presence in Gaming Questionnaire (SPGQ) as a GEQ companion, in order to probe gamers' involvement with their co-players. Previous research has found that collaboration and social ability are of huge importance in MOBA games; thus, in order to assess this effect in our sample, SPGQ will also be used to complement the PENS assessment.

Despite its relevancy and impact in market share, Player Experience in League of Legends is still largely underexplored (Mora-Cantallops & Sicilia, 2018). Ghuman and Griffiths (2012) noticed how online gaming research literature tended only to examine a single genre: MMORPG games such as World of Warcraft. Therefore, their study aimed to examine player behaviour and characteristics in these three different online gaming genres: First Person Shooter (FPS) Games, Role-Playing Games (RPGs) and RTS Games. However, MOBA Games were left out in most of those studies, which could be partially explained because of their novelty. Social interaction and social network formation has also been a topic of interest for World of Warcraft and other MMORPGs (Bardzell, Bardzell, Pace, & Reed, 2008; Ducheneaut & Moore, 2004; Ducheneaut, Yee, Nickell, & Moore, 2006a, 2006b) and for online FPS (Xu, Cao, Sellen, Herbrich, & Graepel, 2011).

Kou and Gui (2014) conducted an ethnographic study to understand how temporary teams fulfilled complex tasks in League of Legends, while Kim et al. (2016) and Ong, Deolalikar, and Peng (2015) explored optimal team compositions in different perspectives: the former explored how players negotiate the proficiency-congruency dilemma (whether selecting roles that best match their experience or roles that best complement the other roles in the team) while the latter looked at optimal team compositions based on individual play style combinations. Shores et al. (2014) conducted a comprehensive study on deviant behaviour and focused on player toxicity and its relation to retention, which could be somehow related to PE.

Implicit social networks were studied by Iosup et al. (2014) and they concluded that MOBA games are also different from other genres from a team perspective as teamwork is key to success. Johnson and Wyeth (2015) built on these and their previous works (Johnson & Gardner, 2010; Johnson et al., 2012) and identified multiple differences in PE among genres. MOBA games in particular emerged as providing a uniquely different PE, showing less presence, less immersion, less autonomy, more frustration and more challenge than other genres. As MOBA player base was small (n = 33), no further intra-genre dive was conducted until the same research team undertook a second study focused exclusively on MOBA players (Tyack, Wyeth, & Johnson, 2016). As a result, they found a duality: while people "most frequently begin to play MOBAs as a shared activity with friends" and "experience significantly improved mood when playing with friends", MOBA players "either don't expect or don't want strangers to display social characteristics", unlike MMORPG or online FPS players.

Additionally, Bonny and Castaneda (2016) examined how MOBA game players use schemas to organize and anticipate information and found that MOBA games (and their players) provide an appropriate environment to study skill acquisition. Bonny, Castaneda, and Swanson (2016) also proposed a novel approach to gaming research in MOBA games, recruiting and testing participants in a MOBA gaming tournament, suggesting that this approach could provide an additional dimension of richness to gaming expertise that might not be available when recruiting players in other environments.

All in all, and according to the existing literature, MOBA games seem to present a unique opportunity to explore group processes and online behaviours, while providing a singular PE that is not found in other genres.

3.5 SOCIAL NETWORKS

Quantification of human behaviour and social dynamics has been a long-lasting challenge for social sciences, hindered by two main factors (Szell & Thurner, 2010): first, dynamics of societies constitute a complex system, characterized by strong and long-range interactions (not treatable, in general, by traditional mathematical methods) and, second, data is of comparably poor availability and quality (Lazer, Brewer, Christakis, Fowler, & King, 2009; Watts, 2007).

Both factors are, however, played down when looking at MMOGs (Castronova, 2005). In the age of Web 2.0 and, more recently, the era of big data (H. Chen & Storey, 2012), a great deal of social and relational data is routinely generated and recorded in the course of everyday life. This is the world that Thrift labelled as the world of "knowing capitalism": a world inundated with complex processes of social and cultural digitalization, with generation, mobilization and analysis of social data becoming ubiquitous (Thrift, 2005). It is also a world where sociologists need to rethink their methodological practices in radically innovative ways, as many assumptions that were central in the 1960s and 1970s no longer pertain in the early years of the 21st century (Savage & Burrows, 2009). These changes go even further, as this digitization reworks the very meaning of social relations, as emphasized by Latour (2007).

This is especially true in online competitive gaming environments, where a wide range of predefined actions for support-ing social interaction reflects either positive or negative connotations among game players, and they are in some cases unobtrusively recorded by game servers (Kwak et al., 2015). Often, data is easily available and can be used to study human and player relations as well as behavioural patterns, providing an unprecedented opportunity to observe social interaction on the large scale (Pobiedina, Neidhardt, Del Carmen Calatrava Moreno, et al., 2013). Stenros, Paavilainen, and Mayra (2011) distinguished between different kinds of in-game social interaction and reflected how massively multiplayer games were characterized by the formation of both micro and macro communities, complex communication channel hierarchies and diverse degrees of player involvement in social interactions. Taking into account that online gaming has become one of the largest collective human activities globally, we depart from the assumption that “such games provide for both sufficient participation numbers and careful control of experimental conditions, unlike any other social science research technology” (Castronova, 2006). Castronova contrasts this unique chance to replicate entire societies to the small-scale experiments that are often extrapolated to whole populations and communities. When studying MMOGs, the number of subjects can reach over several hundred thousands and their related actions can be counted by millions. The measurement process is also benefited by how information is extracted; players are not consciously of participating in a research-oriented data gathering process, thus minimizing bias.

Zhong (2011) examined the impact of collective MMORPG play on gamers’ social capital in both the virtual world and the real world. Ang and Zaphiris (2010) used WoW to investigate the social roles that emerged from the users' behaviour and interaction within its guilds (roughly equivalent to in-game clubs) from an analytical perspective and found that the core members of this communities were highly social-oriented players. In spite of this, Ducheneaut et al. (2006a) showed that while MMOGs were clearly social environments, joint activities were not as prevalent as they expected. In particular, social network degree densities for in-game guilds were surprisingly low, forming "sparsely knit networks." Other popular games explored include, for example, EverQuest (Castronova, 2006) or Pardus (Szell & Thurner, 2010).

As social and business groups are becoming more reliant on online communication (Monzani, Ripoll, Peiró, & Van Dick, 2014), the need to explore group processes, behaviours and relationships in online environments arises. Many studies focus in MMORPG because collaboration, competition and social ability in these environments are of huge importance (Christou, Lai-Chong Law, Zaphiris, & Ang, 2013). However, Buchan and Taylor (2016) suggest that, as team formation and team participation in MMORPG is voluntary, they might not be the most appropriate environment to explore group processes. As they argue, MOBA present an arguably better environment to do so, as "the game objective cannot be completed whilst playing alone".

According to Schlauch and Zweig (2015), there have not been many in-depth analyses of social network in MMOGs and even less in MOBAs that stem from classic one-vs-one games. SNA is the application of network theory and metrics to data that contains actors and connections between them. In their article, they reviewed state-of-the-art for SNA in gaming, with a special focus in the case of MOBA games. Iosup et al. (2014) conducted a quantitative analysis on social network formation in MOBAs, finding possible links between winning games with others and continued play together; these findings, however, were inconsistent across datasets. Few games exhibit a greater need for socially-aware services than this relatively new genre and further research in this area is required to determine how players construct social networks within MOBAs, and how these relationships affect play.

As video games evolve and MMOG's popularity grows, video game and player culture also grow, but do so supported by the relationships that arise from their social activity (both online and offline) (Adamus, 2012). Connection is not only a constitutive fact of social life, but also the pillar where online gaming stands. Players influence each other by means of competition or collaboration, exchange experiences and, sometimes, become involved in longer and meaningful relationships, forming teams or communities. Data extracted from online competitive games such as *League of Legends* can help understanding online players and their habits by looking at the structure of their connections and networks during online play.

Part II

METHODS AND RESULTS

4

DATA COLLECTION AND METHODS

To collect all the required data to explore the PE in LoL, the following steps were executed:

1. A sample of ranked players was selected.
2. A survey that included demographics and questionnaires was distributed over the sample.
3. The resulting dataset was enriched using the *League of Legends* public API.
4. Players were clustered based on the previous information using Social Network Analysis.

Next sections elaborate on the methodology followed in each of these steps, while next chapter will show the obtained results.

4.1 PLAYER SAMPLE

Between July and September 2016, five hundred and forty-seven participants completed an online survey that was distributed (via email) through 20.000 active ranked users in the Liga de Videojuegos Profesional (LVP) database. The complete survey is available in appendix A. The LVP database contains players that are registered in their website and, at the time of the study, it had 68.410 ranked players in it. With over 250,000 registered players in all their supported games, the LVP - Spanish Pro League is the biggest eSports organization in Spain, leading the industry with both online and live tournaments. It manages the most prestigious competitions (Division of Honour), tournaments and other amateur competition systems (LVP Arena) and also broadcasts international events in Spanish such as the *League of Legends* Championship Series and the *Call of Duty* World League. The LVP also covers gaming technology services, events production, online advertising and audio-visual production covering all aspects of the e-sports ecosystem.

The study targeted ranked players specifically because of two main reasons. First, players achieve ranked status only after they get past the thirty level game tutorial. Therefore, there is no ”novice” effect that could impact PE. Second, the League of Legends API only fully records data for ranked matches, converting unranked data in technically unreachable. As Summoner name is considered personal information, it was entered optionally and manually in the questionnaire, reducing the final number of complete entries to four hundred and thirty-nine. Final demographics are, therefore, N=439, age between 13 and 35 years of age (average sits at 19.4 with a standard deviation of 3.45). 93.8% are male (N=411, average 19.2 years of age, SD=3.36) and 6.2% are female (N=27, average 21.96 years of age, SD=3.87).

4.2 SURVEY

The online survey was structured as follows:

4.2.1 *Demographics*

Players were asked for their:

- Birth year (to calculate their age)
- Gender
- Place of residence

As the LVP houses not only *League of Legends* players but also other games', the next question was directed to divide main LoL players from the rest.

In the case of *League of Legends* players, the summoner name was then requested; this was optional as it is considered personal information. Those who filled it accepted the treatment of their data for research purposes. Additionally, summoner name is case sensitive and includes use of symbols; more than a hundred players included incorrect names that didn't correspond to any existing player. This is, probably, the main reason why the final number of complete surveys was limited to 439.

4.2.2 *Practices*

League of Legends players were then asked for their game behaviour in topics such as:

- Teamplay: whether they join the game alone or in different levels of premade teams
- Communication methods: in-game pings, chat, skype...
- Use of plugins for the game

4.2.3 *PENS*

Many questionnaires are available to measure player experience but, eventually, researchers tend to turn to the easily accessible and reliable (validated) questionnaires. As Johnson, Watling, Gardner, and Nacke (2014) discuss in their study, PENS and GEQ are recommended because "they offer multiple subscales designed to assess different components of player experience and they have been widely used in previous research". After examining how PENS and GEQ where structured, Brühlmann and Schmid (2015) concluded that PENS appeared to be more consistent than GEQ in its results, and therefore it will be the main approach to analyse PE in *League of Legends*.

The PENS model includes the following five dimensions: autonomy, competence, relatedness, presence and intuitive controls. In-game autonomy relates at how free players feel to make choices within the game. In-game competence denotes whether game challenges and player competence is balanced. In-game relatedness is concerned about the degree of connection between the player and the other players. Presence relates to physical, emotional and narrative presence, while intuitive controls is connected with the ease of control when playing.

The PENS (Ryan et al., 2006) questionnaire is a 21-item instrument self-assessed using a 7-point Likert-style scale. The PENS questionnaire was used in the current study as originally proposed by the scale authors.

4.2.4 *SPGQ*

As collaboration and social ability are of huge importance in MOBA games, the SPGQ (de Kort et al., 2007) will also be used to complement the PENS assessment. SPGQ is composed of three subscales: two dealing with psychological involvement (Empathy and Negative Feelings, measuring positive and negative feelings towards co-players) and the last one dealing with behaviour (Behavioural Engagement, measuring the degree to which players feel their actions to be dependent on their co-players actions).

The SPGQ is also a 21-item instrument, but it's assessed using a 5-point Likert-style scale instead, valued from 0 to 4.

4.2.5 *Additional information*

Additional behaviour and habit questions were posed to players although not all were used in the final exploration.

- Player Typology: following the questionnaire by Kahn et al. (2015)
- Learning and watching habits: inquiring about how players learn to play new champions or adapt to changes and through what media they do so
- In-game purchases: frequency and level of expense
- Additional free text for comments

4.3 LEAGUE OF LEGENDS API

An API is a set of functions, protocols and tools that developers can use to build software or to easily extract data from a source. APIs are useful because they provide clear methods, clear queries and clear responses that act as building blocks to greater applications.

Riot Games provides a developer API that is free to use for registered players, although two important limitations are present:

- The rate (number of calls in a period of time) is strictly limited
- The information (response) obtained is also limited in content and scope

Although the full API reference is available at Riot's developers website, only the three that will be used are going to be expanded in the next subsections.

4.3.1 *AccountID*

In order to obtain the *accountID* (that will be used to retrieve the list of games played by the user) the summoner name is needed. Using the API function in listing 4.1, the data representation of the summoner is obtained, with the details shown in Table 4.1.

Listing 4.1: Get a summoner by summoner name

```
GET /lol/summoner/v3/summoners/by-name/{summonerName}
```

NAME	DATA TYPE	DESCRIPTION
profileIconId	int	ID of the summoner icon
name	string	Summoner name
summonerLevel	long	Summoner level
revisionDate	long	Date summoner was last modified
id	long	Summoner ID
accountId	long	Account ID

Table 4.1: Result of the summoner API call

4.3.2 *Matchlist*

The *accountID* can then be used to retrieve the player *matchlist* (see listing 4.2). Not all matches are retrieved, however; the call accepts parameters such as the starting index or time, the queue (mode of play) and season. In this case, the data extraction will be from the main mode of play (ranked) and season 6 (which correspond to 2016 data). The result is a list of match identifiers, as seen in tables 4.2 and 4.3.

Listing 4.2: Get the summoner's matchlist

```
GET /lol/match/v3/matchlists/by-account/{accountId}
```

NAME	DATA TYPE	DESCRIPTION
matches	List [MatchReferenceDto]	List of matches
totalGames	int	Total number of games retrieved

Table 4.2: Result of the matchlist API call

NAME	DATA TYPE	DESCRIPTION
gameId	long	ID of the match
champion	int	Champion used
season	int	Season
queue	int	Queue type

Table 4.3: Content of the MatchReferenceDto list

NAME	DATA TYPE	DESCRIPTION
participantIdentities	List [ParticipantIdentityDto]	Participant identity information
teams	List [TeamStatsDto]	Team information
participants	List [ParticipantDto]	Participant information

Table 4.4: Result of the match API call

4.3.3 *Match Details*

After obtaining the match list it is possible to iterate over it and to obtain the details of every single game. It must be taken into account that the information provided by the *match* function (see listing 4.3) is extensive; therefore, only the main results will be represented in table 4.4.

- **participantIdentities**: it is possible to extract the ID information from it
- **teams**: it contains data about the match (such as whether the team won or lose and statistics)
- **participants**: most of the player statistics (including rank) are found here

Listing 4.3: Get the details on a particular match

```
GET /lol/match/v3/matches/{matchId}
```

4.4 SOCIAL NETWORK ANALYSIS

Social networks provide a way of thinking about social systems with a focus on the relationships among the entities that form the network (players in the current case). These players have characteristics (or attributes, such as their rank), as do the relationships between them (for example, the number of matches they played together). The full set of connections builds the network, which is nothing else than a “set of actors and the ties among them” (Wasserman & Faust, 1994). SNA is a discipline of exploring quantitative relationships in the resulting networks, which are non-trivial and irregular in structure.

The most basic distinction in SNA might be the one between egocentric and sociocentric research designs (Perry, Pescosolido, & Borgatti, 2018). The sociocentric approach is more common and starts with a set of actors and their ties. One could say that, once built, the network is a *complete* one (or close to being so); the focus is, therefore, the population. In egocentric research, on the other hand, a set of actors are sampled from a population and networks are build starting from these particular actors; as a result, a set of separate networks (one per ego) are obtained and the focus rests on the individual instead. In the current work, player networks will be analysed individually to understand their playing habits, so the ego network research design will be used.

4.4.1 *Ego networks*

Egocentric network research is focused on individuals and their immediate social environment. In the case of *League of*

Legends, this would mean players and their immediate teammates. The general idea is that each person or player has a personal community and the shape of this community (structure and composition) has consequences on the ego. As Perry et al. (2018) elaborate, “one goal of egocentric research, then, is to predict ego outcomes from variables that describe how ego is connected to alters”. This is, exactly, the methodology that is going to be followed in this section: first, the ego-centric (or player-centric, in this case) networks are going to be generated from the API extracted data; after doing so, indicators are going to be computed to obtain structural information. This structural indicators can be, in turn, used to categorize (or to cluster) the players in categorical groups.

4.4.2 *Network generation*

All matches played in 2016 by each of the 439 respondents (referred as egos from this point) were extracted through the *League of Legends* API provided by Riot Games. As a result, a total of 228.117 matches were obtained, with a mean of 520 matches per ego (SD = 424).

When a player joins a match, he or she does so in a match lobby, where the player is joined by other players until a team of five components is formed to play against five other players. Therefore, for each ego and for each match, the relationship between all team members is registered. Every relationship is counted as many times as it appears; thus, the weight of the link reflects how many matches two players have played together.

After processing all egos, the average number of alters per network is 1535 alters, for a total of 674.205 nodes (egos and alters – but players in the end) overall, but with considerable differences: the smallest network has 18 nodes while the largest has 7896. Approximately 80% of the networks have a number of nodes between 200 and 3500, however. Due to the described construction, all nodes are connected through the ego. Thus, before the subsequent analysis, the ego is removed from the network, highlighting the underlying alter to alter structure under the ego effect.

In summary, the resulting networks are one-mode projections of the two-mode networks connecting players to matches. Matches have, however, one restriction: its degree in the bipartite network is always equal to four. As a result, after removal of the ego, the one-mode network is a network of overlapping four-cliques or K4 complete graphs.

A K4 graph is a graph with four nodes and all possible ties present

For reference, as shown in Figure 4.1a, if an ego played a single match, the network would be a K5 complete graph (a five-node graph in which every pair of vertices would be connected). If an ego played two matches with the same team, the network would still be the same (with double weight in its links), but if an ego played the second match with a complete different team, then the resulting network would look like two K5 graphs linked by a bridge – the ego (Figure 4.1c). Removing the ego in the first case would keep the network connected (Figure 4.1b); doing the same in the second case would leave two disconnected components (Figure 4.1d). The generalization of this example will become key to understand the indicators that follow and their impact in the player networks.

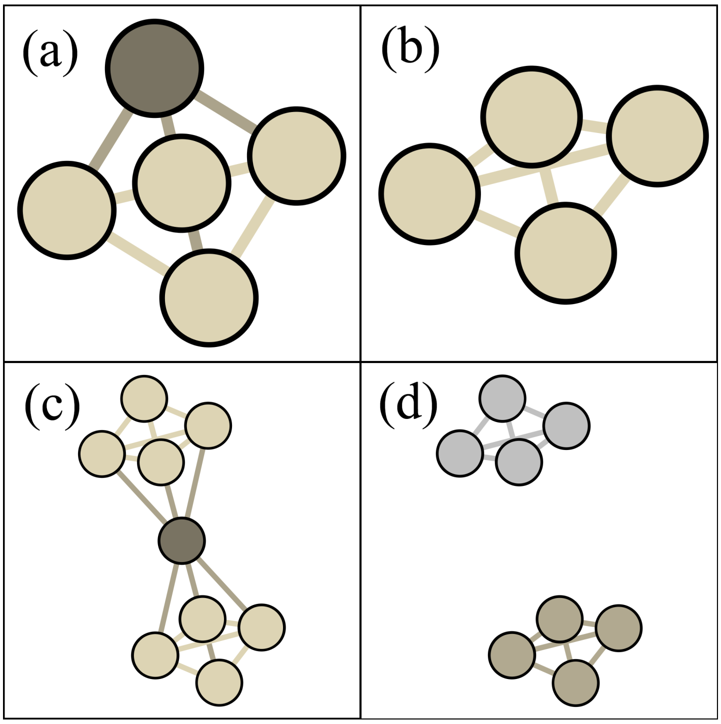

Figure 4.1: Network generation. (a) Ego with a single team (b) Alter network from (a) after ego removal (c) Ego after two matches with complete different players (d) Alter network from (c) after ego removal

4.4.3 *Indicators*

Mathematically, networks are described by graphs (Wasserman & Faust, 1994). An undirected graph G is described by a set of nodes $N = n_1, n_2, ..., n_g$ and a set of links (also called edges) $L = l_1, l_2, ..., l_L$ between pairs of nodes, where $l_k = (n_i, n_j)$. A large number of structural indicators can be computed on a network, some with a clear meaning and others with a more technical one, but in any case all features have an implication when used in the context of the social network analysis. As *League of Legends* is a team-based game with a relevant social component, for the current analysis purpose it was assumed that the most relevant structural features would be those related to node relevancy (as it was expected to find "friends" as relevant nodes) and to cohesion (as social players would see highly knitted networks as opposed to disperse components in non-social users). Node relevancy will be measured through degree and betweenness, while node density, component measures and modularity will represent structural network cohesion.

4.4.3.1 *Degree*

The degree of a node, denoted by $d(n_i)$, is the number of edges that are incident with it. Equivalently, it's the number of nodes that are adjacent to it. Degrees are easy to compute and informative; alters with a small degree will indicate players that played with few other of the ego's alters, while a high degree will show the opposite. In this case, therefore, degree will become a measure somehow related to the ego's social circles: the higher the degree, the closer to the core of the ego's playing community that alter is. For this application, the mean nodal degree (or average degree) will be used to summarize the degrees of all the actors in the network. For a network with g nodes and L links, mean degree $\overline{d}$ can be calculated as:

$$\overline{d} = \frac{\sum_{i=1}^{g} d(n_i)}{g} = \frac{2L}{g} \tag{4.1}$$

4.4.3.2 *Node density*

Every processed match can add up to four different players to the ego network (the fifth player is always the ego). If any of them already exists, the number of new nodes will be less than four. Therefore, by construction, the maximum possible number of nodes g_{max} equals four times the number of matches m the player joined. Node density for a player-centric graph with g nodes is then defined as follows:

$$\text{node density} = \frac{g}{g_{max}} = \frac{g}{4m} \tag{4.2}$$

4.4.3.3 *Betweenness centrality*

Interactions between two non-adjacent nodes might depend on the nodes that lie on the paths between the two. When this happens, these in-between nodes might have some control over their interactions (Wasserman & Faust, 1994). This becomes especially relevant in the player-centric network, as it's highly possible that the ego reaches new players through his or her frequent colleagues or friends. Betweenness centralization c_B for a node $n_k \in G$ can be defined as the number of shortest paths between n_i and n_j that pass through n_k ($\sigma(n_i, n_j|n_k)$) divided by the total number of shortest paths between n_i and n_j ($\sigma(n_i, n_j)$) (Brandes, 2008). Formally:

$$c_B(n_k) = \sum_{n_i, n_j \in G} \frac{\sigma(n_i, n_j|n_k)}{\sigma(n_i, n_j)} \tag{4.3}$$

By convention, this definition applies to disconnected graphs without modification (Freeman, 1977). Although the distance between two disconnected nodes is undefined, the number of shortest paths between them is defined and equal to zero. The resulting contribution to betweenness centrality is then established as zero. The mean betweenness centrality measure is then the average of c_B across all nodes. Additionally, the number of nodes with c_B above three times the average will be counted in each network as it will give an indication of the number of players with a relevant flow control.

4.4.3.4 *Components and largest connected component*

A graph is connected if there is a path between every pair of nodes in the graph. Else, every maximal connected subgraph is a component. Note that if there is only one component the graph is connected. In graphs with infinitely many nodes, the emergence of a giant component is observed after crossing a certain threshold (Dorogovtsev & Mendes, 2003). The same concept can be applied to finite graphs, where the component with the highest number of nodes is called the largest connected component.

For the purpose of this study, an additional measure is calculated. Let g be the total number of nodes in G and g' the number of nodes in the largest connected component. It's then possible to calculate the largest component proportion as g' divided by g. While the number of components might give an indicator of the different groups of play that the ego has, this proportion will provide an indication of how large is his or her main playing group.

4.4.3.5 *Modularity*

A key feature of social networks is high transitivity, meaning that if n_i is connected to n_j and n_j is connected to n_k, there is a high chance of having a connection between n_i and n_k too. This property leads to the formation of clusters called communities, "with groups of nodes within which connections are dense but between which they are sparser" (Newman, 2003). Multiple community detection algorithms have been described (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008; Clauset, Newman, & Moore, 2004; Girvan & Newman, 2002; Pons & Latapy, 2006) but the result is always some division of the vertices into communities. The quality of this division is often measured by the modularity of the partition (Newman, 2003), a scalar value between -1 and 1 that measures the density of links inside the obtained communities as compared to the links between them. This quality function Q, modularity, is defined as follows. Let e_{st} be the fraction of edges in the network that connect nodes in group s to those in group t, and let $a_s = \sum_t e_{st}$. Then

$$Q = \sum_s (e_{ss} - a_s^2) \tag{4.4}$$

is "the fraction of edges that fall within communities, minus the expected value of the same quantity if edges fall at random without regard for the community structure" (Newman, 2003). Note that the expected modularity for a random partition would be zero and any other value reflects a deviation from pure chance. According to Newman, values greater than 0,3 appear to indicate relevant community structure. In the current study, the Louvain method for community detection will be used as defined by Blondel et al. (2008) and implemented using the NetworkX 2.1 (Python 3.6) libraries and the Gephi tool. The Louvain method is an efficient community detection algorithm broadly used that features a modification on equation 4.4 (in order to consider weights) as the function to optimize.

4.4.4 *Clustering*

Cluster analysis is a category of unsupervised machine learning techniques that allow to discover hidden structures in data where the ground truth is unavailable (so, where the right answer, if any, is unknown) such as the one in question. The goal of this technique is, therefore, "to find a natural grouping in data such that elements in the same cluster are more similar to each other than those from different clusters" (Raschka, 2014).

Many clustering algorithms exist. The standard Python *scikit-learn* library has implemented the most popular and it was the package used in this analysis. One of the most used methods is the K-means algorithm (Arthur & Vassilvitskii, 2007), that clusters data by trying to separate samples in n groups of equal variance. For the current sample, however, K-means presented two drawbacks. First, it requires the number of clusters to be specified. Therefore, one should have an idea of how many clusters are expected in the data before applying it, which wasn't the case. Second, due to its implementation, K-means expects a certain normality in the input data, which couldn't be assumed in the player-centric dataset. K-means is also unstable, as its clustering depends on initialization, which was undesirable.

The affinity propagation algorithm (Frey & Dueck, 2007) is a newer method that has some advantages over K-means: the number of clusters doesn't need to be specified beforehand, non-symmetric dissimilarities are supported and it is stable over runs. The affinity propagation algorithm identifies exemplars among data points and forms clusters around these exemplars. It operates by simultaneously considering all points as potential exemplars and exchanging messages between them until a good set of exemplars and clusters emerges. As its characteristics are more appropriate to classify the player-centric network dataset, affinity propagation is going to be the method used for clustering.

Still, two parameters need to be set in advance. Damping is set in all calculations to 0,8 in order to avoid undesired oscillations while computing. Preference is defined as the suitability of a particular data point to serve as an exemplar. High preference values will result in many exemplars found (many clusters), while lower values will lead to a small number of exemplars. When preferences rise above a certain value, it becomes beneficial for multiple subsets of data that have approximately the same intra-subset similarities and approximately the same inter-subset similarities to form distinct clusters simultaneously, so the number of clusters obtained quickly rises. Thus, "different plateaus would correspond to the extraction of different levels of structure" (Frey & Dueck, 2007). Therefore, preference value will be need to be analysed and chosen in each particular instance of the analysis, looking for these "plateaus" in the graph.

A whole different branch of SNA is devoted to blockmodelling, another alternative for analysis. In essence, blockmodelling compares patterns of connection between nodes to cluster them into "blocks" of nodes that enjoy similar position or roles within the network. The goal of blockmodeling is to reduce a large, potentially incoherent network to a smaller comprehensible structure that can be interpreted more readily. In spite of this, blockmodelling techniques are "very unusual in ego-net analysis because ego-nets are generally too small to merit blockmodelling" (Crossley et al., 2015). There are exceptions, however, as ego-nets might be big enough to merit its use, as in the work by Edwards and Crossley (2009).

5

RESULTS

Although the main objective of this chapter is to explore the player experience in ranked *League of Legends*, answering the main objective, two partial objectives must be responded beforehand. Thus, in this chapter:

1. The egocentric networks for each player will be computed, analysed and clustered to obtain a systematic classification that groups players according to their social (online playing) habits.

2. Player's answers to the questions in the survey will be explored.

After both steps are completed, they will be linked to the PE in *League of Legends*.

5.1 PLAYER-CENTRIC NETWORKS

After extracting the data corresponding to all the matches played in 2016 by the 439 players (228.117 matches), the corresponding ego-networks were built and structural indicators computed. First, the resulting variables will be shown. Second, an initial clustering will be proposed. Finally, a simplified (and minimal) model will be used to classify players according to their social behaviour when joining games.

	DEG	DENS	ABC	% IMP
count	439	439	439	439
mean	3.68	0.73	0.02	0.001
std	0.44	0.16	0.09	0.004
min	3	0.06	0.001	$5.2 \cdot 10^{-5}$
25%	3.35	0.64	0.007	$5.2 \cdot 10^{-5}$
50%	3.63	0.75	0.012	$2.2 \cdot 10^{-4}$
75%	3.92	0.85	0.019	$8.1 \cdot 10^{-4}$
max	6.24	1.00	1.00	0.047

Table 5.1: Distribution of the numeric variables in the dataset (I)

5.1.1 *Variables*

For each player-centric network, the properties described in section 4.4.3 were calculated after removal of the ego: average degree (DEG), node density (DENS), average betweenness centrality (ABC), percentage of nodes with betweenness centrality over three times the mean (% IMP), number of separate components (COMP), largest component proportion (LCOMP) and modularity (MOD). As the number of separate components is affected by the number of matches played, it was divided by the total number of matches for every particular player. Once this was done, all variables were standardized by removing the mean and scaling to unit variance. The resulting dataset contained 439 observations with seven indicators per row with the following distribution (see Tables 5.1 and 5.2):

With these variables, and to fulfil the objective of developing a basis for a systematic classification of these player-centric

	COMP	LCOMP	MOD
count	439	439	439
mean	0.42	0.43	0.78
std	0.25	0.27	0.18
min	0.01	0.01	0.04
25%	0.22	0.21	0.68
50%	0.39	0.42	0.82
75%	0.61	0.63	0.92
max	1.00	1.00	1.00

Table 5.2: Distribution of the numeric variables in the dataset (II)

networks, a clustering algorithm (affiliation propagation) will be used. Although there might be alternatives to using clustering techniques, they allow to discover hidden structures in data where the ground truth is unknown and are thus appropriate for this duty.

5.1.2 *Bivariate correlation*

Before proceeding to clustering, the bivariate correlation table between indicators or variables of interest is presented in Figure 5.1 as reference. Two groups can be distinguished; the first one containing measures related to node cohesion and the second one related to node relevancy.

All variables will be included in the initial clustering model, which will be optimized later to reduce the number of indicators.

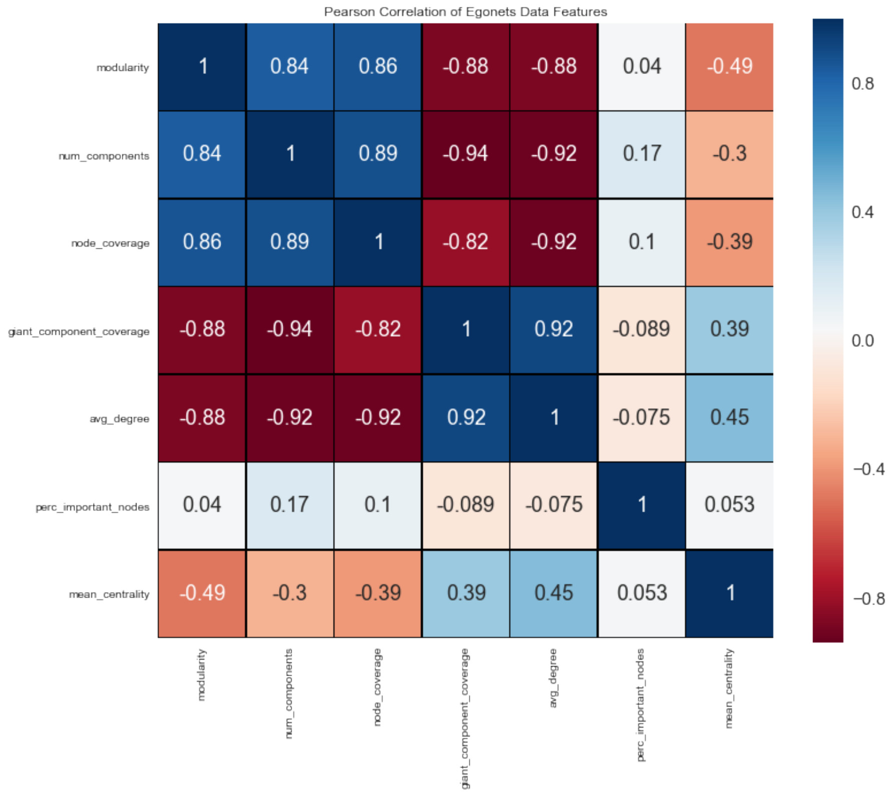

Figure 5.1: Bivariate correlations between variables of interest

5.1.3 *Clustering process*

An affiliation propagation model was build using the obtained dataset. Before proceeding, however, the preference parameter had to be set. To do so, the influence of this parameter to the number of clusters obtained by the model was plotted in order to find a significant plateau (Figure 5.2). A long plateau between [-60, -45] can be observed, resulting in a seven cluster structure. Affinity propagation is then used with preference equal to -45.

As displayed in Figure 5.3, seven clusters are formed. To assess the goodness of fit, the Average Silhouette Width (ASW) (Kaufman & Rousseeuw, 1990) is computed and results in $ASW = 0.533$. ASW assesses the optimal ratio of the intra-cluster dis-

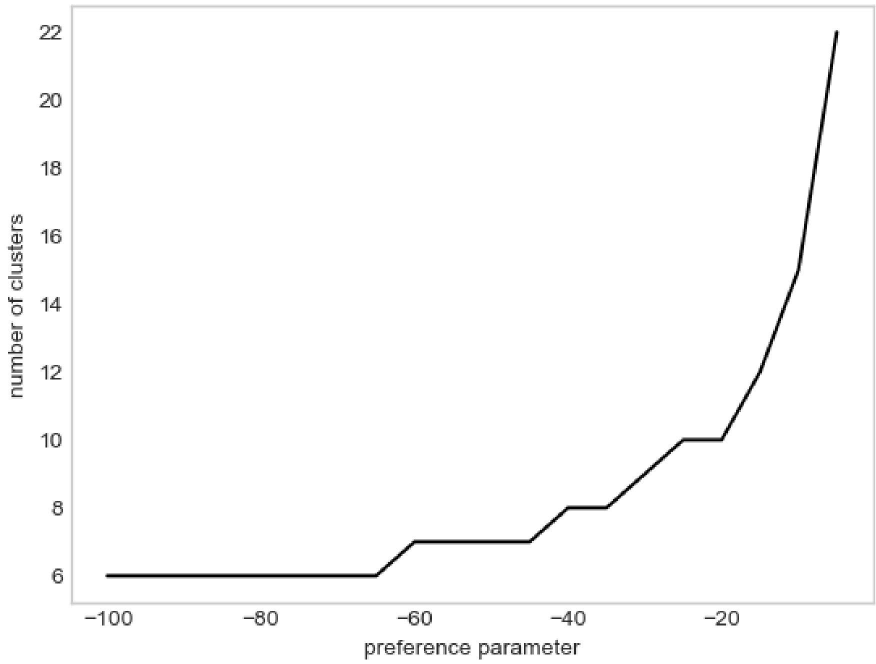

Figure 5.2: Number of clusters derived from affiliation propagation versus shared preference (all indicators included).

similarity of the objects within their clusters and the dissimilarity between elements of objects between clusters. According to Kaufman and Rousseeuw, an ASW between 0.51 and 0.7 indicates that "a reasonable structure has been found," so, with 0.533, the present clustering shows a reasonable preliminary classification of player-centric networks.

5.1.4 *Final model*

It is possible, however, to simplify the model reducing the number of variables. Therefore, the number of indicators that defined the hidden structure that emerged from the networks was reduced. A series of ordered cuts in the variables were executed, iterating as follows: remove indicator, assess preference parameter, run affinity propagation, compare ASW. The

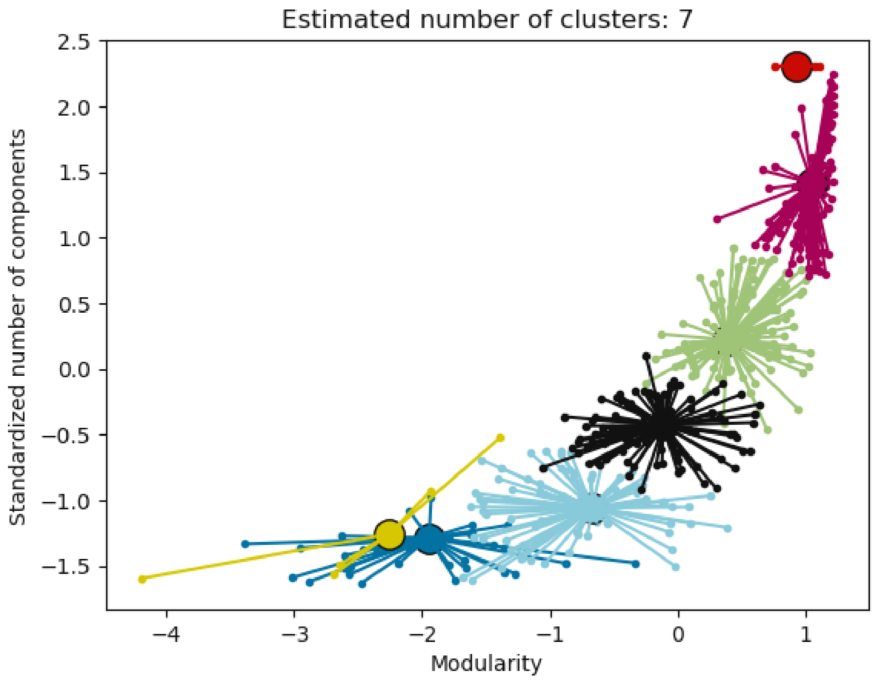

Figure 5.3: Graphical representation of clusters resulting from the affiliation propagation algorithm with preference -45 and all indicators included. This is only a 2D slice of a 7 dimension space for illustration purposes.

final and best result was obtained using only the modularity (MOD), the standardized number of components (COMP) and the largest component proportion (LCOMP), thus reducing the number of indicators from seven to three.

With preference set at -30 (see Figure 5.4, although using the same value as in the previous run wouldn't change the result), the affiliation propagation algorithm results in four clearly defined clusters (Figure 5.5 and Figure 5.6) that assimilate the three small additional clusters that appeared in Figure 5.3 into them. The ASW also improved notably and now equals 0.641, still in the same reasonable structure interval but with a simpler cluster split and closer to the 0.71 that would be the threshold to obtain an excellent fit. From largest to smallest, the num-

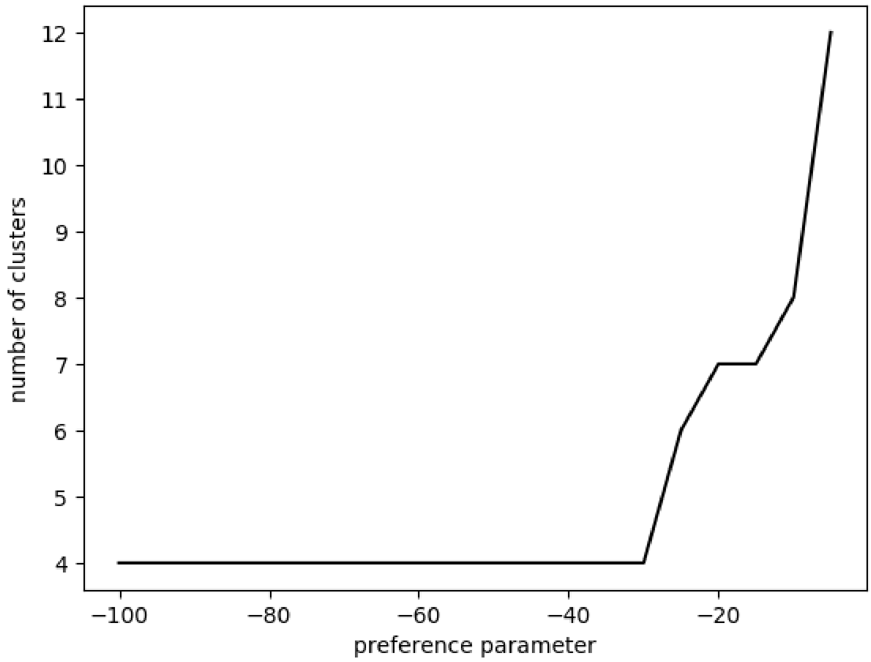

Figure 5.4: Number of clusters derived from affiliation propagation versus shared preference (best three indicators only).

ber of observations per cluster is 65 (C1), 125 (C2), 129 (C3) and 120 (C4).

5.1.5 *Cluster analysis*

Another way to check whether the final proposed clustering has a good fit is to look at the distribution of the indicators per each cluster and compare them. To do so, four violin plots are drawn in Figure 5.7.

Before anything else, a quick test is run on the total number of games per player; the graph shows that they are similar among clusters so size-related side-effects can be discarded. A Kruskal-Wallis test followed by a Dunn's test is then run for all three indicators. Differences are found for all three at p-value

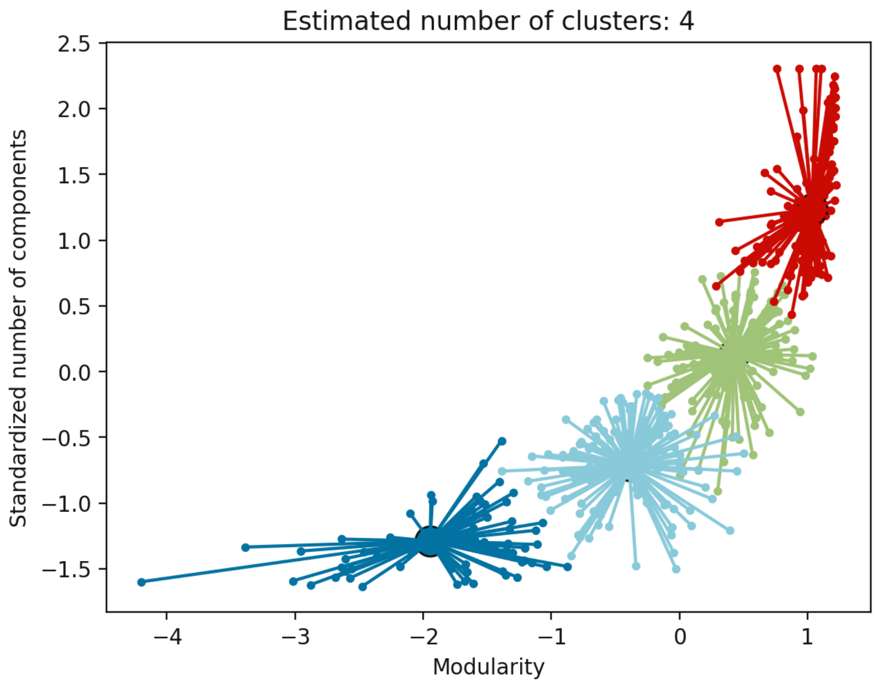

Figure 5.5: Graphical representation of clusters resulting from the affiliation propagation algorithm with preference -30 and restricted to the best three indicators. This is a 2D slice of the 3D space.

$\sim$ 0, and all pairs of clusters present statistically significant differences with p-values $\ll$ 0.001.

Cluster C1 contains player-centric networks that have low modularity (so few communities emerge), a low number of components in proportion to their size and the largest component contains, in average, more than 80% of the total nodes.

Cluster C4 networks have high modularity (close to the highest possible value), a massive number of components in proportion to their size and the largest component contains, in average, less than 20% of the total nodes.

In-between these two extremes, clusters C2 and C3 are found. Both have higher modularity and component counts than C1 but notably lower than C4. Moreover, both have largest com-

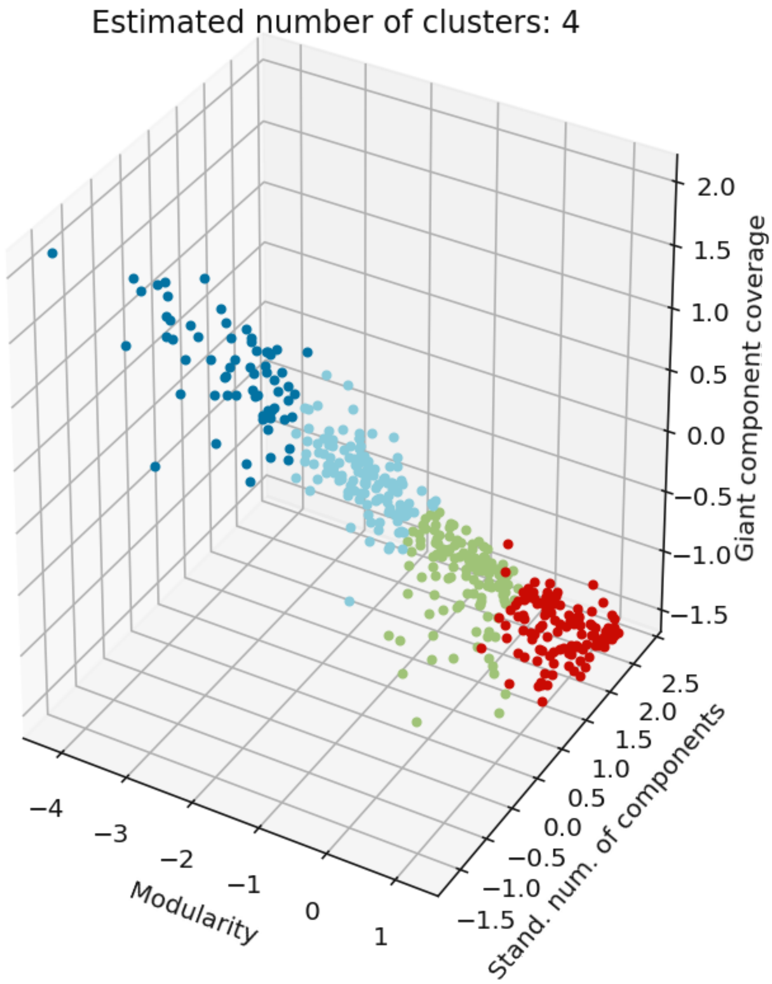

Figure 5.6: 3D representation of the resulting clusters. Note that figure 5.5 is the 2D view from above.

ponents with less nodes than C1 (around 60% and 40%, respectively) but with a significant increase versus C4. Although these similarities, they are still quite different, and it is assumed that they represent two distinct groups of players.

An observation is chosen at random from each cluster to illustrate the described typology. For both visualization and comparison purposes, it's selected randomly from similar sized networks (range between 500 and 800 games played). Their dimensions and indicators can be found in Table 5.3, while

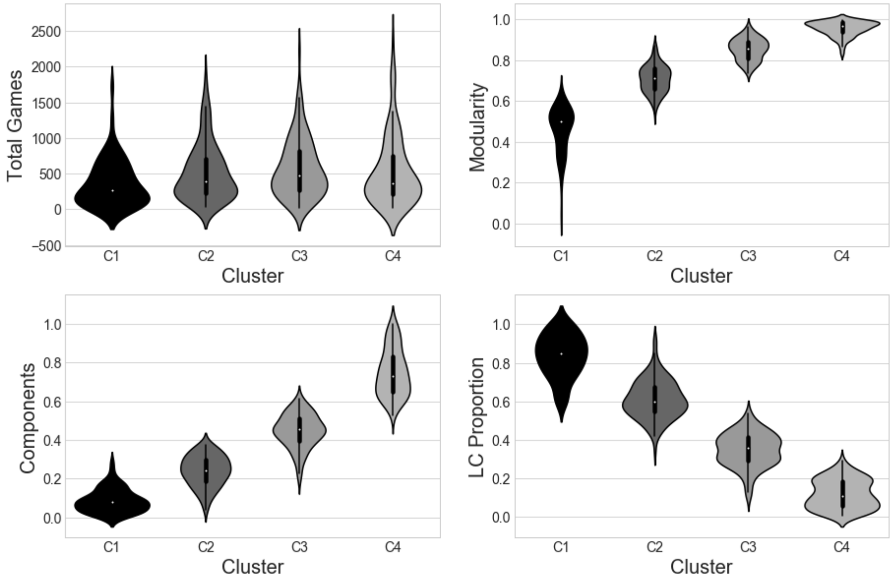

Figure 5.7: Violin plots for total games, modularity, components and largest component proportion per cluster.

the graphical representation is presented in Figure 5.8, where thicker edges represent higher link weights.

5.1.5.1 *Team player*

C1 would correspond to a *team player*. The alter network (without the ego) is not only highly connected and with a huge largest component, but also exhibits strong connections between some alters. This implies that the ego a) almost always

	MATCHES	NODES	MOD	COMP	LCOMP
C1	693	1335	0.323	0.059	0.878
C2	668	1606	0.598	0.178	0.690
C3	699	2069	0.775	0.383	0.423
C4	699	2641	0.992	0.816	0.058

Table 5.3: Indicators extracted from sample player-centric networks

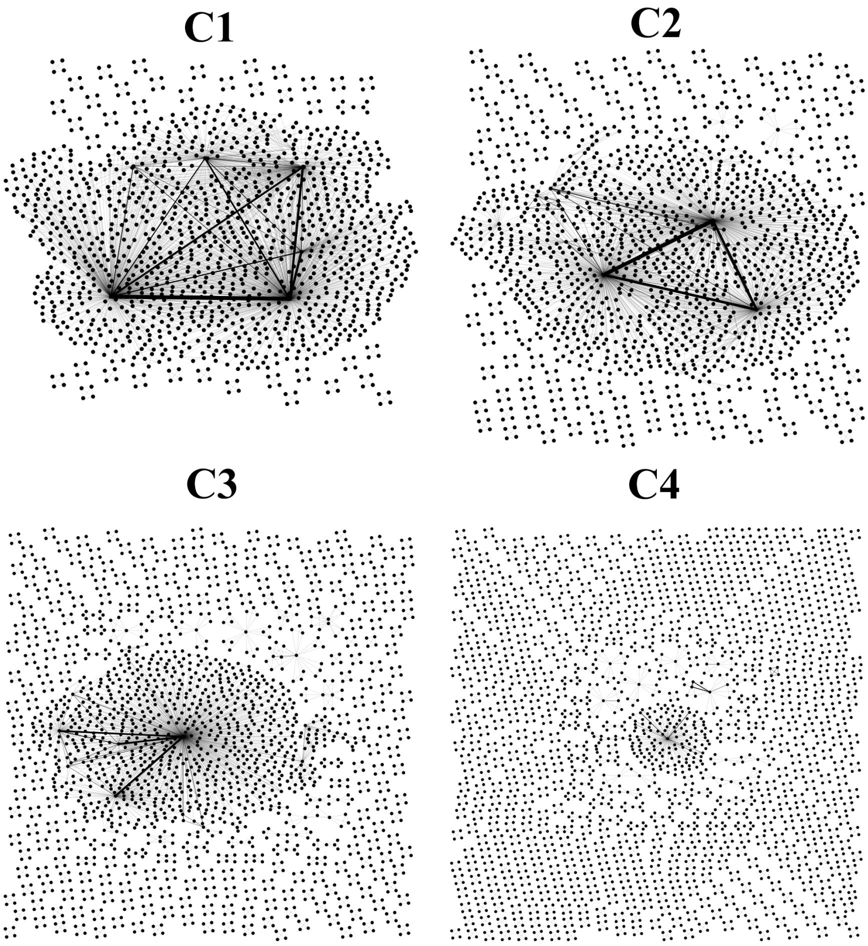

Figure 5.8: Graphical representation of sample player-centric networks.

plays with the same players and b) they do so together. As many matches are played sharing alters, the total network contains notably less nodes than the other clusters (as can be noted in Figure 5.8). These players often join the game with a team full of known people (or, at least, players with whom they already played in the past).

5.1.5.2 *Group player*

C2 would then correspond to a *group player* instead. Compared to C1, there are fewer strong links between alters (in this particular case it's basically a triangle), the largest component is smaller and there are more disconnected components. This kind of player a) regularly plays with two or three friends and b) occasionally plays with people in other circles or alone. Therefore, *group players* (whenever possible) join with a group (but that group is not large enough as to cover a full team). Else, they play with smaller groups or even solo as a last option.

5.1.5.3 *Cell player*

C3 shows much less strong relationships between alters, so this cluster could be labelled as *cell players*. The largest component covers less than half of the network and connections inside are weaker. Two tendencies are found: strong dyadic relationships in the alter network are translated into matches played in trios (but note that these trios are not fully connected between them; if they were, they would become C2). Additionally, many small star-shaped components outside the largest one represent games played in duo (therefore sharing only one player between matches). Players in C3 join the game in small and variable cells of two to three members; they also go solo more often than the previous two types.

5.1.5.4 *Solo player*

C4 would then be the *solo* player. Their graphs show how the largest component is almost inexistent, no relevantly strong links are present with any other player and the landscape is mostly composed of spare components of four unknown players that the ego will never met again. This is the least social of all players. Therefore, not only their games are always automatically filled with four strangers by the matchmaking system, but also rarely results in links established between them.

5.2 PLAYER SOCIAL HABITS AND RANK

Although the official *League of Legends* API provides little information about the player's attributes, rank is available. Therefore, it is possible to enhance the obtained clustering with a few insights about their skill level (as determined by the game). Figure 5.10 displays rank distribution within each cluster.

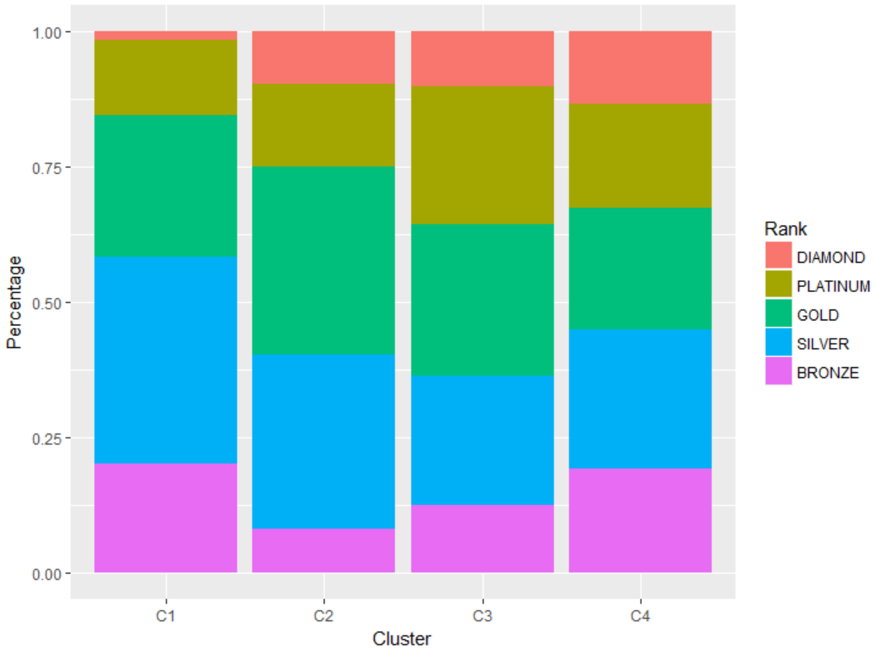

Figure 5.9: Rank distribution per cluster. C1 has less high ranked players than other clusters. C3 and C4 are disproportionally higher ranked.

Taking into account that bronze, silver and gold are the lowest ranks and platinum and diamond are the highest ones before the exclusive master and challenger:

- The first cluster, C1, formed by team players, presents notably less high ranked players than the other clusters.
- On the other hand, C3 and C4, the duo and solo players, have a higher proportion of platinum plus diamond players, even over the expected distribution across all player base.

At first sight, this is somehow contradictory, as collaboration and trust between team members in *League of Legends* is crucial for success so it would make sense to see better collaboration (and, therefore, better performance) in teams formed by friends. In spite of this, two reasons why this happens could be suggested.

First, the higher the rank the less players there are. When a player climbs in the ladder, not only there are less players available, but less friends too, as players need to join the games with players either in their own division or one up/down. This keeps true until platinum, where restrictions apply, as only highly ranked platinum players can join games with diamond players. Diamond gets more extreme, as there are even restrictions within its divisions. Therefore, higher ranked players are forced to be solitary players in regard to their friendships.

Second, in ranked competition all games matter. It is not only important to play well, but also to keep winning in order to advance. A bad streak can bring a player down in the ladder and promotions are long and difficult. It is thus likely that friendly team playing is left for lower categories (suggesting more “casual” playing) while higher ranked players might tend to select their teammates more in detail. It is even possible that, in order to prevent disputes and negative feelings, joining with real-life friends is avoided in these almost professional ranks of skill.

5.3 PLAYER SURVEY

Before moving on to the results of the PE questionnaires in the following section, the demographics and behavioural questions will be explored in this section.

It must be noted that one participant was removed from the 439 player sample as he or she was the only one ranked master (way above the rest) so it was considered an outlier.

5.3.1 *Demographics*

Participants were asked for their year of birth and gender. As shown in table 5.4, players were mostly young (range from only 13 years old up to 35). This, together with a mean of 19.4 years, indicates that most *League of Legends* ranked players are either teenagers or in their early twenties. The 50% of the players sit between 17 and 21 years, actually.

Gender is disproportionally male dominated. In the resulting sample there were only 27 female players, which represent a 6% of the total sample. This is consistent, however, with the findings from Yee (2017). With a 270.000 player sample, MOBA games had, in average, around 10% female players only; although a drill down showed how *League of Legends* figures could be up to 14%, *DOTA* 2 numbers were at 6%. As the current sample is restricted to active ranked players, it is natural that female quota is closer to the *DOTA* numbers.

	AGE
Min	13
25%	17
Median	19
Mean	19.4
75%	21
Max	35

Table 5.4: Age demographics

5.3.2 *Player Rank*

The ladder is the road that players must climb from the bottom to reach the higher divisions

In *League of Legends*, players are ranked accordingly to their skill level. There are seven tiers in the so called "ladder", in increasing order of skill: Bronze, Silver, Gold, Platinum, Diamond, Master and Challenger. After a few placement matches, players get placed in competition categories (League tiers), and subcategorized into Divisions. The main objective becomes then to climb the ladder by continuously winning matches.

As said before, behind this ranking (and using an undisclosed calculation in the case of League of Legends) there is an Elo rating system similar to the one originally used for chess players. In short, it is assumed that a player's performance has a normal variation among games; the mean of that distribution is the Elo rating, which is determined by the win/loss statistics. Therefore, a player with a high Elo performs, in average, better than a player with a lower Elo. This is important as, once players are ranked accordingly, it's much easier to set "fair" matches

TIER	REAL	%	REPORTED	%
Bronze	62	14.16	22	5.02
Silver	127	29.00	65	14.84
Gold	123	28.08	146	33.33
Platinum	84	19.18	122	27.85
Diamond	42	9.59	69	15.75
Master	0	0.00	0	0.00
Challenger	0	0.00	6	1.37

Table 5.5: Sample size per tier in the survey

between players of a similar skill level, which is crucial for a good PE (Véron et al., 2013).

Players were asked for their perceived skill (rank tier) in the survey. Afterwards, that rank was checked using the *League of Legends* API and substantial differences were found (Table 5.5) between the reported and the real rank and the end of the Season 6, which will be used for the analysis.

It is easy to notice how players overstate their rank level when asked in a survey, but it is also easy to extract this information directly from the game to contrast it.

5.3.3 *Seniority*

To avoid confusion with player experience, in-game experience (as in number of matches played or time spent in the game) will be referred as *seniority*. Is rank related with seniority? If that was the case, both would be exchangeable concepts, as number of games played would be roughly equivalent

	MATCHES
Min	7
25%	185
Median	347
Mean	460
75%	659
Max	2023

Table 5.6: Number of ranked matches played by players

to time spent in the game. The distribution of ranked games played by the players in the sample is shown in table 5.6

To assess their relationship, a Kruskal-Wallis test was run grouping by rank. Resulting p-value was significant and smaller than 0.001. Thus, a Dunn test, corrected by the Holm-Bonferroni method, followed to draw further conclusions on differences among groups. All binary relationships were found significant at 95% confidence level except for two: Silver and Gold ranks didn't show statistical difference (p-val=0.39) and neither do Platinum and Diamond (p-val=.28). Therefore, three groups could be formed in ascending number of played games. Bronze players are, according to the "ladder", the less skilled players but also the less experienced (or less senior) players. Silver and Gold players have both a similar number of games played in average, but they are significantly below the number of ranked games played by the most skilled players in the sample, Platinum and Diamond ones. It could be expected, therefore, that Silver and Gold ranked players show similar PE in the later analysis (and the same for the other pair, Platinum and

SURVEY	NUMBER	CLUSTERING	NUMBER
Full Team	40	C1	65
3-4 group	159	C2	125
Duo	163	C3	129
Solo	77	C4	120

Table 5.7: Play preference among players and clustering

Diamond). In figure 5.10, the relationship between tier and total number of wins in ranked is depicted.

Players have, in average, a 50% win rate

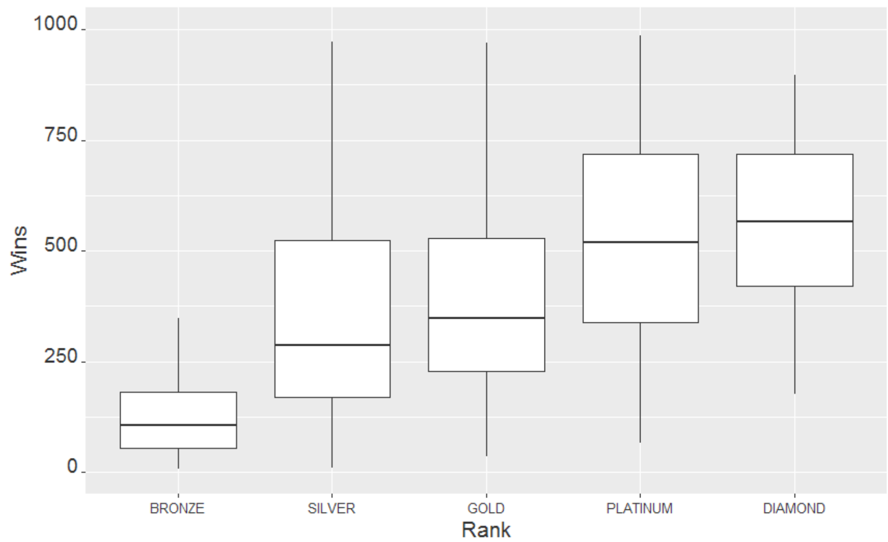

Figure 5.10: Rank Tier and Total Number of Ranked Wins

5.3.4 *Play preference*

As part of the survey, players were also asked for their play preferences. Although not directly comparable to the results of the clustering in section 5.1 (as the categories are slightly different), it is possible to use them for assessment.

In *League of Legends*, teams are composed by five human players each, but these five players can be joined in multiple different combinations. In our sample (Table 5.7), 18% of the players (N=77) claim they go “Solo”, which means that the player enters the queue alone and the matchmaking system finds the rest of the team to play with. As *League of Legends* has a strong social component, however, more often than not players enter the queue with friends: 37% of them go in “Duo” (N=163) while 36% (N=159) usually form pre-made teams of three or four people. Finally, 9% (N=40) answered that they usually join the queue with a full pre-made team (that’s a five player team, so no unknown players will join).

Compared to the previous results of the clustering, a similar distribution is found; however, the amount of players that underestimate the amount of games that they join alone is notable. This is probably due to the answer to the survey expressing a wish or a preference instead of the reality the players find in their everyday matches. Therefore, in order to be the most faithful possible to the actual conditions, PE will be assessed using the calculated clustering for every player instead of their answers.

5.3.5 *Communication*

Communication in team games such as *League of Legends* is crucial to success, but ranked amateur players mostly play from their homes, physically alone. How do players communicate with their friends or teammates, then?

Results can be found in table 5.8 and show how more than 70% of the players choose voice-based communication tools

METHOD	NUMBER
Skype	194
Teamspeak	119
Pings and text chat	53
Pings only	10
Other (unknown)	62

Table 5.8: Number of ranked matches played by players

(such as Skype or Teamspeak) as their preferred option. Only a few opt for the in-game pings as the main method of communication. What is interesting about this data is to notice how players prefer voice-based options while the game, *League of Legends*, doesn't provide an integrated one - so players need to find and use external tools to communicate.

5.3.6 *Role*

When joining a *League of Legends* match, each player takes a role in the team. Current matchmaking system actually lets players express their preferences and assigns them to a role, which also has an effect on the range of avatar characters (known as Champions in the game) that the player will choose, as some are better suited for a role than others depending on the metagame at the time (Donaldson, 2015). Role definitions have evolved from season to season, but stabilized at five main roles (see Figure 5.11). Three players control the lanes (Top, Mid and Bottom) while Support provides utility to the team (spending most of the game paired with Bottom) and Jungle makes use of the resources in-between lanes. Players can also choose to "Fill", which means that they will take any free role. Role distribution in the sample can be found in Table 5.9.

Figure 5.11: Champion select screen, with team roles illustrated at the centre

Roles are rather uniformly distributed in the sample. One could think about comparing them to the API results, but that wouldn't be the best option, as players express two options when joining the game (and they are not even guaranteed receiving one of them), so the preference expressed by the player (as is) will be the variable used for this study.

5.3.7 *Champion selection*

The weekly rotation is a set of 10 champions that are free to play or try during a week

Although *League of Legends* is a free-to-play game, champions outside the free weekly rotation need to be purchased, either in Riot Points (real currency) or Influence Points (slowly earned in-game currency). Therefore, players need to think carefully about their purchases. They can have:

ROLE	NUMBER	PERCENTAGE
Top	64	15%
Mid	81	18%
Bot	97	22%
Support	98	22%
Jungle	66	15%
Fill	33	8%

Table 5.9: Role distribution in sample

OPTION	NUMBER
1 (All)	186
2 (Liked)	54
3 (Preferred role)	53
4 (Two roles)	73
5 (Balanced)	72

Table 5.10: Champion selection owned by players

1. As many champions as possible, with no special criteria.
2. The champions they like best.
3. The champions that are best suited to their preferred playing role.
4. The champions that adapt to their two preferred role choices.
5. Or a balance: a few champions that cover all possible roles.

Table 5.10 shows how most players either try to accumulate as many champions as possible or try to, at least, achieve a balance that allows them to play comfortably in two or more roles. This makes sense, as no player has a guaranteed starting role when joining a ranked *League of Legends* game, so players need to have at least two choices available.

5.3.8 *Adaptation*

One of the most particular aspects of *League of Legends* is how things change every two weeks. Riot Games, the developer, releases regular patches that change how the game is played. These changes can range from minor adjustments to, for example, champion characteristics, to huge changes such as new champions or reworks of existing champions. Therefore, players need to adapt every two weeks to changing conditions. How do they adapt? Players were asked about what do they do when their main champion is changed in a patch and had the following options available:

1. I seldom read the patch announcements or changes.
2. I usually read the announcement and adapt my build to the changes.
3. I usually read the announcement but I keep playing the same.
4. I use another champion because I don't like changes to mine.

As shown in table 5.11, most players read the announcements regularly and at least try to adapt to the changes.

OPTION	NUMBER
1 (Don't read)	28
2 (Adapt)	349
3 (Read but don't adapt)	44
4 (Change champion)	17

Table 5.11: Player adaptation to changes

OPTION	NUMBER
Never	80
Once a month	317
Once a week	37
Many times a week	4

Table 5.12: Purchase frequency

5.3.9 *In-game purchases*

As said previously, players can avoid any kind of monetary expense in *League of Legends*; often, however, players prefer some champions over others and want to add them to their account or express aesthetic and customization preferences buying and using custom "skins" for their champions.

A skin is an alteration of the aspect of the champion with no game effect other than eye-candy

How often do players purchase from the game? According to the obtained player sample, the vast majority (82%) purchase something at least once a month. Still, a relevant number of players opt for playing LoL at no cost (Table 5.12).

It is also relevant to note how much do players spend in every purchase (Table 5.13). Half of them (46%) claim to spend

OPTION	NUMBER
Nothing	71
Less than 5€	40
Between 5€ and 10€	202
More than 10€	125

Table 5.13: Player expense per purchase

between 5€ and 10€ per purchase; it actually makes sense, as the cost of a single champion or skin is, in average, slightly over 5€ but below 10€. Players who spend over 10€ might purchase both a champion and a complimentary skin at the same time, while players spending less than 5€ are probably taking advantage of the weekly sales and offers that lower the costs of four different champions and four different skins every week.

5.3.10 *Viewership*

According to the latest Newzoo's survey (Pannekeet, 2017) (see Figure 5.12), up to 55% of the total *League of Legends* users are also (or exclusively) viewers of the game. According to Newzoo, 45% of the people that interact with *League of Legends* does only play, while a 29% plays and spectates (watching other players online or professional tournaments). Most surprising is, however, the remaining 26%, which is formed by people who only watches the game and don't play at all. In other words (and numbers), the 39% of the total player base is also part of the audience, while a 53% of the audience is also playing the game. Thus, a 47% of the *League of Legends* does not actually play. To add a measure of time, 8,5% of the players spend 15 hours or more, weekly, spectating matches.

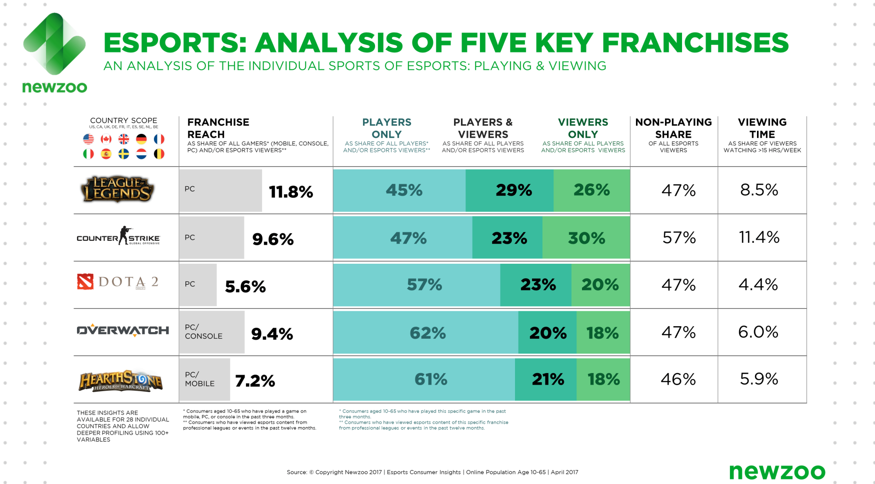

Figure 5.12: Analysis of five key franchises. Source: Newzoo (Pannekeet, 2017)

Among the players in the sample, up to 88% claimed to be a regular watcher of the EU LCS (official European League Series) or the LVP, while 69% mentioned using YouTube to watch *League of Legends* related content. These included not only matches, but also guides and entertainment (Mora-Cantallops, 2017). Comparing to Newzoo's figures, these are much higher; it must be taken into account, however, that the player sample was extracted from the LVP database and, therefore, players are more prone to be knowledgeable about the tournaments.

5.4 PLAYER EXPERIENCE

After reviewing the survey results, all the relevant variables will be used to study PE using both the PENS and the SPGQ as response variables.

5.4.1 *Reliability*

Before starting, an internal reliability check was conducted for the survey. Cronbach's alpha resulted in .68. According to Kline (1993), values over .7 indicate good reliability, so .68 can be deemed as acceptable. Cronbach's alpha wouldn't improve significantly if any variable would be dropped. Significant positive correlations between all 5 subscales of the PENS were found but most were relatively small ($r \leq .35$). Only Competence-Controls ($r = .4$) and Autonomy-Presence ($r = .64$) showed higher correlation.

5.4.2 *Dimensions*

Although PENS and SPGQ dimensions have been previously explained, a brief reminder is written again for convenience.

The PENS model includes the following five dimensions: autonomy, competence, relatedness, presence and intuitive controls.

- In-game *autonomy* relates at how free players feel to make choices within the game.
- In-game *competence* denotes whether game challenges and player competence is balanced.
- In-game *relatedness* is concerned about the degree of connection between the player and the other players.
- *Presence* relates to physical, emotional and narrative presence in the game.

- Intuitive *controls* is connected with the ease of control when playing.

SPGQ is composed of three subscales, two dealing with psychological involvement and one with behaviour:

- *Empathy*, measuring positive feelings towards co-players.
- *Negative Feelings*, measuring negative feelings towards co-players.
- *Behavioural Engagement*, measuring the degree to which players feel their actions to be dependent on their co-players actions.

5.4.3 *PE and skill level*

First, all five PENS dimensions are compared as a function of the player's rank (Figure 5.13). In this case, as there were more than two groups to compare, the Kruskal-Wallis test was used. A Dunn's test (corrected using the Holm-Bonferroni method) was executed afterwards to follow up all multivariate effects where significant differences were found. For Dunn's test results, only significant p-values are listed (Table 5.14).

Results highlight how only Competence and Presence show statistical differences, although in the case of the latter, Dunn's test differences are only marginally significant at a 95% confidence level, so they will not be assumed as relevant.

Statistically, different levels of Competence define two groups: the masses (Bronze, Silver and Gold), theoretically composed by 90% of the players, and the elites (Platinum and Diamond),

DIMENSION	χ^2	P-VALUE
Competence	38.272	$\ll 0.001$
Autonomy	3.7986	0.434
Relatedness	2.9997	0.558
Presence	12.726	0.013
Controls	2.3261	0.676
MORE > LESS	Z	ADJ P-VALUE
COMPETENCE		
Platinum > Bronze	3.489	0.003
Platinum > Silver	3.532	0.003
Platinum > Gold	2.894	0.019
Diamond > Bronze	4.816	$\ll 0.001$
Diamond > Silver	4.916	$\ll 0.001$
Diamond > Gold	4.409	$\ll 0.001$
PRESENCE		
Silver > Diamond	2.8134	0.049
Silver > Gold	2.7774	0.049

Table 5.14: PENS results for rank

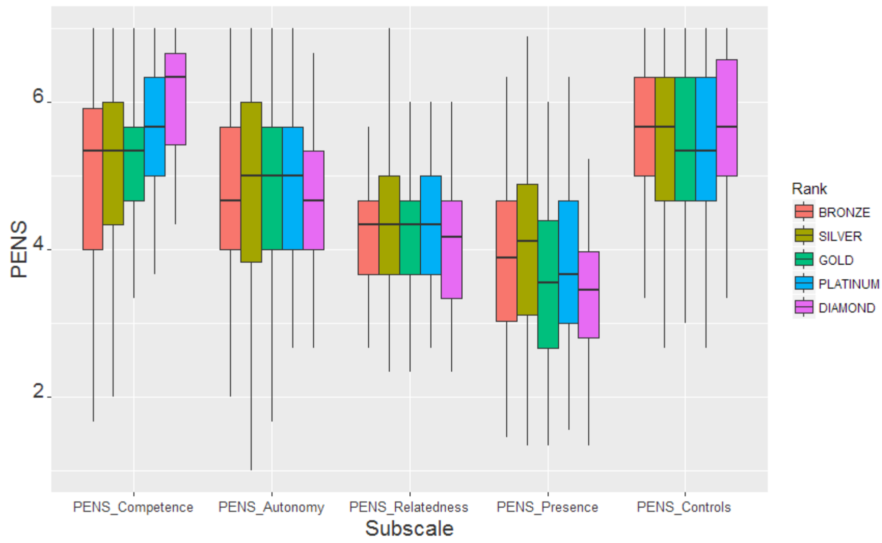

Figure 5.13: PE in League of Legends per Rank tier

formed by the top 10% players. As it would be expected, players in the top divisions (Platinum or Diamond) feel more competent (or good at the game, as validated by their placement) and therefore perceive the game as more balanced (or, in other words, "fairer" to them).

On the other side, Bronze, Silver and Gold players are stuck with the vast majority (approx. 90%) of the population. While is possible that many players acknowledge their lower level of skill (compared to their higher ranked counterparts), others might simply blame *League of Legends'* balance for their placement, as most players in the sample tended to overestimate their perceived skill, leading to lower scores in their answers to in-game competence related questions.

SPGQ results (Table 5.15), on the other hand, show how feelings towards other players, both positive and negative, are similar at all ranks. Although the Kruskal-Wallis test delivered a significant p-value for Empathy (.037) in the first place, no multivariate effect was found once adjusted using the Holm-

DIMENSION	χ^2	P-VALUE
Empathy	10.219	0.0369
Neg. Feelings	4.1303	0.3887
Behavioural Eng.	2.9605	0.5645

Table 5.15: SPGQ results for rank

Bonferroni method. Behavioural engagement didn't show any significant difference either.

5.4.4 *Team formation effect in PE*

After obtaining the clusters in section 5.1, they will be used to further assess whether the structural differences found in the player-centric networks have an effect in PE.

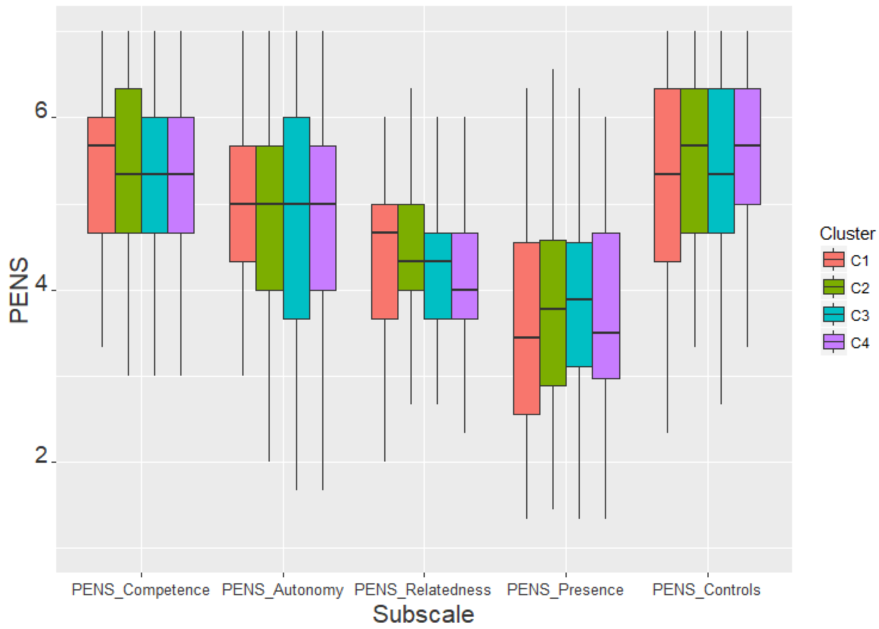

Figure 5.14: PE in League of Legends per Rank tier

Team formation didn't show statistical relevance in any of the PENS measures at 95% confidence level except for one: relatedness (see Figure 5.14). Once the Dunn's test (corrected using the Holm-Bonferroni method) is executed (Table 5.16), it is found that players in clusters C1 and C2 experiment a higher feeling of relatedness; this means that they feel more connected to other players. It makes sense, thus, to see this effect as significant in team or group players (C1, C2) versus solo players (C4). Previous studies show how social interactions (and friends and particular) are relevant to MOBA games. For Tyack et al. (2016) "people most frequently begin to play MOBAs as a shared activity with friends" while "the strong social motivation for beginning play stands in sharp relief to its absence among the most popular reasons for churning." Another finding from the same study showed how MOBA players either don't expect or don't want strangers to display social characteristics, as game system indirectly discourages long-term group formation, in contrast to MMORPGs' required collaboration to achieve higher challenges.

This finding is consistent with the SPGQ results (Table 5.17), as players in all clusters show the same level of positive and negative feelings towards teammates. It's like it doesn't matter; playing with strangers or with friends, social feelings might be similar. In spite of this, Tyack et al. (2016) found that team formation impacted player mood, with players experiencing "significantly improved mood when playing with friends, as opposed to strangers". This wasn't the case in the current study.

DIMENSION	χ^2	P-VALUE
Competence	0.92908	0.8184
Autonomy	0.44055	0.9317
Relatedness	11.495	0.009
Presence	2.2716	0.518
Controls	1.4261	0.6994
MORE > LESS	Z	ADJ P-VALUE
RELATEDNESS		
C1 > C4	2.590	0.047
C2 > C4	2.853	0.026

Table 5.16: PENS results by cluster

DIMENSION	χ^2	P-VALUE
Empathy	5.3826	0.1458
Neg. Feelings	2.9212	0.4039
Behavioural Eng.	1.2567	0.7395

Table 5.17: SPGQ results by cluster

5.4.5 *Roles in PE*

Results for Role are shown in Table 5.18, with Dunn's test results corrected using the Holm-Bonferroni method. Results show how although PE might differ across roles, it would only do it so slightly and mainly points to Mid as a particular case that deserves further exploration.

The extra feeling of autonomy expressed by the Mid laners could be explained for their central position in the map, leading to more courses of action available for Mid players, while other roles such as Jungle spend their time going over their optimal routes in the Jungle (leaving little space to exploration). Furthermore, in the case of professional teams, good Mid players are usually considered as "mechanically gifted" (meaning their level of competence with the controls is extraordinary as they need to react in fractions of a second) but the sample didn't include professional players and, therefore, it is not possible to relate mechanically gifted players to Mid.

SPGQ results displayed no statistically significant differences in neither empathy, nor negative feelings, nor behavioural engagement, with p-values over 0.65. Players' social presence seems to be, therefore, unaffected by the role played within the team.

5.4.6 *Economy and PE*

It's indeed interesting to note how players perceived Autonomy and Presence (Table 5.20 and Figure 5.15) are impacted by their purchasing power within the game.

DIMENSION	χ^2	P-VALUE
Competence	4.1686	0.53
Autonomy	13.977	0.016
Relatedness	3.5658	0.6135
Presence	10.969	0.052
Controls	12.428	0.0294
MORE > LESS	Z	ADJ P-VALUE
AUTONOMY		
Mid > Jungle	3.143	0.025
Mid > Bot	2.853	0.044

Table 5.18: PENS results by role

DIMENSION	χ^2	P-VALUE
Empathy	3.3093	0.6524
Neg. Feelings	1.3715	0.9274
Behavioural Eng.	2.1476	0.8284

Table 5.19: SPGQ results by role

DIMENSION	χ^2	P-VALUE
Competence	1.8778	0.5981
Autonomy	16.404	$\ll 0.001$
Relatedness	0.51673	0.915
Presence	28.102	$\ll 0.001$
Controls	5.7783	0.123
MORE > LESS	Z	ADJ P-VALUE
AUTONOMY		
+10€ > 0€	3.143	0.025
+10€ > 5-10€	2.853	0.044
PRESENCE		
+10€ > 0€	5.064	$\ll 0.001$
5-10€ > 0€	4.277	$\ll 0.001$

Table 5.20: PENS results by expense

DIMENSION	χ^2	P-VALUE
Empathy	4.3619	0.2249
Neg. Feelings	1.2729	0.7356
Behavioural Eng.	1.5005	0.6822

Table 5.21: SPGQ results by expense

Players who spend more money in Champions and skins for the game (which is actually outside where the action happens) feel freer to make decisions and choices in the game, while also feeling more immersed, more emotionally "in the game". It looks as if Autonomy and Presence in *League of Legends* were somehow related not only to the freedom of choice but also to the affordability of such choices.

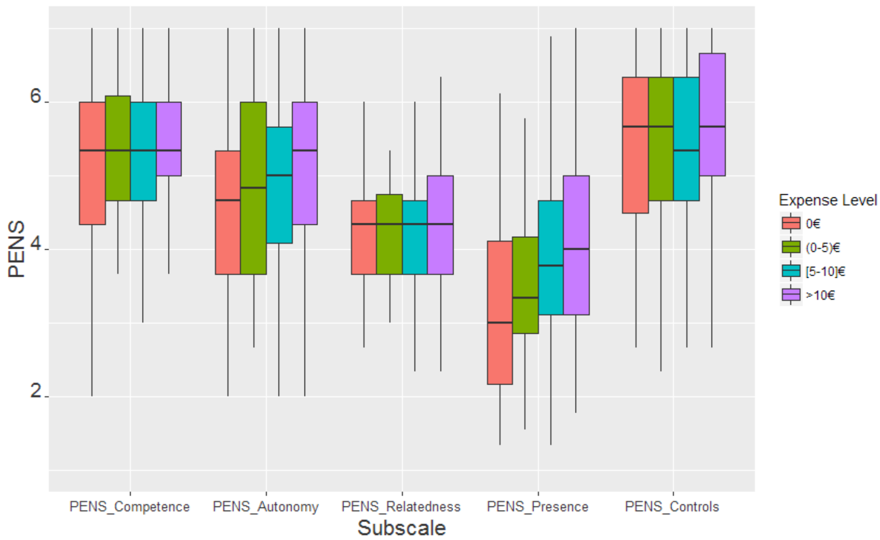

Figure 5.15: PE in League of Legends per expense level

SPGQ, on the other hand, shows no differences in feelings across expense levels at all.

5.4.7 *Gendered Play Experience*

Ratan et al. (2015) conducted a survey during the early days of *League of Legends* (in 2010) and reached many relevant conclusions regarding gender disparity in the game, the most relevant of which was that “females are not as confident in their gameplay ability as males”. In comparison, Ratan and colleagues had 4.1% players reported as female in their sample, relatively close to the 6.2% found in the current study. In a recent report, Yee (2017) found a figure of 14% for the number of female players in *League of Legends*, although his study considers the full population of players and not only ranked.

Ratan et al. (2015) also supported, among others, three hypothesis that are going to be tested before proceeding. First, that male players played more games in average than female players (R.H1 in their study). Second, that average skill was higher in males than females (R.H2a in their study). And third, that female players played Support roles in a large proportion than males (R.H5a).

According to the player sample, male players (Mean = 464.75, SD = 366.38) and female players (Mean = 409.44, SD = 343.12) doesn’t differ statistically in number of ranked games played (the Mann-Whitney U test results in a p-value=.496) so R.H1 doesn’t hold true. A similar result is found for R.H2a; when a Pearson’s Chi-squared test is run to assess whether skill (Rank) is higher in males than females, the found p-value is .204, so we can’t reject the null hypothesis that rank and gender are independent. Last but not least, when checking whether role proportions and gender are related, a significant p-value ($\ll$ 0.001) is obtained as a result of the Pearson’s Chi-squared test.

	RANK				
GENDER	BRONZE	SILVER	GOLD	PLAT.	DIAM.
Male	60	114	116	80	41
Female	2	13	7	4	1

Table 5.22: Gender-Rank frequency table

	RANK				
GENDER	TOP	JUN.	MID	BOT	SUP.	FILL
Male	64	66	79	89	81	32
Female	0	0	2	8	16	1

Table 5.23: Gender-Role frequency table

Once corrected pairwise tests are ran, significant differences are found in Support-Top (p-val=.019) and in Support-Jungle (p-val=.021). Therefore, R.H5a still holds true as females play Support roles disproportionally more than males do. Tables 5.22 and 5.23 contain the resulting frequency tables for rank and role.

After these preliminary checks, knowing that in the sample the number of games played and the skill level is comparable among genders, PE in function of gender is analysed. As only two groups need to be compared in this case (Male versus Female) a series of Mann-Whitney U tests are executed, one for each PENS dimension. Table 5.25 shows the results and p-values per dimension, while the corresponding boxplot is drawn in Figure 5.16.

DIMENSION	W	DIRECTION	P-VALUE
Competence	4175.5	Male > Female	0.030
Autonomy	4370.5	Not significant	0.064
Relatedness	6420.5	Not significant	0.168
Presence	5221	Not significant	0.608
Controls	4448.5	Not significant	0.083

Table 5.24: Mann-Whitney U test on PENS dimensions depending on gender

DIMENSION	W	DIRECTION	P-VALUE
Empathy	6261	Not significant	0.263
Neg. Feelings	4599.5	Not significant	0.1359
Behavioural Eng.	5273	Not significant	0.6655

Table 5.25: Mann-Whitney U test on SPGQ dimensions depending on gender

According to the obtained results, female players feel indeed less competent than their male counterparts. The same result was obtained in Ratan et al. (2015). This feeling of lower competence happens even when their ranks and in-game experience is similar. No significant differences are obtained in the SPGQ tests.

This being said, however, and given the disparity in roles, an additional test was conducted. The 16 female support players were compared to the 81 male support players using Mann-Whitney U tests and, interestingly enough, differences disappeared. Not only PENS competence became statistically non-significant (p-value=.265) but the rest of the PENS dimensions also stayed non-significant at 95% confidence level. This basically means that there are no differences in competence feelings between groups when controlling by role.

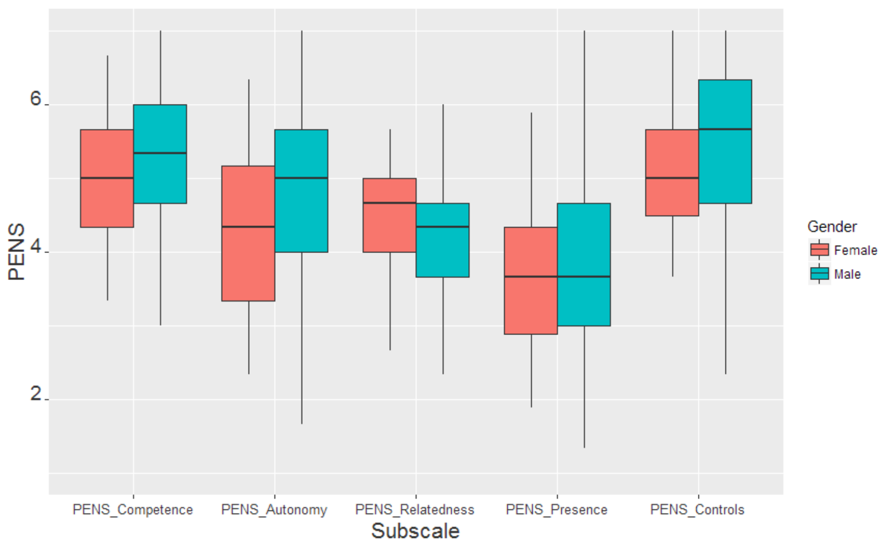

Figure 5.16: PE in League of Legends by gender

6

DISCUSSION

The final objective of the present work was to explore PE in *League of Legends* as a function of its players' attributes. To do so, however, it was needed to pass through a few steps in form of partial objectives.

6.1 PARTIAL OBJECTIVES

6.1.1 *Literature review*

As part of the background review for MOBA games, the main lines of research were identified.

On modelling and prediction "current work has only begun to tap into the rich and varied behavioural data available from MOBAs" (Drachen et al., 2015). However, tactical and strategy analysis has been almost exclusively been data-based, without including a qualitative complement from players that could help understand the variables that predict most of the variance related to success in matches. Some of the identified gaps in this subject would be:

- Tactical gameplay analysis using encounter detection: team fights are, most probably, the most decisive encounters in a MOBA match. A deeper understanding of how these encounters should be managed optimally would be required, together with validation using insights from professional players.

- Tactical behaviour changes and shifts in professional teams and their impact in the rest of players: metagame shifts happen over time in MOBA games that change the champions that are played and the strategies and tactics that are used. What's the impact of a champion selection in a professional competition that is seen by millions of players (e.g. in the LCS - League of Legends Championship Series) and how does this propagate into the thousands of matches played every day?

- Mining eSport's tracks is opening interest in further application of these tools for analysing real time sport (Rioult et al., 2014). APIs ease the process of getting quantitative and empirical results from data extracted from servers. This information can be used to predict the outcome of a match or improve a team performance. If that's so, why couldn't it be an open door to reapply it to real sports? And the other way round? Traditional sport could benefit from what is learned in virtual venues in an unprecedented way in history, especially in terms of collaboration and competition in team-based sports. A MOBA match can be imagined as a basketball match with a variation of the rules that puts three balls (lanes) in the field, where each player takes his or her role while playing together to win the game. Team formation and team success should be linked closely with modelling and prediction to have a global picture that brings a better understanding.

MOBA research should also get closer to the players in order to understand their experience playing MOBA games and what's the impact on well-being. It is suggested that measures related to competition, teamwork and sense of mastery (Johnson & Wyeth, 2015), not so present across most of the genres, should be incorporated and further investigated in studies on player experience in MOBA games. It is in this line where the need to include the MOBA industry is identified: matchmaking, player churn and toxic behaviour cannot be accurately researched without involving all parties and sharing their findings. For example, *League of Legends* developer, Riot Games, has a large Game User Research group that focuses on their own game. Their research, however, is undisclosed and is rarely disclosed to the general public as it's considered strategic and, therefore, confidential. And while matchmaking and player churn are relevant topics for the industry, mainly related to player retention, both could be left in a second plane when toxic behaviour is present. Toxic players affect negatively on the development of online communities and represent a social problem that could even lead to the undesired cyberbullying or gender and cultural discrimination. Designers should take an active role in teaching and encouraging positive community norms, especially when interacting with newer players and researchers could help by defining and testing what these norms should be in order to be effective. Furthermore, a deeper understanding of the factors that can be used to identify toxic players is needed as variables in (Shores et al., 2014) were not experimentally manipulated and this causal inferences are limited.

Beyond gaming, toxic behaviour studies have great potential because teams are an essential building block of modern organizations. Also, in the current globally distributed workspace, collaboration through an electronic channel is pervasive. This often results in a goal-oriented group that lacks social connections. Such settings can accelerate the tendency to blame others, further escalated by the individuals' unfamiliarity with remote partners (Cramton, 2001). Competitive games in general, and the (disappeared) LoL Tribunal in particular, are thus a valuable asset to capture group conflicts in the virtual space and test effective treatments for them. Solutions for toxic play in team competition online games could have huge impact for real-world scenarios, and not just virtual spaces (Kwak et al., 2015).

The field of social-networks research applied to networked games is rich and could lead to important improvements in gameplay, with direct repercussions to networked-resource consumption and quality-of-experience (Iosup et al., 2014). This same study identifies the need to complement this work with other theories, mainly social and psychological.

Two very promising research lines for MOBA games appear close to the border between the virtual and the real world, as these are topics omnipresent in forums and wikis related to the genre, and so of utmost relevancy to their users and players:

- Understanding the metagame: the world formed around MOBA games is way bigger than the games themselves. Of special interest is to look at the effects of unconventional forms of play.

- Temporary teams: more research needs to be done to uncover player experience of playing with strangers and dynamics within temporary teams. For example, to what extent do players enjoy playing with strangers? How much does the temporary team setting contribute to LoL's enormous popularity? Since being successful in LoL requires not only competent in-game skill but also necessary social skills, how do players learn these skills? How do Riot Games' efforts, such as the Tribunal and the Honor systems, affect players' in-game interaction? (Kou & Gui, 2014).

Related to this last point, learning seems to be an under-explored topic as no research has been found that works on the subject. The main question would be to understand what the learning path of a player is. This could bring valuable insights for other topics outside of the game, e.g. on personal development or learning style of the subject player.

- Learning: what does a player learn when levelling up? What does an experienced player that is different than a low level or new entry player? How does the community shape the player? What factors distinguish a professional player from an amateur one? What's the style of the learning curve?

- Teaching: YouTube and its tutorial videos are seen by millions of players to help on their builds and game improvement. Do "youtubers" (internet celebrities who are popular because of their videos) act as teachers? What is their impact on players and on the metagame?

Gender, violence and cultural studies on MOBA games also have a long way to go. In some cases they should also be linked closely with toxic behaviour – as one could relate to the other -, but a deeper understanding of the MOBA player is also needed. Why is competition largely and disproportionally male dominated? This was examined in Ratan et al. (2015) but additional research targeting female players needs to be carried out, as two interviews and a survey with only 4,1% female participation might fall short as a sample.

Since research within immature disciplines tends to be more exploratory in nature than research in mature fields (which focus more on testing hypothesis, methods or tools), most of the studies found recognize this nature by themselves and agree in the early stages of MOBA game research.

6.1.2 *Player sample*

After emailing 20.000 users in the LVP database, five hundred and forty-seven responses were received, although only 439 were complete. All 439 players were ranked players (so, they were experienced) and this also allowed for data extraction from the API (as more casual games are not recorded).

The obtained information from the survey covered all aspects, from demographics to in-game behaviours, passing through the standard PENS and SPGQ questionnaires and fulfilled this partial objective. While this was enough information to explore PE in a later stage, additional demographics data would have been needed for stronger demographic-based analysis.

6.1.3 *Player information extraction*

Using the summoner unique names that players provided in the survey, their account ID, match list from Season 6 (year

2016) and complete match details were extracted. The extraction was thus composed of 439 players that played 228.117 matches over a year; the complete database size was over 40 GB, although only a small portion of the information was used for the purpose of this study.

APIs such as the one provided by Riot Games provide a convenient method for extracting information, although research depends on the information that the company decides to make publicly available and on the allowed rates of extraction.

6.1.4 *Systematic classification of player social behaviour*

Typologies are useful to compare networks systematically and player-centric networks become more and more relevant as online gaming grows. Although data in games such as League of Legends is recorded by game servers, demographic data is not available, so the proposed systematic classification limited its scope to the purely structural characteristics of the ego-networks formed by 439 players (439 egos and 673.766 alters) and all their matches (228.117) over a period of a season (all matches in 2016).

Using the player data extracted from the API, networks were built in Python using NetworkX. The resulting networks were then analysed and eight structural indicators were computed for each of them. In order to infer the underlying hidden structure, machine learning techniques were used, applying an affinity propagation algorithm. After a few iterations and removal of individual variables, the best clustering was achieved with three indicators.

The player-centric networks obtained in the current study were complex and heterogeneous, but their underlying structure can be described and typified using the following three features: modularity, number of components (standardized) and the proportion of nodes covered by the largest emerging component found in the network. Together, they establish four degrees or categories that describe how social the ego (or the player) is in his or her gaming habits.

6.1.5 *Player perception*

While preparing the indicators to assess PE in *League of Legends*, two main discrepancies in player perception versus reality were found.

First, regarding player rank. Most players claim to be better at the game (or of a higher rank) than they actually are. This is not uncommon in surveys, where many respondents try to "look better" for the record. The information available from the API, however, allows to compare their responses to the actual rank in the game, and, as seen in the results section, most players claim to be at least a level higher than they are. This can be seen as a grudge against the classification system, that lower ranked players might perceive as "unfair" and it is important to keep in mind, as this might also impact their PE.

Second, the systematic classification of player-centric network allowed to compare the expressed team play preferences to the real pattern of interaction. Most players would like to play with friends more often, as they claim their favourite team setup is often composed of at least a couple of friends, but this is not always possible. Therefore, although most of them claim to be group or team players, the truth is that happens much less often than they would like; thus, it is needed to consider the systematic classification to assess the PE, as it is closer to the reality these players find in their everyday matches, allowing for a more accurate PE analysis.

6.2 PLAYER EXPERIENCE IN LEAGUE OF LEGENDS

The main objective of this study was to assess PE in *League of Legends* and, to do so, the PENS and SPGQ questionnaires were assessed using all available variables as possible indicators.

Overall, differences in PENS were found in many of its dimensions. In order:

- Autonomy, which relates at how free players feel free to make choices within the game, shows two different influences. First, autonomy seems to change in function of the role developed within the team; it makes sense to think that some roles (as mid, in this case) feel more freedom to move across the map than some others that might be more delimited. On the other hand, economic power also shows an effect; autonomy is not only considering the choices within a match, but also within the game in general. Therefore, players seem to feel more autonomous when they can purchase any champion or any skin they want.

- Competence, which relates at how balanced the game is (so, how the player skill compares to the challenge) according to players, shows a clear line that separates lower ranked players (which are the vast majority) from the higher ones. This is, again, a result of the "ladder" system; lower ranked players, who feel unfairly ranked, are also frustrated because they feel trapped in the lower ranks, building a lower feeling of balance. This is not the only difference that showed at a competence level; it was also shown how female players experience a lower level of competence in the game, but this result becomes non-significant when controlling by role.

- Relatedness is concerned about the level of connection between the player and the other players in the game and, thus, the only observed effect occurs in the team play preference, where group or team players experience a higher level of relatedness than solo players.
- Presence, which relates to the physical, emotional and narrative presence in the game, is weakly related to rank (almost non-significant) but it is strongly related to the in-game expense instead. Players who are able to spend more money in the game (buying their favourite champions and customizations) feel more identified within the game. This is interesting as it shows how presence is not only related to the gameplay itself, but also to the choices and personalization available to the player.
- Intuitive controls, or the ease of control when playing, seems to be comparable at all levels, so no differences were found to discuss.

On the other hand, SPGQ found no statistically relevant differences in any dimension. Although this might seem less important, it is not. Two of the SPGQ subscales measure positive and negative feelings towards teammates; it is worth noting than in all ranks, in all levels of team play and in all genres these feelings are comparable. MOBA game players seem to express the exact same intensity of positive or negative feelings across all ranks but, what's more interesting, across all levels of "friend" interaction. It doesn't matter whether they play with friends; their social experience is similar to when playing with strangers.

Part III

CLOSING REMARKS

7

CONCLUSION

The conclusions will be presented at three levels: social playing typologies (or player-centric networks), conclusions regarding the results obtained in the survey and the final conclusions on player experience.

7.1 SOCIAL PLAYING TYPOLOGIES

The proposed presented typology provides an intuitive and systematic method to characterize the social behaviour of *League of Legends* players looking only at the structure of their player-centric network. Even though only the most popular online competitive game was assessed, this methodology could be generalized to any online competitive game that provides enough data to compute its player-centric networks.

The obtained information can then be used for player segmentation, both to improve player experience (by adapting the game to their structural social needs) and to improve the game (adapting its matchmaking system). Players that go “solo” are focused in the game; they need quick access to their matches so team formation or discussion might be less important for them, but they would expect to be paired against other “solo” or isolated players. On the other side, pure “team players” could need access to additional social features to empower their social relationships, to better means of communication (that are natively limited to text chat in *League of Legends*) and to fair matchmaking against other "team players" instead of spare groups of "solo" players or "cell players".

This typology, however, could be influenced by ego or alter attributes. Rank, for example, seems to have an influence on the structural characteristics of the resulting player-centric networks. Higher ranked players are more often "duo" or "solo" players, while "team players" are overrepresented in the lower categories. This suggests that other attributes that were not captured in this study (or were not available for extraction) could also present a relevant influence, so further research is required.

Implications of these findings also go beyond the scope of the game. For the industry it is not only relevant to dimension their players' egocentric networks but also to be able to find patterns that cluster them together. MOBA games such as *League of Legends* are always played against the developer's servers, so this profiling could then be used to improve service, clustering players that show either similar or complementary patterns together. Loyalty rewards could also be adapted according to player's behaviour. As of today, players receive rewards individually; this might be enough for solo players, but team players might be more satisfied if rewards were matched across the team (for example, with matching themed skins for their characters). Matchmaking could also see a social improvement: if a regular team player (so, a highly social player) joins the game alone for once, it might be more appropriate to match him or her with a four player team which misses one player than with four solo players, as his or her experience will then be similar to the one he or she is used to. This is the kind of socially-aware services that are needed as online gaming becomes more and more popular.

7.2 PLAYER SURVEY

League of Legends players are mainly young players, averaging 19 years, and the player base is disproportionally male dominated (94%).

Their rank distribution is, as expected, biased towards lower ranks. Bronze, silver and gold tiers are inhabited by more than 70% of the players in the sample, while the higher ranks (platinum and diamond) only have a 30%. It's also important to note how there are no master or challenger players in the final sample (one master player was removed as it was too small to form a statistical group). Although the number of higher ranked players is slightly over the "official" numbers from Riot (that are rarely made public and change over the year), it is also true that the sample is composed by ranked players in the LVP database; therefore, it is expected that these players have a higher interest in the game than the pure average player - so it's more likely to see higher ranked players in average.

Most players play quite a lot. While the mean sits at 460 games in season 6 per player, the median is not much lower, at 347 games. This means that most players play at least one game per day during a year; considering that most games last around one hour (taking everything into account), this indicates that players in the sample spend, in average, between one and two hours in the game every day. In spite of this, significant relevances were found across groups; bronze players play less games in average than silver or gold players and, in turn, these players play less than platinum or diamond players. Seniority (or number of games played) is, thus, an indicator related to rank.

While the vast majority of players express their preference for playing with at least one friend, the truth is they can do so less often than they would like to; comparing the survey responses to the clustering obtained from the player networks it can be seen how almost a third of the players have a "solo" experience even though they probably mention "duo" or "group" play as their preferred option. This is an important venue for improving PE, as many players who would like to join with friends are unable to do so.

Another surprising issue in *League of Legends* is to notice how a majority of the players need to use external tools for communicating via voice. Although this is their preferred option for talking when in a game, Riot is not offering any voice chat option within the game, which most surely affects PE.

Role distribution in *League of Legends* is quite uniform across all roles. A slightly higher number of players go bot or support, but this is again natural due to their "duo" composition nature. If players, as seen previously, like to play with at least one friend, the most direct way to do so is to play as a duo botlane (bot plus support). This shows in the role distribution, although they are only over the fair share (20%) by a mere 2% each.

Approximately a 42% of the players opt for accumulating as many champions as possible in their accounts; together with players opting to own at least champions to cover two roles, the figure goes up to 76%. This means that three of every four players try to have alternatives to play not only their favourite champions in their favourite roles but also other champions and roles. As no player is guaranteed a specific starting role when joining a game, this makes sense, but it is also relevant to notice how player choices are not only influenced by their preferences. Additionally, the vast majority of players claim to read and adapt to the changes introduced in the game by Riot every two weeks; this is also consistent with the idea of having multiple champions available, just in case the favourite one is heavily altered.

Regarding purchasing behaviour, 82% of players purchase something from the in-game store at least once a month, with purchases between 5€ and 10€ as the most frequent ones. It can be thus inferred that most players buy a champion and a customization for it (most probably, a skin) at least once a month.

Last but not least, many players (88%) are also viewers of the LVP or EU LCS tournaments, while a majority (69%) use YouTube channels to watch *League of Legends* related content, which means not only games but also playing guides or pure entertainment around the game.

7.3 PLAYER EXPERIENCE

Here, an attempt to provide a broader look at the results of each research question beyond the findings reported in the discussion is conducted.

Higher ranked players feel more confident on their competence level. As players climb the ladder they apparently become more confident than other players and assess their competence level as more appropriate to the challenges of the game than their lower ranked counterparts. Empathy and negative feelings toward other teammates seem to be, however, not related to their ranks or skill levels.

Therefore, players in *League of Legends* have a feeling of competence that is proportional to their in-game assigned level. Is this feeling of fairness what engages players? According to Smeddinck et al. (2016), getting the level of challenge to match the capabilities and needs of a player is a core element of good player experience. In the case of competitive FPS, differences in skill levels affect enjoyment: weaker players become frustrated and stronger players become less engaged (Vicencio-Moreira, Mandryk, & Gutwin, 2015), so balance is key. According to the obtained results, the *League of Legends* ranking system seems to balance perceived skill levels fairly accurately. Przybylski, Deci, Rigby, and Ryan (2014) linked perceived competence to "a behaviorally measured motivation to play a game". This was corroborated by Neys, Jansz, and Tan (2014) who found an additional insight: this was truer for "hardcore gamers" over less frequent gamers. It is possible, thus, that ranked players in *League of Legends* could be considered "hardcore gamers" with an accurate feeling of competence that drives their motivation to keep playing.

In this sample, team formation (as obtained from the previous clustering) show significant impact in one of the PENS dimensions for *League of Legends*: relatedness. It's worth noting that the sample is purely composed of ranked players, and competitive players tend to value play-focused attributes over social characteristics. Still, differences are found that show how team and group players (C1 and C2) feel more connected to their teammates than solo (C4) players. In contrast, Vella, Johnson, and Hides (2015) compared solitary and social modes of play over games in general and found significant differences in autonomy and presence, which were not present in our study, so MOBA games might display differences versus other genres. On the other hand, SPGQ shows no difference in negative feelings between playing with friends or strangers. This calls for additional research, as it might be expected to observe lower levels of negative feelings. Results show otherwise; why are negative feelings equally observed among friends as they are among total strangers? Is this common to all online competitive games or is it particularly relevant on team-based MOBA games? The exploration of negative emotions by Bopp, Mekler, and Opwis (2016) showed how "players did value their experience not in spite of negative emotions, but actually thanks to the game inspiring strong emotional reactions". Would it be possible for the strong negative feelings of frustration to actually have a positive effect on engagement? While the collected data is unable to answer these questions, further studies should aim to understand this apparent contradiction.

Different player roles, however, could bring different player experiences with them. The reason to check the impact of player roles was, initially, to understand whether Support players, for example, felt less autonomous as they are usually quite at the disposal of their team. Nevertheless, no such difference appeared in the current sample. Only two small significant effects were found and pointed at the Mid role, that might present some singularities, namely a higher feeling of autonomy. This feeling of autonomy could be explained for its central position in the map, leading to more courses of action available for Mid players, while other roles such as Jungle spend their time going over their optimal routes in the Jungle (leaving little space to exploration). Furthermore, in the case of professional teams, good Mid players are usually considered as "mechanically gifted" (meaning their level of competence with the controls is extraordinary as they need to react in fractions of a second) but our sample didn't include professional players and we are not able to relate mechanically gifted players to Mid, so this would be a long shot at best.

Players who spend more real money in *League of Legends* feel more freedom of choice and presence. Although the game is free-to-play and in-game purchases don't offer any direct benefit to the player (other than aesthetics), PE seems to differ among different levels of expense. Players whose level of expense is higher feel more autonomous and immerse in the game, as if their freedom of choice and emotional presence depended on whether they could afford their desired choices. One player can feel constrained, for example, in case he or she likes one particular Champion (or Skin) and he or she cannot afford it. The player would then be forced to play another Champion character (or the default Skin) and therefore feel less identified with it, less emotionally connected and less immerse in general.

It's also a relevant subject to understand gender disparity in *League of Legends*. And here, although in the sample both males and females played a similar number of games in similar ranks, female players feel less competent than their male counterparts. These observations build on findings by Ratan et al. (2015), adding an additional layer where, even at the same skill level, female players in *League of Legends* felt less prepared to confront the challenges presented by the game. In spite of this difference, it has also been noticed that the Support role is disproportionally chosen by females and that, when controlling for role, male and female players show no difference in PE in any dimension.

Overall, the present research looks deeper into the particular PE that players have in *League of Legends* as the most relevant example of a wider genre, MOBA games. Using the gathered player sample, extracted using the database from the biggest eSports organization in Spain (the LVP), it was possible to explore PE in this relatively new genre.

Player Experience has proven to be beneficial in improving the quality of interaction between players and game software, as it takes their emotions and perception into account, making it easier to influence its effects and thus providing a more pleasant experience to users. Knowledge about PE in *League of Legends* can not only be employed to improve LoL or MOBA games, but also to develop better and more engaging games while improving their quality.

8

LIMITATIONS AND FUTURE WORK

While results show the potential of retrieving game data to understand player-centric networks and to profile player social behaviour systematically in any online competitive game, additional work would be needed to assess whether the conclusions of the initial part of this study could be extrapolated to other online MOBA games or other genres. At least initially, one could extrapolate these results to other online competitive games, as long as configuration is similar (teams of five collaborating players facing five other players). The general idea is that, through the player-centric network described by his or her matches, a player can be classified as a more or less social player, which might need additional features in order to keep playing or to improve his or her experience. For example, it was noticed that in *League of Legends*, most social players are ranked low. This brings additional questions. Are teams formed by friends more frustrated than solo players? Are they more prone to abandon the game? This study does not have enough data to verify whether this happens, but at least it is something that the developer (or developers of future games) could take into account when designing their rank system. Would it make sense, for example, to have separate ranks or ladders by type of social player? Could rank depend on more than pure results (e.g. playing with honour, being a good teammate, helping others)? Players might have a better experience and feeling of fairness if ranking systems adapted to their preferences and, as a result, they might spend more time in the platform which could translate into additional purchases or loyalty.

Another limitation (due to the method used for extraction of data) is the unavailability of demographic or personal information about the players. Sensitive personal data cannot be obtained from the API so this study has been limited to purely structural network information. Future work should find a way to include individual attributes of the egos or alters (e.g. gender, age, nationality, studies, other games played, etc.) to fine-tune the proposed typology or to link the findings to "real-world" issues, such as the relationships among the player-centric networks and the players offline social circles.

There is also a technical limitation as of today; with 439 egos and 228.117 matches, almost 40GB of data was obtained (most of it, irrelevant for this study) and the process took approximately a week with a computer running 24/7. The total number of alters obtained from these networks is 674.000, over 1500 times the number of original egos. The data needed to extract and compute the number of matches of alters alone would therefore go over 61 Terabytes and take around 29 years to complete. It's likely that in the coming years new techniques and technical resources will be available, but as of today extracting additional data from the alters is not feasible.

As discussed, online games such as *League of Legends* represent an unprecedented chance and a unique opportunity to study complex social systems on an entirely different scale. The scale is so massive, however, that the study of hidden structures and systematic classification becomes critical for their understanding. If this study has been able to find a non-trivial structure related to the playing habits of each ego, further structures could be found, showing the potential of this method to get closer to a comprehensive understanding of the complex and unscaled social interactions happening online among players at every moment.

On the other hand, the PE results explored in the current work provide both confirmation of findings from previous studies and some insights into avenues for future research. Findings from the survey included a sufficient number of players to extract conclusions in the bronze to diamond ranks (basically amateur), but didn't have enough players to cover higher ranks (such as Master and Challenger, which are semi-professional to professional). Further research should also point directly to professional players playing (or working for) professional teams, players who play as work (getting paid for doing so) and whose PE could differ from that of those playing for enjoyment. On top of this, additional knowledge could be obtained interviewing a relevant sample of players to further understand these insights and to detect existing nuances on conclusions.

For the current study, the PENS questionnaire (combined with SPGQ insights) was chosen because it is a test that has already been widely used and validated in previous works. As seen, however, there are multiple other options available that could have been used and could have brought additional validation to the obtained results. Future work could also include developing or adapting these general tests to the particular case and opportunity that MOBA games represent, with explicit focus on the social component that they exhibit.

League of Legends, as many other online games, is regularly patched. Every two weeks, updates are rolled out, and while the core might be the same, gameplay is changed. How do players adapt to these changes and how is PE affected should be a question that should trigger interest to scientists and game designers alike. Studying how patching influences players and their behaviours could be influential not only to tune player experience to the desired engagement levels but also to minimize their impact as users frequently complain (which might lead to abandoning the game) when these changes happen.

Future studies should also look at the impact of economic transactions inside the game, as purchasing power emerged as a relevant factor in PE and this might not only apply to MOBA games but also to a wider range of free-to-play games or games with in-game transactions such as smartphone games or social network games.

Finally, gender studies on games which player base is disproportionally male still have a long way to go; finding a relevant enough sample of female players that can be compared to their male counterparts requires a balancing effort that could easily derive in sampling bias. In any case, further research is still needed to find and tackle the barriers that female players find when entering or playing *League of Legends*.

Part IV

APPENDIX

A

SURVEY

The complete survey (in Spanish) that was distributed to the LVP players is attached starting on the following page.

Cuestionario de Experiencia de Jugador

Este cuestionario está orientado a jugadores habituales de deportes electrónicos con una distinción inicial, jugadores de League of Legends (LOL) y jugadores de cualquier otro juego. No hay restricción de qué juego usar como referencia. Su objetivo es obtener datos sobre la experiencia del jugador tanto en uno como en el otro entorno.

El tiempo aproximado que requiere contestar todas las preguntas es de unos 5-10 minutos para los jugadores de no-LOL y unos 15-20 para jugadores de LOL.

Cualquier dato es totalmente CONFIDENCIAL y no será usado sin consentimiento expreso.

Muchas gracias por tu tiempo. Allá vamos con las preguntas.

* Required

Antes de seguir...

Algunos datos sobre ti.

1. **¿Cuál es tu año de nacimiento? Escríbelo con cuatro cifras (por ejemplo: 1992)** *

____

2. **Género:** *

   Mark only one oval.

   ( ) Masculino

   ( ) Femenino

3. **Indica tu lugar (ciudad, país) de residencia habitual** *

____

Skip to question 98.

¿Juegas a League of Legends?

4. **¿Eres jugador de League of Legends?** *

   Mark only one oval.

   ( ) Si *Skip to question 6.*

   ( ) No *Skip to question 5.*

Si no es de LOL, entonces eres jugador de...

Selecciona el juego que practicas.

5. **¿Qué juego es?** *
Mark only one oval.

- ◯ Call of Duty *Skip to question 56.*
- ◯ FIFA *Skip to question 77.*
- ◯ Hearthstone *Skip to question 77.*
- ◯ Clash Royale *Skip to question 77.*

Skip to question 77.

Cuestionario para jugadores de League of Legends

¿Puedo hacerte unas preguntas sobre tu juego ?

6. **¿Cuánto hace que juegas a League of Legends? Índicalo brevemente con el tiempo que llevas jugando a él y en qué grado de implicación (por ejemplo, empecé hace dos años pero llevo un año jugando mucho más).** *

7. **¿Cuál es tu nombre de summoner, alias o nickname? Por favor, escríbelo exactamente igual que en tu cuenta, incluyendo mayúsculas, minúsculas, números y signos de puntuación.** *

NOTA IMPORTANTE

Sabemos que poner el nombre de invocador es algo muy personal, así que, ante todo, ten claro que ese dato se tratará con total confidencialidad, nunca será usado en relación individual y solo será utilizado de forma automática con el fin de obtener estadísticas generales en el sí de la presente investigación, ligada a la Universidad de Alcalá de Henares.

¿Cómo juego a League of Legends?

¿Juego en equipos premade? ¿Con qué me comunico?

8. **¿Cómo juegas habitualmente?** *
Mark only one oval.

- ◯ Solo
- ◯ Premade de dos personas
- ◯ Premade de tres o cuatro
- ◯ Equipo completo premade

9. **¿Cómo te comunicas, principalmente, con tus compañeros?** *
Mark only one oval.

- Usando los pings del juego
- Usando pings y el chat de texto integrado en el juego
- Hablamos por Skype
- Hablamos usando Teamspeak
- Other: ______

10. **¿Usas alguna herramienta de apoyo externo (como Overwolf), plugins o similares?** *
Mark only one oval.

- Si
- No

Experiencia en League of Legends

Por favor, reflexiona en tu experiencia de juego con League of Legends y expresa tu acuerdo con las siguientes afirmaciones desde el 1 (más en desacuerdo con la afirmación) hasta el 7 (completamente de acuerdo con la afirmación).

En caso que creas que una pregunta no aplica a League of Legends, por favor, indícalo con un 1.

11. **Cuando juego a League of Legends, me siento transportado a otro tiempo y lugar.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco transportado								Muy transportado

12. **Experimento mucha libertad cuando juego a League of Legends.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poca libertad								Mucha libertad

13. **Lo que me sucede en League of Legends no me afecta emocionalmente.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Me afecta mucho								No me afecta en absoluto

14. **Encuentro que las relación que tengo con otros jugadores en League of Legends son importantes.** *
Mark only one oval.

	1	2	3	4	5	6	7	
No son importantes								Son muy importantes

15. **Los controles de League of Legends son intuitivos.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco intuitivos	◯	◯	◯	◯	◯	◯	◯	Muy intuitivos

16. **Explorar en League of Legends es una experiencia parecida a viajar a un sitio nuevo.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco parecida	◯	◯	◯	◯	◯	◯	◯	Muy parecida

17. **Las relaciones que tengo con otros jugadores en League of Legends me parecen satisfactorias.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco satisfactorias	◯	◯	◯	◯	◯	◯	◯	Muy satisfactorias

18. **Me considero muy capaz y efectivo cuando juego a League of Legends.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco capaz y efectivo	◯	◯	◯	◯	◯	◯	◯	Muy capaz y efectivo

19. **Cuando alcanzo un logro en League of Legends siento verdadero orgullo.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco orgullo	◯	◯	◯	◯	◯	◯	◯	Mucho orgullo

20. **Cuando me muevo dentro de los mundos en League of Legends siento como si realmente estuviese allí.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Lo siento poco	◯	◯	◯	◯	◯	◯	◯	Lo siento mucho

21. **Aprender los controles de League of Legends se me hizo fácil.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Dificil	◯	◯	◯	◯	◯	◯	◯	Fácil

22. **Considero que soy competente jugando a League of Legends.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco competente	◯	◯	◯	◯	◯	◯	◯	Muy competente

23. **No me siento unido a otros jugadores en League of Legends.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco unido	◯	◯	◯	◯	◯	◯	◯	Muy unido

24. **Experimento sensaciones en League of Legends similares a otras que tengo en la vida real.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco similares	◯	◯	◯	◯	◯	◯	◯	Muy similares

25. **Tengo reacciones a eventos y personajes de League of Legends como si fuesen de la vida real.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco	◯	◯	◯	◯	◯	◯	◯	Mucho

26. **Cuando juego a League of Legends me siento como si fuese parte de la historia.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco	◯	◯	◯	◯	◯	◯	◯	Mucho

27. **Cuando quiero hacer algo en League of Legends, recordar los controles correspondientes es fácil.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Difícil	◯	◯	◯	◯	◯	◯	◯	Fácil

28. **League of Legends me permite hacer cosas interesantes.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Pocas	◯	◯	◯	◯	◯	◯	◯	Muchas

29. **Mi habilidad cuando juego a League of Legends se corresponde bien con los retos que el juego plantea.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Se corresponde poco	◯	◯	◯	◯	◯	◯	◯	Se corresponde mucho

30. **League of Legends me cautiva emocionalmente.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Me cautiva poco	◯	◯	◯	◯	◯	◯	◯	Me cautiva mucho

31. **League of Legends me ofrece elecciones y opciones interesantes.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Me ofrece pocas	◯	◯	◯	◯	◯	◯	◯	Me ofrece muchas

Rango y artículos en League of Legends

¿Qué nivel tengo? ¿Cuántos champions tengo?

32. **En League of Legends, creo que mi nivel de habilidad es equivalente a rango...** *
Mark only one oval.

- ◯ No juego ranked
- ◯ Bronze
- ◯ Silver
- ◯ Gold
- ◯ Platino
- ◯ Diamante
- ◯ Challenger

33. **Mi posición de juego favorita es...** *
Mark only one oval.

- ◯ Top
- ◯ Jungle
- ◯ Mid
- ◯ Bot - ADC
- ◯ Support
- ◯ No tengo preferencia alguna, relleno el hueco que quede

34. **Sobre los champions que tienes en tu cuenta... ***

Mark only one oval.

- ( ) Son los que más me gustan, sea cual sea su posición o rol
- ( ) En general, son champions adecuados a mi rol habitual en el juego
- ( ) En general, son champions adecuados para mis dos posiciones más habituales
- ( ) Tengo una variedad limitada de champions que cubren todas las posiciones posibles
- ( ) Tengo un número muy elevado de champions en mi cuenta, cercano a la totalidad de los disponibles

Juego en equipo en League of Legends

Cuando juegas en equipo, ¿cómo te sientes?

35. **Cuando el resto del equipo se siente feliz, yo también lo estoy. ***

Mark only one oval.

	1	2	3	4	5	
Nada	( )	( )	( )	( )	( )	Mucho

36. **Cuando yo estoy feliz, el resto del equipo también lo está. ***

Mark only one oval.

	1	2	3	4	5	
Nada	( )	( )	( )	( )	( )	Mucho

37. **Empatizo (me siento identificado) con los otros miembros de mi equipo. ***

Mark only one oval.

	1	2	3	4	5	
Nada	( )	( )	( )	( )	( )	Mucho

38. **Me siento conectado a los otros miembros de mi equipo. ***

Mark only one oval.

	1	2	3	4	5	
Nada	( )	( )	( )	( )	( )	Mucho

39. **Admiro al resto de miembros de mi equipo. ***

Mark only one oval.

	1	2	3	4	5	
Nada	( )	( )	( )	( )	( )	Mucho

40. **Lo paso bien y me gusta estar con mi equipo.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

41. **Comprendo a los otros miembros de mi equipo.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

42. **He tendido a ignorar a mis compañeros.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

43. **Me he sentido ignorado por mis compañeros.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

44. **He sentido ganas de vengarme.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

45. **He sentido placer por el fracaso de otro.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

46. **Me he sentido celoso de otro.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

47. **He envidiado a otro.** *
Mark only one oval.

	1	2	3	4	5	
Nada						Mucho

48. **Mis acciones dependen de las acciones de los otros.** *
Mark only one oval.

	1	2	3	4	5	
Nada						Mucho

49. **Las acciones de los otros dependen de las mías.** *
Mark only one oval.

	1	2	3	4	5	
Nada						Mucho

50. **Lo que hicieron los otros afectó a lo que hice yo.** *
Mark only one oval.

	1	2	3	4	5	
Nada						Mucho

51. **Lo que yo hice afectó a lo que hicieron los otros.** *
Mark only one oval.

	1	2	3	4	5	
Nada						Mucho

52. **Los otros estuvieron muy pendientes de mi.** *
Mark only one oval.

	1	2	3	4	5	
Nada						Mucho

53. **Estuve muy pendiente de lo que hacían los otros.** *
Mark only one oval.

	1	2	3	4	5	
Nada						Mucho

54. **Mis intenciones estaban claras al resto.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

55. **Tenía claras las intenciones del resto del equipo.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

Skip to question 113.

Juego en equipo en COD

Cuando juegas en equipo, ¿cómo te sientes?

56. **Cuando el resto del equipo se siente feliz, yo también lo estoy.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

57. **Cuando yo estoy feliz, el resto del equipo también lo está.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

58. **Empatizo (me siento identificado) con los otros miembros de mi equipo.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

59. **Me siento conectado a los otros miembros de mi equipo.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

60. **Admiro al resto de miembros de mi equipo.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

61. **Lo paso bien y me gusta estar con mi equipo.** *
Mark only one oval.

	1	2	3	4	5	
Nada	◯	◯	◯	◯	◯	Mucho

62. **Comprendo a los otros miembros de mi equipo.** *
Mark only one oval.

	1	2	3	4	5	
Nada	◯	◯	◯	◯	◯	Mucho

63. **He tendido a ignorar a mis compañeros.** *
Mark only one oval.

	1	2	3	4	5	
Nada	◯	◯	◯	◯	◯	Mucho

64. **Me he sentido ignorado por mis compañeros.** *
Mark only one oval.

	1	2	3	4	5	
Nada	◯	◯	◯	◯	◯	Mucho

65. **He sentido ganas de vengarme.** *
Mark only one oval.

	1	2	3	4	5	
Nada	◯	◯	◯	◯	◯	Mucho

66. **He sentido placer por el fracaso de otro.** *
Mark only one oval.

	1	2	3	4	5	
Nada	◯	◯	◯	◯	◯	Mucho

67. **Me he sentido celoso de otro.** *
Mark only one oval.

	1	2	3	4	5	
Nada	◯	◯	◯	◯	◯	Mucho

68. **He envidiado a otro.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

69. **Mis acciones dependen de las acciones de los otros.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

70. **Las acciones de los otros dependen de las mías.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

71. **Lo que hicieron los otros afectó a lo que hice yo.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

72. **Lo que yo hice afectó a lo que hicieron los otros.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

73. **Los otros estuvieron muy pendientes de mi.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

74. **Estuve muy pendiente de lo que hacían los otros.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

75. **Mis intenciones estaban claras al resto.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

76. **Tenía claras las intenciones del resto del equipo.** *
Mark only one oval.

	1	2	3	4	5	
Nada	⬭	⬭	⬭	⬭	⬭	Mucho

Experiencia de juego

Por favor, reflexiona en tu experiencia de juego con el juego que hayas elegido en el paso anterior y expresa tu acuerdo con las siguientes afirmaciones desde el 1 (más en desacuerdo con la afirmación) hasta el 7 (completamente de acuerdo con la afirmación).

En caso que creas que una pregunta no aplica a tu juego, por favor, indícalo con un 1.

77. **Cuando juego al juego, me siento transportado a otro tiempo y lugar.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco transportado	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Muy transportado

78. **Experimento mucha libertad cuando juego al juego.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poca libertad	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Mucha libertad

79. **Lo que me sucede en el juego no me afecta emocionalmente.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Me afecta mucho	⬭	⬭	⬭	⬭	⬭	⬭	⬭	No me afecta en absoluto

80. **Los controles del juego son intuitivos.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco intuitivos	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Muy intuitivos

81. **Explorar en el juego es una experiencia parecida a viajar a un sitio nuevo.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco parecida	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Muy parecida

82. **Encuentro que las relación que tengo con otros jugadores en el juego son importantes.** *
Mark only one oval.

	1	2	3	4	5	6	7	
No son importantes	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Son muy importantes

83. **Cuando me muevo dentro de los mundos en el juego siento como si realmente estuviese allí.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Lo siento poco	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Lo siento mucho

84. **Me considero muy capaz y efectivo cuando juego al juego.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco capaz y efectivo	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Muy capaz y efectivo

85. **Cuando alcanzo un logro en el juego siento verdadero orgullo.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco orgullo	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Mucho orgullo

86. **No me siento unido a otros jugadores en el juego.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco unido	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Muy unido

87. **Experimento sensaciones en el juego similares a otras que tengo en la vida real.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco similares	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Muy similares

88. **Considero que soy competente jugando al juego.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco competente	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Muy competente

89. **Tengo reacciones a eventos y personajes del juego como si fuesen de la vida real.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Mucho

90. **Aprender los controles del juego se me hizo fácil.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Dificil	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Fácil

91. **Cuando juego al juego me siento como si fuese parte de la historia.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Mucho

92. **Las relaciones que tengo con otros jugadores en el juego me parecen satisfactorias.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco satisfactorias	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Muy satisfactorias

93. **Cuando quiero hacer algo en el juego, recordar los controles correspondientes es fácil.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Difícil	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Fácil

94. **El juego me permite hacer cosas interesantes.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Pocas	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Muchas

95. **Mi habilidad cuando juego al juego se corresponde bien con los retos que el juego plantea.** *

Mark only one oval.

	1	2	3	4	5	6	7	
Se corresponde poco	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Se corresponde mucho

96. **El juego me cautiva emocionalmente.** *

Mark only one oval.

	1	2	3	4	5	6	7	
Me cautiva poco	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Me cautiva mucho

97. **El juego me ofrece elecciones y opciones interesantes.** *

Mark only one oval.

	1	2	3	4	5	6	7	
Me ofrece pocas	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Me ofrece muchas

Skip to question 127.

Interés en los videojuegos

¿Qué aspectos me atraen de los juegos que habitualmente juego? Piensa en general, no hace falta que te centres en un juego o género en particular, solo en tus gustos.

98. **Me gusta chatear con mis amigos mientras juego.** *

Mark only one oval.

	1	2	3	4	5	
Poco	⬭	⬭	⬭	⬭	⬭	Mucho

99. **Para mí es importante jugar con un grupo estrechamente unido.** *

Mark only one oval.

	1	2	3	4	5	
Poco	⬭	⬭	⬭	⬭	⬭	Mucho

100. **Juego para ganar.** *

Mark only one oval.

	1	2	3	4	5	
Poco	⬭	⬭	⬭	⬭	⬭	Mucho

101. **Me gusta dominar todos los elementos del juego.** *
Mark only one oval.

	1	2	3	4	5	
Poco						Mucho

102. **Me gusta explorar todas las opciones, probar qué es posible hacer.** *
Mark only one oval.

	1	2	3	4	5	
Poco						Mucho

103. **Que gane es una de las razones más importantes para mí para jugar.** *
Mark only one oval.

	1	2	3	4	5	
Poco						Mucho

104. **Para mí es importante ser el jugador más rápido y más habilidoso en el juego.** *
Mark only one oval.

	1	2	3	4	5	
Poco						Mucho

105. **Me gustan las historias en los juegos.** *
Mark only one oval.

	1	2	3	4	5	
Poco						Mucho

106. **Me gusta usar sistemas de chat de voz cuando juego.** *
Mark only one oval.

	1	2	3	4	5	
Poco						Mucho

107. **Los juegos me hacen más listo.** *
Mark only one oval.

	1	2	3	4	5	
Poco						Mucho

108. **Los videojuegos me permiten sentirme como otra persona o como si estuviese en otro sitio.** *
Mark only one oval.

	1	2	3	4	5	
Poco	◯	◯	◯	◯	◯	Mucho

109. **Me gusta hacer cosas en el juego que no puedo hacer en la vida real.** *
Mark only one oval.

	1	2	3	4	5	
Poco	◯	◯	◯	◯	◯	Mucho

110. **Me gusta entender cómo funciona el juego de arriba a abajo, completamente.** *
Mark only one oval.

	1	2	3	4	5	
Poco	◯	◯	◯	◯	◯	Mucho

111. **Me gusta sentirme parte de una historia.** *
Mark only one oval.

	1	2	3	4	5	
Poco	◯	◯	◯	◯	◯	Mucho

112. **Juego con el fin de mejorar mis habilidades intelectuales.** *
Mark only one oval.

	1	2	3	4	5	
Poco	◯	◯	◯	◯	◯	Mucho

Skip to question 4.

¿Cómo aprendo a jugar a League of Legends?

¿Dónde me informo? ¿Cómo practico?

113. **Supongamos que obtienes un Champion que todavía no has usado nunca. ¿Cómo decides qué build usar?** *
Mark only one oval.

- ◯ A través de canales de YouTube o YouTubers
- ◯ Busco en portales especializados o foros
- ◯ Pregunto a mis amigos
- ◯ Experimento por mí mismo
- ◯ Uso otras redes sociales que no son las anteriores
- ◯ Other: ____________________

114. **Si visitas canales de YouTube que se centren en League of Legends habitualmente, ¿podrías indicar brevemente cuáles recomendarías y por qué?**

115. **Si visitas portales especializados o foros sobre League of Legends habitualmente, ¿podrías indicar brevemente cuáles recomendarías y por qué?**

116. **Si te informas a través de otras redes sociales, ¿podrías decir cuáles y en qué cuentas? (Por ej., Facebook, Twitter, ...)**

117. **Esta semana aparece un nuevo Patch que cambia algunas características de tu main, tu personaje principal. ¿Qué haces?** *

Mark only one oval.

- Lees el anuncio del parche y adaptas tu build a las novedades
- Lees el anuncio, juegas como si nada hubiese cambiado (ya te adaptarás otro día, quizás)
- Usas otro champion porque no te gustan los cambios al tuyo
- Habitualmente ni lees los anuncios de los parches ni sus cambios

118. **¿Ves habitualmente competiciones oficiales de LOL? (Por ejemplo, la LCS o la LVP)** *

Mark only one oval.

- Sí
- No

Compras en el juego

¿Qué compro en el juego? ¿Cuánto invierto habitualmente?

119. **¿Cuántas veces compro algo en el juego?** *
Mark only one oval.

- Nunca
- Poco, una compra al mes o menos
- Una vez por semana o menos, pero más de una vez al mes
- Varias veces por semana
- A diario

120. **Cuando compro, ¿cuánto suelo gastar por compra?** *
Mark only one oval.

- Nada
- Menos de 5 euros
- Entre 5 y 10 euros
- Más de 10 euros

Por favor, indica tu grado de conformidad con las siguientes afirmaciones.

121. **Creo que las compras en el juego ayudan a ganar.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco								Mucho

122. **Creo que las compras en el juego son la única forma de ganar y subir de rango en el juego.** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco								Mucho

123. **Me siento mejor cuando dispongo de elementos personalizados (skins, por ejemplo).** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco								Mucho

124. **Los jugadores con skin personalizado son mejores jugadores (ganan más partidas).** *
Mark only one oval.

	1	2	3	4	5	6	7	
Poco								Mucho

125. **El juego me recompensa de forma suficiente y balanceada.** *

Mark only one oval.

	1	2	3	4	5	6	7	
Poco								Mucho

126. **Gasto demasiado dinero dentro del juego.** *

Mark only one oval.

	1	2	3	4	5	6	7	
Poco								Mucho

Una última pregunta...

127. **¿Algún comentario adicional, sea general o específico?**

128. **En caso que la investigación siguiese con una entrevista personal....** *

Mark only one oval.

- Me gustaría ser entrevistado.
- No me interesa. *Stop filling out this form.*

Datos de contacto

Por si procede la entrevista...

129. **¿Podrías dejarme tu correo electrónico?** *

130. **Teléfono móvil, si lo deseas (opcional). El modo de contacto primario será el correo electrónico.**

BIBLIOGRAPHY

Adamus, T. (2012). Playing computer games as electronic sport: In search of a theoretical framework for a new research field. In *Computer Games and New Media Cultures: A Handbook of Digital Games Studies* (pp. 477–490). doi:10.1007/978-94-007-2777-9_30

Ang, C. S., & Zaphiris, P. (2010). Social roles of players in mmorpg guilds: A social network analytic perspective. *Information Communication and Society*, *13*(4), 592–614. doi:10.1080/13691180903266952

Arthur, D., & Vassilvitskii, S. (2007). K-Means++: the Advantages of Careful Seeding. *Proceedings of the eighteenth annual ACM-SIAM symposium on Discrete algorithms*, *8*, 1027–1025. doi:10.1145/1283383.1283494

Bardzell, S., Bardzell, J., Pace, T., & Reed, K. (2008). Blissfully productive: grouping and cooperation in world of warcraft instance runs. In *Proceedings of the ACM 2008 conference on Computer supported cooperative work - CSCW '08* (p. 357). doi:10.1145/1460563.1460621

Batsford, T. E. (2014). Calculating Optimal Jungling Routes in DOTA2 Using Neural Networks and Genetic Algorithms. *Game Behaviour*, *1*(1).

Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, *2008*(10), 1–12. doi:10.1088/1742-5468/2008/10/P10008

Bonny, J. W., & Castaneda, L. M. (2016). Impact of the Arrangement of Game Information on Recall Performance of Multiplayer Online Battle Arena Players. *Applied Cognitive Psychology*, *30*(5), 664–671. doi:10.1002/acp.3234

Bonny, J. W., Castaneda, L. M., & Swanson, T. (2016). Using an International Gaming Tournament to Study Individual Differences in MOBA Expertise and Cognitive Skills. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems - CHI '16* (pp. 3473–3484). doi:10.1145/2858036.2858190

Bopp, J. A., Mekler, E. D., & Opwis, K. (2016). Negative Emotion, Positive Experience?: Emotionally Moving Moments in Digital Games. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems - CHI '16* (pp. 2996–3006). doi:10.1145/2858036.2858227

Brandes, U. (2008). On variants of shortest-path betweenness centrality and their generic computation. *Social Networks*, *30*(2), 136–145. doi:10.1016/j.socnet.2007.11.001

Brockmyer, J. H., Fox, C. M., Curtiss, K. A., McBroom, E., Burkhart, K. M., & Pidruzny, J. N. (2009). The development of the Game Engagement Questionnaire: A measure of engagement in video game-playing. *Journal of Experimental Social Psychology*, *45*(4), 624–634. doi:10.1016/J.JESP.2009.02.016

Brown, E., & Cairns, P. (2004). A grounded investigation of game immersion. In *Extended abstracts of the 2004 conference on Human factors and computing systems - CHI '04* (p. 1297). doi:10.1145/985921.986048

Brühlmann, F., & Schmid, G.-M. (2015). How to Measure the Game Experience?: Analysis of the Factor Structure of Two Questionnaires. In *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems - CHI EA '15* (pp. 1181–1186). doi:10.1145/2702613.2732831

Buchan, A., & Taylor, J. (2016). A Qualitative Exploration of Factors Affecting Group Cohesion and Team Play in Multiplayer Online Battle Arenas (MOBAs). *The Computer Games Journal*, *5*(1-2), 65–89. doi:10.1007/s40869-016-0017-0

Calvillo-Gámez, E. H., Cairns, P., & Cox, A. L. (2015). Assessing the Core Elements of the Gaming Experience. (pp. 37–62). doi:10.1007/978-3-319-15985-0_3

Carrillo Vera, J. A. (2015). La dimensión social de los videojuegos 'online': de las comunidades de jugadores a los 'e-sports'. *Index Comunicación*, *10*(1), 39–51.

Castronova, E. (2005). *Synthetic worlds: the business and culture of online games*. University of Chicago Press.

Castronova, E. (2006). On the research value of large games: Natural experiments in Norrath and Camelot. *Games and Culture*, *1*(2), 163–186. doi:10.1177/1555412006286686

Chen, H., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data To Big Impact. *Mis Quarterly*, *36*(4), 1165–1188. doi:10.1145/2463676.2463712

Chen, Z., Nguyen, T.-H. D., Xu, Y., Amato, C., Cooper, S., Sun, Y., ... Seif El, M. (2018). The Art of Drafting: A Team-Oriented Hero Recommendation System for Multiplayer Online Battle Arena Games. (9).

Chen, Z., Xu, Y. [Yuyu], Nguyen, T.-H. D., Sun, Y., & Seif El-Nasr, M. (2018). Modeling Game Avatar Synergy and Opposition through Embedding in Multiplayer Online Battle Arena Games.

Christou, G., Lai-Chong Law, E., Zaphiris, P., & Ang, C. S. (2013). Challenges of designing for sociability to enhance player experience in Massively Multi-player Online Role-playing Games. *Behaviour & Information Technology*, *32*(7), 724–734. doi:10.1080/0144929X.2012.754497

Clauset, A., Newman, M. E. J., & Moore, C. (2004). Finding community structure in very large networks. *Physical Review E*, *70*(6), 066111. doi:10.1103/PhysRevE.70.066111

Cramton, C. D. (2001). The Mutual Knowledge Problem and Its Consequences for Dispersed Collaboration. *Organization Science*. doi:10.1287/orsc.12.3.346.10098

Crossley, N., Bellotti, E., Edwards, G., Everett, M. G., Koskinen, J., & Tranmer, M. (2015). *Social network analysis for ego-nets*. SAGE Publications.

Daneels, R., van Rooij, T., Koeman, J., & Van Looy, J. (2017). "Should I Stay or Should I Go?" : Exploring the Determinants of Player Cessation in Moba Games.

de Kort, IJsselsteijn, W., tuenl Yvonne de Kort, tuenl Karolien Poels, Jurgelionis, A., & Bellotti, F. (2007). Characterising and measuring user experiences in digital games, 1–4.

Denisova, A., Nordin, A. I., & Cairns, P. (2016). The Convergence of Player Experience Questionnaires. In *Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play - CHI PLAY '16* (pp. 33–37). doi:10.1145/2967934.2968095

Do, V., Silva, N., & Chaimowicz, L. (2017). On the Development of Intelligent Agents for MOBA Games.

Donaldson, S. (2015). Mechanics and Metagame: Exploring Binary Expertise in League of Legends. *Games and Culture*, 1–19. doi:10.1177/1555412015590063

Dorogovtsev, S. N., & Mendes, J. F. F. (2003). Evolution of Networks: From Biological Nets to the Internet and WWW. *Oxford University Press*, *57*, 280. doi:10.1063/1.1825279

Drachen, A., Yancey, M., Maguire, J., Chu, D., Wang, I. Y., Mahlmann, T., … Klabajan, D. (2015). Skill-based differences in spatio-Temporal team behaviour in defence of the Ancients 2 (DotA 2). *Conference Proceedings - 2014 IEEE Games, Media, Entertainment Conference, IEEE GEM 2014*, *2*(DotA 2). doi:10.1109/GEM.2014.7048109

Ducheneaut, N., & Moore, R. J. (2004). The social side of gaming: a study of interaction patterns in a massively multiplayer online game. In *Proceedings of the 2004 ACM conference on Computer supported cooperative work - CSCW '04* (p. 360). doi:10.1145/1031607.1031667

Ducheneaut, N., Yee, N., Nickell, E., & Moore, R. J. (2006a). "Alone Together?" Exploring the Social Dynamics of Massively Multiplayer Online Games. *Chi 2006*, (March), 407–416. doi:10.1145/1124772.1124834

Ducheneaut, N., Yee, N., Nickell, E., & Moore, R. J. (2006b). Building an MMO With Mass Appeal: A Look at Gameplay in World of Warcraft. *Games and Culture*, *1*(4), 281–317. doi:10.1177/1555412006292613

Edge, R. (2013). Predicting Player Churn in Multiplayer Games using Goal-Weighted Empowerment.

Edwards, G., & Crossley, N. (2009). Measures and Meanings: Exploring the Ego-Net of Helen Kirkpatrick Watts, Militant Suffragette. *Methodological Innovations Online*, *4*(1), 37–61. doi:10.1177/205979910900400104

Eggert, C., Herrlich, M., Smeddinck, J., & Malaka, R. (2015). Classification of Player Roles in the Team-based Multi-player Game Dota 2.

Ferrari, S. (2013). From Generative to Conventional Play : MOBA and League of Legends. *DiGRA Conference Proceedings 2013*.

Freeman, L. C. (1977). A Set of Measures of Centrality Based on Betweenness. *Sociometry*, *40*(1), 35. doi:10.2307/3033543

Frey, B. J., & Dueck, D. (2007). Clustering by passing messages between data points. *Science*, *315*(5814), 972–976. doi:10.1126/science.1136800

Gao, G., & Shih, P. C. (2018). Does Platform Matter? A Game Design Analysis of Female Engagement in MOBA Games.

Gerling, K. M., Miller, M., Mandryk, R. L., Birk, M. V., Smeddinck, J. D., Gerling, K. M., ... Smeddinck, J. D. (2014). Effects of balancing for physical abilities on player performance, experience and self-esteem in exergames. In *Proceedings of the 32nd annual ACM conference on Human factors in computing systems - CHI '14* (pp. 2201–2210). doi:10.1145/2556288.2556963

Ghuman, D., & Griffiths, M. (2012). A Cross-Genre Study of Online Gaming: player demographics, motivation for play, and social interactions among players. *International Journal of Cyber Behavior, Psychology and Learning*, *2*(1), 13–29. doi:10.4018/ijcbpl.2012010102

Girvan, M., & Newman, M. E. J. (2002). Community structure in social and biological networks. *Proceedings of the National Academy of Sciences*, *99*(12), 7821–7826. doi:10.1073/pnas.122653799

Griffiths, M. (2017). Work stressed and play? A brief look at competitive gaming.

Heidbrink, S., Knoll, T., & Wysocki, J. (2015). "Venturing into the Unknown"(?) Method(olog)ical Reflections on Religion and Digital Games, Gamers and Gaming. *Online - Heidelberg Journal of Religions on the Internet*, *7*(0). doi:10.11588/REL.2015.0.18508

Iosup, A., van de Bovenkamp, R., Shen, S., Lu Jia, A., & Kuipers, F. (2014). Analyzing Implicit Social Networks in Multiplayer Online Games. *IEEE Internet Computing*, *18*(3), 36–44. doi:10.1109/MIC.2014.19

Jennett, C., Cox, A. L., Cairns, P., Dhoparee, S., Epps, A., Tijs, T., & Walton, A. (2008). Measuring and defining the experience of immersion in games. *International Journal of Human-Computer Studies*, *66*(9), 641–661. doi:10.1016/j.ijhcs.2008.04.004

Johansson, M., Verhagen, H., & Kou, Y. (2015). I Am Being Watched By The Tribunal - Trust and Control in Multiplayer Online Battle Arena Games.

Johnson, D., & Gardner, J. (2010). Personality, motivation and video games. In *Proceedings of the 22nd Conference of the Computer-Human Interaction Special Interest Group of Australia on Computer-Human Interaction - OZCHI '10* (p. 276). doi:10.1145/1952222.1952281

Johnson, D., Watling, C., Gardner, J., & Nacke, L. E. (2014). The edge of glory: the relationship between metacritic scores and player experience. In *Proceedings of the first ACM SIGCHI annual symposium on Computer-human interaction in play - CHI PLAY '14* (pp. 141–150). doi:10.1145/2658537.2658694

Johnson, D., & Wyeth, P. (2015). All about that Base : Differing Player Experiences in Video Game Genres and the Unique Case of MOBA Games. (April), 18–23.

Johnson, D., Wyeth, P., Sweetser, P., & Gardner, J. (2012). Personality, genre and videogame play experience. In *Proceedings of the 4th International Conference on Fun and Games - FnG '12* (pp. 117–120). doi:10.1145/2367616.2367633

Kahn, A. S., Shen, C., Lu, L., Ratan, R. A., Coary, S., Hou, J., ... Williams, D. (2015). The Trojan Player Typology: A cross-genre, cross-cultural, behaviorally validated scale of video game play motivations. *Computers in Human Behavior*, *49*, 354–361. doi:10.1016/J.CHB.2015.03.018

Kaufman, L., & Rousseeuw, P. J. (1990). *Finding Groups in Data: An Introduction to Cluster Analysis (Wiley Series in Probability and Statistics)*. doi:10.1007/s13398-014-0173-7.2

Keller, J. M. (2010). The Arcs Model of Motivational Design. In *Motivational Design for Learning and Performance* (pp. 43–74). doi:10.1007/978-1-4419-1250-3_3

Kim, J., Keegan, B. C., Park, S., & Oh, A. (2016). The Proficiency-Congruency Dilemma: Virtual Team Design and Performance in Multiplayer Online Games. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems - CHI '16* (pp. 4351–4365). doi:10.1145/2858036.2858464

King, D., Delfabbro, P., & Griffiths, M. (2010). Video Game Structural Characteristics: A New Psychological Taxonomy. *International Journal of Mental Health and Addiction*, *8*(1), 90–106. doi:10.1007/s11469-009-9206-4

King, D., Delfabbro, P., & Griffiths, M. (2011). The Role of Structural Characteristics in Problematic Video Game Play: An Empirical Study. *International Journal of Mental Health and Addiction*, *9*(3), 320–333. doi:10.1007/s11469-010-9289-y

Kline, P. (1993). *The handbook of psychological testing (2nd ed.)* Taylor and Francis/Routledge.

Knuth, D. E. (1974). Computer Programming as an Art. *Communications of the ACM*, *17*(12), 667–673.

Kou, Y., & Gui, X. (2014). Playing with Strangers : Understanding Temporary Teams in League of Legends, 161–169.

Kou, Y., & Nardi, B. (2013). Regulating Anti-Social Behavior on the Internet : The Example of League of Legends. *iConference 2013 Proceedings*, (2011), 616–622. doi:10.9776/13289

Kuss, D. J., & Griffiths, M. (2012). Internet Gaming Addiction: A Systematic Review of Empirical Research. *International Journal of Mental Health and Addiction*, *10*(2), 278–296. doi:10.1007/s11469-011-9318-5

Kwak, H., Blackburn, J., & Han, S. (2015). Exploring Cyberbullying and Other Toxic Behavior in Team Competition Online Games. doi:10.1145/2702123.2702529

Latour, B. (2007). Beware, your imagination leaves digital traces. *Times Higher Literary Supplement*, *6*(04), 2007.

Lazer, D., Brewer, D., Christakis, N., Fowler, J., & King, G. (2009). Life in the network: the coming age of computational social science. *Science*, *323*(5915), 721–723. doi:10.1126/science.1167742.Life

Lazzaro, N. (2008). The Four Fun Keys. In *Game Usability: Advice from the Experts for Advancing the Player Experience*. doi:10.1016/b978-0-12-374447-0.00020-2

Lemmens, J. S., Valkenburg, P. M., & Peter, J. (2009). Development and Validation of a Game Addiction Scale for Adolescents. *Media Psychology*, *12*(1), 77–95. doi:10.1080/15213260802669458

Li, Q., Xu, P., Chan, Y. Y., Wang, Y., Wang, Z., Qu, H., & Ma, X. (2016). A Visual Analytics Approach for Understanding Reasons behind Snowballing and Comeback in MOBA Games. *IEEE Transactions on Visualization and Computer Graphics · IEEE TRANSACTIONS ON VISUALIZATION AND COMPUTER GRAPHICS*, *23*(1). doi:10.1109/TVCG.2016.2598415

McDonald, E. (2017). The Global Games Market 2017 | Per Region & Segment | Newzoo. Retrieved from https://newzoo.com/insights/articles/the-global-games-market-will-reach-108-9-billion-in-2017-with-mobile-taking-42/

McEwan, M., Johnson, D., Wyeth, P., & Blackler, A. (2012). Videogame control device impact on the play experience. In *Proceedings of The 8th Australasian Conference on Interactive Entertainment Playing the System - IE '12* (pp. 1–3). doi:10.1145/2336727.2336745

McMahan, A. (2003). Immersion, Engagement, and Presence: A method for Analysing 3-D Video Games The video game theory reader'. *The video game theory reader, Routledge, New York, NY, US*.

McWhertor, M. (2012). The League of Legends team of scientists trying to cure 'toxic behavior' online - Polygon. Retrieved July 3, 2018, from https://www.polygon.com/2012/10/17/3515178/the-league-of-legends-team-of-scientists-trying-to-cure-toxic

Monzani, L., Ripoll, P., Peiró, J. M., & Van Dick, R. (2014). Loafing in the digital age: The role of computer mediated communication in the relation between perceived loafing and group affective outcomes. *Computers in Human Behavior*, *33*, 279–285. doi:10.1016/J.CHB.2014.01.013

Mora-Cantallops, M. (2017). Análisis de usos de YouTube en la comunidad española de League of Legends. In D. Aranda,

J. Sánchez-Navarro, & A. J. Planells (Eds.), *Game & Play: La cultura del juego digital* (pp. 11–22). Ediciones Egregius.

Mora-Cantallops, M., & Sicilia, M.-Á. (2016). Motivations to read and learn in videogame lore. In *Proceedings of the Fourth International Conference on Technological Ecosystems for Enhancing Multiculturality - TEEM '16* (pp. 585–591). doi:10.1145/3012430.3012578

Mora-Cantallops, M., & Sicilia, M.-Á. (2018). MOBA games: A literature review. *Entertainment Computing*, *26*, 128–138. doi:10.1016/j.entcom.2018.02.005

Mortensen, T. E. (2006). WoW is the new MUD: Social gaming from text to video. *Games and Culture*, *1*(4), 397–413. doi:10.1177/1555412006292622

Myślak, M., & Deja, D. (2015). Developing Game-Structure Sensitive Matchmaking System for Massive-Multiplayer Online Games. (pp. 200–208). doi:10.1007/978-3-319-15168-7_25

Nakamura, J., & Csikszentmihalyi, M. (2014). The Concept of Flow. In *Flow and the Foundations of Positive Psychology* (pp. 239–263). doi:10.1007/978-94-017-9088-8_16

Nakatsu, R., Rauterberg, M., & Vorderer, P. (2005). A New Framework for Entertainment Computing: From Passive to Active Experience. (pp. 1–12). doi:10.1007/11558651_1

Newman, M. E. J. (2003). Fast algorithm for detecting community structure in networks. (2), 1–5. doi:10.1103/PhysRevE.69.066133

Neys, J. L., Jansz, J., & Tan, E. S. (2014). Exploring persistence in gaming: The role of self-determination and social identity. *Computers in Human Behavior*, *37*, 196–209. doi:10.1016/J.CHB.2014.04.047

Nuangjumnonga, T., & Mitomo, H. (2012). Leadership development through online gaming. Retrieved from http://www.econstor.eu/handle/10419/72527

Nuyens, F., Deleuze, J., Maurage, P., Griffiths, M., Kuss, D. J., & Billieux, J. (2016). PO-25: impulsivity in Multiplayer Online Battle Arena (MOBA) gamers: Preliminary results on experimental and self-report measures. *Journal of Behavioral Addictions*, *5*(S1), 56–57.

Ong, H. Y., Deolalikar, S., & Peng, M. (2015). Player Behavior and Optimal Team Composition for Online Multiplayer Games.

Pannekeet, J. (2017). Esports, a Franchise Perspective: 70% Watch only one Game, 42% of Esports Viewers Don't Play. Retrieved May 11, 2017, from https://newzoo.com/insights/articles/esports-franchises-70-watch-only-one-game-and-42-dont-play/

Pavlas, D., Jentsch, F., Salas, E., Fiore, S. M., & Sims, V. (2012). The Play Experience Scale. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *54*(2), 214–225. doi:10.1177/0018720811434513

Pérez-Latorre, Ó., Oliva, M., & Besalú, R. (2017). Videogame analysis: a social-semiotic approach. *Social Semiotics*, *27*(5), 586–603. doi:10.1080/10350330.2016.1191146

Perry, B. L., Pescosolido, B. A., & Borgatti, S. P. (2018). *Egocentric network analysis : foundations, methods, and models*. Cambridge university press.

Phan, M. H., Keebler, J. R., & Chaparro, B. S. (2016). The Development and Validation of the Game User Experience Satisfaction Scale (GUESS). *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *58*(8), 1217–1247. doi:10.1177/0018720816669646

Pirker, J., Rattinger, A., Drachen, A., & Sifa, R. (2018). Analyzing player networks in Destiny. *Entertainment Computing*, *25*, 71–83. doi:10.1016/j.entcom.2017.12.001

Pobiedina, N., Neidhardt, J., Del Carmen Calatrava Moreno, M., Grad-Gyenge, L., & Werthner, H. (2013). On Successful Team Formation: Statistical Analysis of a Multiplayer Online Game. In *Business Informatics (CBI), 2013 IEEE 15th Conference on* (pp. 55–62). IEEE.

Pobiedina, N., Neidhardt, J., Moreno, M., & Werthner, H. (2013). Ranking factors of team success. *WWW 2013 Companion - Proceedings of the 22nd International Conference on World Wide Web*, 1185–1193.

Poels, K., de Kort, Y., & IJsselsteijn, W. (2008). FUGA-the fun of gaming: measuring the human experience of media enjoyment. *Deliverable D3*, *3*.

Pons, P., & Latapy, M. (2006). Computing Communities in Large Networks Using Random Walks. *Journal of Graph Algorithms and Applications*, *10*(2), 191–218. doi:10.7155/jgaa.00124

Pramono, M. F., Renalda, K., Kristiadi, D. P., Warnars, H. L. H. S., & Kusakunniran, W. (2018). Matchmaking Problems in MOBA Games. *Indonesian Journal of Electrical Engineering and Computer Science*, *11*(3). doi:10.11591/IJEECS.V11.I3.PP%P

Przybylski, A. K., Deci, E. L., Rigby, C. S., & Ryan, R. M. (2014). Competence-impeding electronic games and players' aggressive feelings, thoughts, and behaviors. *Journal of Personality and Social Psychology*, *106*(3), 441–457. doi:10.1037/a0034820

Przybylski, A. K., Rigby, C. S., & Ryan, R. M. (2010). A Motivational Model of Video Game Engagement Motivation and Video Games. doi:10.1037/a0019440

Raschka, S. (2014). *Python Machine Learning*. doi:10.1007/s13398-014-0173-7.2

Ratan, R. a., Taylor, N., Hogan, J., Kennedy, T., & Williams, D. (2015). Stand by Your Man: An Examination of Gender Disparity in League of Legends. *Games and Culture*, 1–25. doi:10.1177/1555412014567228

Rioult, F., Métivier, J.-p., Helleu, B., Scelles, N., & Durand, C. (2014). Mining Tracks of Competitive Video Games. *AASRI Procedia*, *8*(Secs), 82–87. doi:10.1016/j.aasri.2014.08.014

Ripamonti, L. A., Granato, M., Trubian, M., Knutas, A., Gadia, D., & Maggiorini, D. (2018). Multi-agent simulations for the evaluation of Looting Systems design in MMOG and MOBA games. *Simulation Modelling Practice and Theory*, *83*, 124–148. doi:10.1016/J.SIMPAT.2017.12.002

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *The American psychologist*, *55*(1), 68–78. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/11392867

Ryan, R. M., Rigby, C. S., & Przybylski, A. K. (2006). The Motivational Pull of Video Games: A Self-Determination Theory Approach. *Motivation and Emotion*, *30*(4), 344–360. doi:10.1007/s11031-006-9051-8

Sapienza, A., Goyal, P., & Ferrara, E. (2018). Deep Neural Networks for Optimal Team Composition. (10).

Savage, M., & Burrows, R. (2009). Some further reflections on the Coming Crisis of Empirical Sociology. *Sociology*, *43*(4), 762–772. doi:10.1177/0038038509105420

Schlauch, W. E., & Zweig, K. A. (2015). Social Network Analysis and Gaming: Survey of the Current State of Art. In *JCSG*

2015: Serious Games (pp. 158–169). doi:10.1007/978-3-319-19126-3_14

Shim, J. Y., Kim, T. H., & Kim, S. W. (2014). Decision support of Bad Player Identification in MOBA Games using PageRank based Evidence Accumulation and Normal Distribution based Confidence Interval. *International Journal of Multimedia and Ubiquitous Engineering*, *9*(8), 13–24. doi:10.14257/ijmue.2014.9.8.02

Shores, K. B., He, Y., Swanenburg, K. L., Kraut, R., & Riedl, J. (2014). The identification of deviance and its impact on retention in a multiplayer game. In *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing - CSCW '14* (pp. 1356–1365). doi:10.1145/2531602.2531724

Silva, M. P., Do, V., Silva, N., & Chaimowicz, L. (2017). Dynamic Difficulty Adjustment on MOBA Games.

Smeddinck, J. D., Mandryk, R. L., Birk, M. V., Gerling, K. M., Barsilowski, D., & Malaka, R. (2016). How to Present Game Difficulty Choices? Exploring the Impact on Player Experience. doi:10.1145/2858036.2858574

Stenros, J., Paavilainen, J., & Mayra, F. (2011). Social interaction in games. *International Journal of Arts and Technology*, 4(3), 342. doi:10.1504/IJART.2011.041486

Superdata. (2017). *2017 Year in review*. SuperData Research Holdings, Inc.

Suznjevic, M., Matijasevic, M., & Konfic, J. (2015). Application Context Based Algorithm for Player Skill Evaluation in MOBA games.

Sweetser, P., & Wyeth, P. (2005). GameFlow: a model for evaluating player enjoyment in games. *Computers in Entertainment*, *3*(3), 3. doi:10.1145/1077246.1077253

Szell, M., & Thurner, S. (2010). Measuring social dynamics in a massive multiplayer online game. *Social Networks*, *32*(4), 313–329. doi:10.1016/j.socnet.2010.06.001

Takatalo, J., Häkkinen, J., Kaistinen, J., & Nyman, G. (2010). Presence, Involvement, and Flow in Digital Games. (pp. 23–46). doi:10.1007/978-1-84882-963-3_3

Taylor, T. L. (2012). *Raising the Stakes: E-sports and the Professionalization of Computer Gaming*. MIT Press.

Thrift, N. (2005). Knowing capitalism. *Knowing Capitalism*, 1–65. doi:10.4135/9781446211458

Trepte, S., Reinecke, L., & Juechems, K. (2012). The social side of gaming: How playing online computer games creates online and offline social support. *Computers in Human Behavior*, *28*(3), 832–839. doi:10.1016/j.chb.2011.12.003

Triberti, S., Milani, L., Villani, D., Grumi, S., Peracchia, S., Curcio, G., & Riva, G. (2018). What matters is when you play: Investigating the relationship between online video games addiction and time spent playing over specific day phases. *Addictive Behaviors Reports*. doi:10.1016/J.ABREP.2018.06.003

Tyack, A., Wyeth, P., & Johnson, D. (2016). The Appeal of MOBA Games: What makes people start, stay, and stop. In *Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play - CHI PLAY '16* (pp. 313–325). doi:10.1145/2967934.2968098

Vella, K., Johnson, D., & Hides, L. (2015). Playing Alone, Playing With Others: Differences in Player Experience and Indicators of Wellbeing. In *Proceedings of the 2015 Annual Symposium on Computer-Human Interaction in Play - CHI PLAY '15* (pp. 3–12). doi:10.1145/2793107.2793118

Véron, M., Marin, O., & Monnet, S. (2013). Matchmaking in Multiplayer On-line Games: Studying User Traces to Improve the User Experience. *Proceedings of Network and Operating System Support on Digital Audio and Video Workshop*, 7:7–7:12. doi:10.1145/2578260.2578265

Vicencio-Moreira, R., Mandryk, R. L., & Gutwin, C. (2015). Now You Can Compete With Anyone: Balancing Players of Different Skill Levels in a First-Person Shooter Game. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems - CHI '15* (pp. 2255–2264). doi:10.1145/2702123.2702242

Walker, A. (2017). Gaming addiction, motivation, and identity: investigating the effects of competitive play in a Multiplayer Online Battle Arena game. Retrieved from https://e-space.mmu.ac.uk/619180/

Wasserman, S., & Faust, K. (1994). Social network analysis: Methods and applications. *Cambridge University Press*, *1*, 116. doi:10.1525/ae.1997.24.1.219

Watts, D. J. (2007). A twenty-first century science. *Nature*, *445*(7127), 489. doi:10.1038/445489a

Wiemeyer, J., Nacke, L., Moser, C., et al. (2016). Player experience. In *Serious Games* (pp. 243–271). Springer.

Woolley, A. W., & Malone, T. W. (2017). What Makes a Strong Team?: Using Collective Intelligence to Predict Team Performance in League of Legends. doi:10.1145/2998181.2998185

Wu, M., Xiong, S., & Iida, H. (2016). Fairness Mechanism in Multiplayer Online Battle Arena Games. doi:10.1109/ICSAI.2016.7810986

Xia, B., Wang, H., & Zhou, R. (2017). What Contributes to Success in MOBA Games? An Empirical Study of Defense of the Ancients 2. *Games and Culture*. doi:10.1177/1555412017710599

Xu, Y. [Yan], Cao, X., Sellen, A., Herbrich, R., & Graepel, T. (2011). Sociable Killers: Understanding Social Relationships in an Online First-Person Shooter Game.

Yang, P., Harrison, B., & Roberts, D. L. (2014). Identifying Patterns in Combat that are Predictive of Success in MOBA Games. *Proceedings of Foundations of Digital Games 2014*, 1–8.

Yee, N. (2017). Beyond 50-50: Breaking Down The Percentage of Female Gamers By Genre. Retrieved July 6, 2018, from https://quanticfoundry.com/2017/01/19/female-gamers-by-genre/

Zhong, Z. J. (2011). The effects of collective MMORPG (Massively Multiplayer Online Role-Playing Games) play on gamers' online and offline social capital. *Computers in Human Behavior*, *27*(6), 2352–2363. doi:10.1016/j.chb.2011.07.014

COLOPHON

This document was typeset using the typographical look-and-feel `classicthesis` developed by André Miede and Ivo Pletikosić. The style was inspired by Robert Bringhurst's seminal book on typography "*The Elements of Typographic Style*". `classicthesis` is available for both LaTeX and LyX:

https://bitbucket.org/amiede/classicthesis/

Thank you very much for reading this.

Final Version as of September 13, 2018 (classicthesis v4.6).