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Exploring Stress in Esports Gaming: Physiological and Data-driven approach on Tilt

DISSERTATION

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in Informatics

by

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DEDICATION

This dissertation is dedicated to my wife, Seungmin,
who has been a constant source of support and encouragement
during the challenges of graduate school and life.
Every time I collapse, you put me together.
I am truly thankful for having you in my life.

This work is also dedicated to my parents, grandparents, and family,
who have always loved me unconditionally
and whose good examples have taught me to work hard for the things that I aspire.

To all the music, games, videos, places, people, culture that I loved and inspired me.

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VITA

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ABSTRACT OF THE DISSERTATION

Exploring Stress in Esports Gaming: Physiological and Data-driven approach on Tilt

by

Je Seok Lee

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Professor Constance Steinkuehler, Chair

As esports has gained a growing audience, parents and educators have raised concerns about deviant behaviors associated with it (tilt). The present study investigated players' stress levels and emotions around in-game stress events by means of physiological measurements (heart rate [HR], heart rate variability [HRV], and facial expressions) to find out how in-game stress events affect player's stress levels according to different groups of players and different event contexts. While groups of young players (N = 119) aged 14-25 played three matches of League of Legends, their in-game logs, video recordings of gameplay, in-game communication, and physiological data (HR, HRV, and facial expressions) were collected. Linear mixed-effects models were fitted to explore the effects of different player groups and in-game contexts related to the stressful events during the gameplay. The higher game skill level and later in-game phase were positively associated with earlier recognition and anticipation of upcoming events before they occur. Winning a match, later in-game phase, Enemy and Myself events were positively associated with a higher increase of HR during a stress event. Older age and Team and Teammate events were positively associated with a smaller decrease in HR after stress events. Lower game

skill level, older age, and later in-game phase are associated with a bigger drop of HRV during stress events, which implies higher stress levels. Overall, the contribution of this study lies in exploring the in-game variables that impact player tilt employing physiological measures of players' emotions.

Chapter 1: Introduction

Esports has grown into an essential part of digital youth culture in recent years (Wagner, 2006). Esports can be defined as “a form of sport where the primary aspects of the sport are facilitated by electronic systems; the input of players and teams, as well as the output of the system, are mediated by human-computer interfaces” (Hamari, 2017). As it is a form of sports, being an esports player is considerably different from playing games for leisure in terms of the purpose and the skills involved (Witkowski, 2012; Seo & Jung, 2016; Wagner, 2006).

At a certain level, esports is a competitive activity. It requires players to practice highly sophisticated physical and emotional skills, such as motor skills, team coordination, strategic thinking, and emotion control. The result of each match affects the player's rank, which represents a player’s skill level as a numerical score or a tier. Esports is important not only to professional-level players but also to general hobbyist gamers, who also view it as a serious activity—sometimes even more serious than aspects of their real life.

Like other traditional games and sports, esports games are designed to be competitive in nature, which is one factor that engages players by stimulating their desire to win (Lee & Schoenstedt, 2016). At times, this competition becomes overly serious for leisure activity. Vigorous play often rouses intense emotions and leads to social and emotional challenges. It was often related to the social stigmas that video games have already had, such as toxicity and violence.

In some cases, excessive playtime is required to accomplish their goal. Even members of gaming communities recognize and admit that they experience moments when their immersion results in a loss of self-control. “Tunnel vision” and “tilt” are widely used terms among gamers to describe this phenomenon. On the gamers’ online discussion platforms, many users recognize a correlation between this phenomenon and repetitive failures during their play. “Just one victory and I’m done.” is what many gamers report as their mental state when they confront failure streaks. Kou et al. (2018) explain this streakiness of the game as an unavoidable phenomenon that appears for a short period while playing esports games. This is where many players lose self-control and are pulled into excessive playtime.

Playing competitive esports involves making strategic decisions, training and improving performance as an individual player or as a team, and mastering socio-emotional skills. The goal of this study is to observe the in-game behavior, physical/emotional response, and team dynamics of esports players while they play competitive video games and examine the relationships among these areas across groups of differing levels of expertise. This project collects a wide range of quantitative data (in-game telemetry and players’ physiological response) and qualitative data (audio and text logs of team communication, video observation of gameplay, and user interviews) to investigate diverse aspects of the behaviors and responses of players during esports play.

Statement of Purpose and Research Question

The primary goal of this research is to explore the first-hand experience of esports players during stressful moments of the gameplay. By conducting controlled gameplay sessions with 120 participants, the change of their biological stress responses was measured and analyzed when in-game stress events occurred. Simultaneously, diverse in-game contexts related to the player’s traits and game events were explored as variables that impact the stress level of players. Below is the research question of this study.

Research Question: What variables impact the change in physiological responses during and after the stress event?

Participants were recruited from different player groups and exposed to varying types of stress events in diverse in-game contexts. Physiological responses (i.e., heart rate and facial expression) around each stressful event were measured and analyzed to answer this question. A series of linear mixed-effects analyses was performed to find the relationship between explanatory variables and the stress level change of players.

Research Hypothesis

Heart rate responses were measured to explore the change of stress level before, during, and after stress events. During a stress event, players undergo a stressful event in the following order: Baseline - Anticipation - Action - Recovery. The concept of different periods refers to past studies in physiology; Notterman et al. (1953) distinguished HR measurement periods as Basal - Conditioning - Extinction - Spontaneous Recovery. The concept of anticipation was additionally adopted from Epstein & Roupenian (1970), which measured HR through the Anticipatory - Impact - Recovery phase. By the nature of the gameplay, experienced players can expect immediate events before they actually occur. For example, when a teammate detects the opponent team grouped near an objective, the player promptly knows that there will be a teamfight over the object soon and starts preparing for the fight. After events are concluded, players recover from the stress after a few seconds (Borst et al., 1982) and stress levels would decrease spontaneously (Notterman et al., 1953; Borst et al., 1982) until a new stimulus appears. Referring to those past studies, the present study also measures HR and HRV to find stress level changes in Anticipation-Impact-Recovery stages of stress events. Additionally, players' facial expressions were recorded and analyzed during the 3-seconds time window around stress events to catch an instant change of emotion before and after events.

Hypothesis 1: *During the anticipatory phase, player traits and in-game context will significantly affect how early players mentally respond (HR) to a stress event.*

Hypothesis 2: *During the impact phase, player traits and in-game context will significantly affect how much players' stress level (HR/HRV) increases from the base level.*

Hypothesis 3: *During the recovery phase, player traits and in-game context will significantly affect how much players' stress level decreases (HR/HRV) from the peak level.*

Hypothesis 4: *Before and after a stress event, player traits and in-game context will affect players' emotions, displayed through facial expressions.*

Chapter 2: Literature Review

Introducing Esports

Esports, also known as competitive gaming, is now an essential part of the digital culture of youths (Wagner, 2006). As it originated from the networked play of video games, the phenomenon of esports started after the wide popularization of the internet around the late 1990s. Esports has risen in popular culture and has become a lucrative business model in the game industry, with diverse statistics and market numbers as proof. For example, the number of unique viewers of the League of Legends Championship Final (a popular esports video game) increased from 32 million (2014) to 100 million (2019) over a 5-year span (Goslin, 2017; Webb, 2019). Some successful esports titles have surpassed traditional sports in terms of viewership and player salary. The National Basketball Association's (NBA) final match was viewed by 31 million people in 2016, while the League of Legends World Finals had 36 million unique viewers. The viewership trends of the Super Bowl and League of Legends crossed in 2018: whereas the viewership of the Super Bowl dropped from 111 million to 98 million between 2017 and 2019, League of Legends' viewership increased from 58 million to 100 million (Goslin, 2017; Pei, 2019). Salaries vary by team and individual, but the player known simply as Faker, one of the most prominent players of League of Legends, earns \$2.5 million a year as a basic salary, \$1.1 million from prize pools, and additional revenue from his streaming on Twitch, a livestreaming platform dedicated to video games and esports (Newell, 2018).

Following the growth of League of Legends, the pool of professional and amateur players is also expanding. In the early stage of professional esports, only a few select players were able to become professional gamers. Players who pursue careers as professional gamers must sacrifice other interests and valuable time to pursue gaming (Chee, 2006). But the landscape is now changing. The number of audience of global esports marked 380.2 million in 2018 and is expected to increase to 557 million by 2021 (Khromov et al, 2019; Newzoo, 2018), and beyond a cult-like phenomenon, esports has become part of contemporary consumer culture (Seo & Jung, 2016). Although players can compete from their bedrooms, they appear in person in an offline competition to "authenticate their consumption in a real-world, traversing the boundaries between the online and offline experience of competitive computer games" (Seo, 2013). Just as traditional sports players are trained at their schools and play in amateur youth leagues, more and more high school esports clubs and varsity esports teams are being spontaneously created in the United States. There are more than 50 universities that have a varsity esports program (Morrison, 2018), and universities run scholarship-sponsored esports teams. Organizations like the NASEF (North America Scholastic Esports Federation) support high school leagues across the nation. The remarkable growth of esports as a school-based activity in the U.S. is interesting because video games are eliminating their own stigma and are starting to be viewed as a healthy and beneficial leisure activity. This wide and solid base of competitive esports players cultivates a richer environment across all tiers of esports competitions.

Esports as a Sport

In sport sciences terms, esports can be defined as "a form of sport where the primary aspects of the sport are facilitated by electronic systems; the input of players and teams, as well as the output of the system, are mediated by human-computer interfaces" (Hamari & Sjoblom, 2017). As esports became a mainstream leisure activity throughout the world, it has created its own system like other traditional sports, such as football and baseball. In many ways, the governance and practitioners of the esports industry imitate the structure of traditional sports

(Chao, 2017). But with the recent global rise of esports, the scope of what constitutes a sport has been widely debated.

Jenny et al. (2017) summarize the characteristics of a sport presented by Guttmann (1978) and Suits (2007). Whether or not esports qualify as a sport can be investigated by comparing these characteristics to the traits of esports. According to Jenny et al., a sport must demonstrate these seven elements:

1. Include play (voluntary, intrinsically motivated activity)
2. Be organized (governed by rules)
3. Include competition (outcome of a winner and loser)
4. Be comprised of skill (not a chance)
5. Include physical skills (skillful and strategic use of one's body)
6. Have a broad following (beyond a local fad)
7. Have achieved institutional stability where social institutions have rules which regulate it, stabilizing it as an important social practice

Jenny et al. decided that esports qualify as having all of these characteristics except 5 and 7; physical skills and institutional stability are debatable factors that shake esports' status as a sport.

A debate on the physical activeness of esports is the most controversial topic among researchers. Hallmann and Giel (2018) mention a detailed definition of physical activity brought from Pate et al. (1995): "[m]oderate physical activity is an activity performed at an intensity of 3–6 METs," and "the metabolic equivalent of task (MET) is a physiological measure for the amount of energy that physical activities take" (Hallmann & Giel, 2018). 3-6 METs are generally equivalent to walking at 5-6 km per hour (Pate et al., 1995), which the activeness of playing esports cannot reach. On the other hand, Hemphill (2005) stated that prowess implicated in certain games is “sufficiently physical and skillful to qualify them as a sport in their own right.” Esports is often compared to golf, poker, or chess regarding their physicality, which are all at the borderline of sports and recreation (Chao, 2017). Esports does not require as much physical movement as golf, but it requires physical dexterity to play successfully, unlike chess (Hallmann & Giel, 2018). Jonasson and Thiborg (2010) argue, “eSports will definitely fill a void in the sports family; no sport requires such a diversified coordination of the fingers as eSport(s).” Esports can be compared to archery or bowling since it does not require much physical movement or strength but requires accurate motor control, coordination, quick reflexes, visual acuity, and mental focus (Hallmann & Giel, 2018).

The other debatable factor is that esports has established organizational play, but no institutional stability as of yet. Chao (2017) compares the structure of the esports industry with the traditional sports industry. Chao concludes that the esports industry is comprised of many stakeholders: the game developers, the league or tournament organizational bodies, the teams that contract to play within the organizational body, the professional players that contract to play on teams, the sponsors, and often a streaming site as the content distributor. Chao highlights differences between esports and traditional sports derived from the different structure of stakeholders: (a) variable rules of gameplay, (b) lack of regional ties, (c) online broadcast, and (d) anticompetitive practices. The governance of esports rests on game developers because they often modify game rules and the specifications of playable characters. In esports, while the basic rules remain the same, the detailed balance among different characters is constantly adjusted to find balance and encourage players to continually adapt to the new meta interactions. Those frequent updates sustain player retention in their games, but it compromises the stability of esports as a sport. Also, esports competitions are hosted solely by game corporations because they hold the entire copyright of the intellectual property. Recently, social institutions have been losing control over esports events and players, and the power is moving towards giant game publishers like Riot Games and Blizzard Entertainment (Go0g3n, 2009). Thus, Chao warns of a potentially unfair monopolization by game publishers and proposes a federal regulatory body for the esports ecosystem.

Although several other points are debatable, esports has established a wide fan base and an ecosystem as a standalone form of sports. Accordingly, many progressive efforts to include esports in sports are being done through the existing governance of sports. Discussion to add esports games to the Olympic Games is one such example. The International Olympic Committee (IOC) was opposed including esports as an Olympic event before (Chakraborty, 2018), but the IOC now encourages discussions by hosting the esports forum and inviting professional esports players and practitioners to it (IOC, 2019). The 2018 Asian Games featured five different esports titles as exhibition events (The Esports Observer, 2018), and there is a high chance that esports games will be promoted as official events in future Asian Games. Since the Asian Games are "the biggest multi-sport games after the Olympic Games" (Graham, 2017), the inclusion of esports in them is a huge milestone towards esports becoming an official form of sport (Hallmann & Giel, 2017).

Differences between Esports and Video Games

Esports is a specific form of computer game where multiple players compete with each other in a virtual space. To the general population, the concept of esports is sometimes mixed up with online games because most esports game titles support online play. Seo and Jung (2016) examine esports consumption from the perspective of social practices, which include playing, spectating, and being institutionally governed. These are common elements in other past studies (Taylor, 2012; Ma et al., 2013; Seo & Jung, 2016; Witkowski & Manning, 2017; Witkowski, 2012) that discuss the differences between esports and games.

When playing esports, serious activity is expected from players. In contrast to video games that provide a narrative immersion and escapism, esports games demonstrate player rivalry under predetermined rules (Seo, 2016; Wagner, 2007). Esports also includes complying with a particular subculture, mastering a profession, playing games as a professional player and with a level high of performance, and routinized training (Seo & Jung, 2016). Obviously, playing on a professional or amateur team and participating in a league can be defined as an esports activity. But it also implies that an avid player's serious endeavor to master a game and win in competitions can also be defined as an esports activity.

However, spectating is the element that drastically distinguishes esports from other games because the activity of spectating does not include the essential part of gameplay: active interaction with the computer system. People find entertainment in watching others play, especially those with exceptional skills (Christophers & Scholz, 2011). Watching esports has generated a common perception of public competitive games as a form of sport, as this is an activity that is commonly found in traditional sports (Seo & Jung, 2016; Taylor, 2012). But watching is not a purely passive activity because viewers must internalize knowledge about the game and the rules. This is an interactive process between players (or viewers) and the game; players are drawn to watch esports, and they improve their own gameplay by watching other esports players' extraordinary plays.

Lastly, governance or social institution is the final factor that distinguishes esports from general video games. Organizations like Major League Gaming (MLG) and the International

Esports Federation (IeSF) have started to represent professional gamers and envision esports as an emerging cultural influence. Their main goal is to provide coherence among the diverse stakeholders, thus making esports more institutionalized (Seo, 2013). Esports governance aims to mediate the differing stakeholder interests in a fair way as a social organization that pursues the public good.

Esports Players

A player is commonly regarded as a consumer of video games, framing the activity of gameplay as a pastime. But being a player of esports is considerably different from playing for leisure in terms of the purpose and the skills involved (Witkowski, 2012). The borderline between consumers and producers is often blurred because playing as a professional esports player is a type of consumption with a very high level of expertise. Seo (2016) explains this ambilateral activity as professionalized consumption. When a leisure activity becomes professionalized or more serious, individuals who engage in such activity assume the role of both producers and consumers in their field (Seo, 2016; Stebbins, 1992).

Many professional players start playing games as leisure, but it becomes their full-time job, as they devote their youth to becoming the best. Professional players are also called "cyber-athletes" (Whalen, 2013). This term emphasizes the similarities between professional gamers and traditional sports players. For these groups, playing competitively matters more than it does for players who play for fun (Seo & Jung, 2016). It is a serious activity which can be compared to playing sports (Wagner, 2007). Past researchers determined the degree of seriousness of play by analyzing the level of skill involved and the level of obedience to the established rules of esports. To maintain their skills at the highest level, players are expected to practice persistently, just like traditional sports players. A critical component of the deliberate practice model is the number of hours spent practicing a skill and participating in a particular performance domain (Ericsson et al., 1993). Murphy (2009) looked at esports players for traits that were commonly found in the concepts of sport psychology literature, such as achievement motivation, fitness, teamwork, competition, flow, transfer of skill, leadership, and psychological skills (Lieberman, 2006). Moreover, professional esports players must obey socially constructed rules of esports, especially in public presentations like tournaments and video streaming, and players must "routinize and sustain" these rules (Seo, 2016).

High Gameplay Skill

The most distinguishable characteristic of professional players is that their gameplay skill is at the highest level among the entire player group. Esports players exhibit their skill in public spaces (virtual or physical), and their performances act as content that many general players can enjoy while watching esports. Past research on video games has shown that significant differences exist between novice and expert game players in terms of skill. The expert group shows enhanced short-term memory, executive control/self-monitoring, pattern recognition, visual-spatial abilities (e.g., object rotation), and task-switching efficiency, along with more efficient problem-solving skills (Faust et al., 2013). Skilled components would likely include psychological, technical, cognitive, and emotional aspects of performance (Janelle & Hillman, 2003). Being an expert in esports requires an intellectual capacity to understand all the mechanics of the game, teamwork to play as a team, and better skills to overcome the opposing team (Hinnant, 2013).

Physical Skills

Reeves et al. (2009) observe expert players in Counter-Strike, another esports game, and summarize the different skills required to play competitively in the first-person shooter (FPS) genre of esports games. Since FPS games require higher levels of reflex and control, this study illustrates technical skills with more detail compared to other skills. Skilled movement in Counter-Strike allows players to manage their appearance and presence. A good movement consists of an accurate mouse movement that enables the player to direct their viewpoint and keyboard control that directs their character's movement and other functions like reloading and crouching (Reeves et al., 2009). Witkowski (2012) suggests other important technical skills are motor skills, naturally mapped movement, bodily engagement, body control, and haptic engagement. Movements of expert-level Counter-Strike players are skilled, practiced, and timely (Witkowski, 2012). In Counter-Strike, the "sporting movement" is acquired by maintaining a controlled body while navigating the surroundings, moving the character accurately with accordance to the team, physically executing with the muscles and tendons of the hands and fingers, and the subtle control of breathing (Witkowski, 2012). Hinnant's (2013) study on League of Legends (LoL) players states that physical acuity may not be as important in LoL as it is in football or baseball; however, some physical aspects like hand-eye coordination and micro-control are important. In multiplayer online battle arena (MOBA) and real-time strategy (RTS) games like LoL and StarCraft, technical abilities such as landing manually targeted skills and rapidly manipulating different characters' actions at the same time distinguish novice and expert players (Hinnant, 2013).

Cognitive Skills

Under cognitive skills, two related aspects contribute to expertise in sport: tactical skills and decision-making capabilities (Janelle & Hillman, 2003). Faust et al. (2013) argue that competitive StarCraft players perform on a different level than novice players in terms of strategy. Novice StarCraft players operate simple strategies with slow actions, while expert players think multiple steps ahead with faster, time-efficient decisions and actions (Faust et al., 2013). Teams develop strategies over repeated matches, and anticipation about recurring flashpoints (strategically important spots) helps build better strategies (Reeves et al., 2009). Expert players choose the right tool for the job (Reeves et al., 2009) such as the right weapon in Counter-Strike and the right champion selection in LoL. Awareness is another category of cognitive skills. Reeves et al. (2009) suggest that top-notch players have a high understanding of the terrain, or 3D virtual environments, in the games they play. Also, the presence and awareness of other players give them information about how they should move and play effectively.

Social/Communication Skills

During gameplay, a player's perception is circumscribed by the character's visibility range. By communicating with their teammates, players can fill out their limited peripheral awareness. By using visual (tabs or pings) and audio (voice chat) communication methods, the team can create an informational advantage over the opponent team and leverage that information to move in strategic ways (Reeves et al., 2009). Chen's (2009) investigation suggests that discussion and reflection among team members lead to less of a catastrophic loss after a team's failure during a game. Communication and coordination based on trust are the keys to the success of a team (Whalen, 2013). Failure to control one's emotion is recognized as immature as well as detrimental to gameplay (Whalen, 2013). Peña and Hancock (2006) found that in-game messages between online players contained more socio-emotional information than task information, which suggests that players instinctively understand the importance of caring for each team member's emotions and mentality. Moreover, professional esports players must obey the socially constructed rules of esports, especially in the public's presence during tournaments and video streaming, and players must "routinize and sustain" these rules (Seo, 2016).

Player Experience Research in Esports

The term player experience, or PX, is a combination of “player” and “user experience.” It is also referred to as Game User Experience, or GUX. Playability was a term that refers to the usability of video games (Desurvire et al., 2004), and maintaining it was in the interest of industry game developers (Isbister et al., 2008). However, usability is about the easier use, efficiency, and productivity of the software, and it is not the right criteria for evaluating video games. In a similar context, video games are sometimes called a form of art (Jenkins, 2005; Gee, 2006). Video games combine participatory stories, exploratory environments, graphic elements to present mood and scenery, and satisfying sensory effects (Nacke & Lindley, 2010). Video games include complex environments, and video game players have diverse purposes other than productivity.

Beyond the usability of video games, a player’s comprehensive experience while playing video games has become the interest of PX researchers, who seek to understand “how and why people choose to interact with digital entertainment products” (Nacke, 2010). PX research in the early stage aimed at investigating the “emotional, social, and cognitive components of the experience emerging from the interaction between players and a gaming system,” but at the same time, it only focused on the user experience that happens while the user is interacting with the game software (Nacke & Drachen, 2011).

While early human-computer interaction research (HCI) focused on “[k]nowing your user,” a new influx of contemporary HCI heads toward “making an impact” (Rogers, 2012). The HCI community at this moment has “shifted from efficiency and profit of product towards altruism and alleviating fear, improving lives of impoverished and disadvantaged through designing innovative technology solutions (Rogers, 2012).” In the same direction, PX researchers started to look at the player's experience both before and after gameplay. Nacke and Drachen (2011) suggest three different layers of player experience: concretely graspable and technical game system experience, experience produced by perceptive and operational actions of the player, and interaction with other players, games, and technologies. To simplify, the game system, player, and context are the three layers of player experience and interaction, and the most influential among them is the player. These three layers change over time, and the temporal progression shapes gameplay experience over time (Nacke & Drachen, 2011). Figure 1 describes the abstraction of player experience.

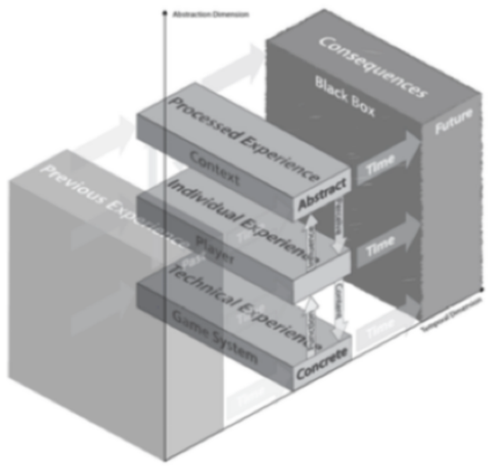

Figure 1. The PX framework in overview (Nacke and Drachen, 2011)

Johnson et al. (2015) analyzed the player experience of games from different genres, focusing specifically on the MOBA genre. MOBA games such as League of Legends, DOTA, and Heroes of the Storm comprise the largest portion of professional esports, and there is a large population that plays these games and follows their leagues regularly. The study found a lack of many components of PX that motivate players' engagement in MOBA games compared to other games. In brief, all esports genres (MOBA, FPS, RTS) showed lower scores than action, adventure, or roleplaying game (RPG) genres in player-needs satisfaction (Johnson et al., 2015).

Moreover, the MOBA genre showed higher levels of frustration and challenge, but lower immersion than all the other genres (Johnson et al., 2015). Overall, the play experience of esports includes several types of negative emotions compared to games of other genres.

Competition

As stated above, esports emphasizes multiple players' competition more than narratives or immersion into the virtual environment (Taylor, 2012; Ma et al, 2013; Seo & Jung, 2016; Witkowski & Manning, 2017; Witkowski, 2012). Competition is an important factor in traditional sports, which "drives many people into the world of sports," and this competitive nature is perceived as a central trait of esports by players (Railsback & Caporusso, 2018). The primary purpose of playing esports is to win, and it creates higher tension while playing, which could lead to both positive and negative experiences. In Johnson et al. (2015), a high frustration level was observed in MOBA games, and it was derived from the focused competition that occurs in MOBA games. The frustration is often stressful to the players, but at the same time, it leads to a higher retention rate of players. In a study on esports consumption motives, competition was revealed as a factor that had a significant impact on the time spent on esports games (Lee & Schoenstedt, 2011). Carter and Gibbs's work (2010) on the EVE Online esports tournament also states that players frequently showed "a desire to compete at a high level," and the high-level competition appeals to players who participate in esports. Losup et al. (2014) observed that while friendship is the main tie of a network in other online games, MOBA players were also motivated by their adversaries.

Challenge and Achievement

The theory of flow (Csikszentmihalyi, 1992) is frequently used to describe the experience of challenge and resolution in player experience. The experience of facing challenges is closely matched with players' problem-solving skills and is rewarding in online games (Leavitt et al, 2016). Unlike other online games, esports has a steep learning curve, and it generates a high frustration level (Hinnant, 2013; Johnson et al. 2015). It might even prevent novice players from entering a new esports game. However, the experience of overcoming those barriers also motivates players. Users highlighted the steep learning curve and difficulty of games in an interview study by Johnson et al. (2015), but they received a greater satisfaction from overcoming the challenges that a game presents (Johnson et al., 2015).

But the value of the challenge and achievement provided by esports games was also often doubted by them. A former collegiate athlete admitted that "playing video games offered him the opportunity to pursue a tangible goal that filled a void in his new life," and half of the participants mentioned the "hollowness and staleness" of individual achievement in video games (Bowers, 2011). There is room to study the addiction of young students to esports games, focusing on the "moderately challenging and achievable goals" of esports, which they hardly experience in a classroom.

Communication and the Social Aspects of Esports

Team play is an essential part of esports activities, especially in MOBA games where the synergy of each player's role is an important part of a winning strategy. Losup et al. (2014) determined that in MOBA games, teamwork was a key element of in-game success. HCI researchers, especially in the Computer-Supported Cooperative Work (CSCW) community, started to pay attention to how multiplayer-game players cooperate to accomplish their goals (Kou & Gui, 2014; Freeman & Wohn, 2018). There are different types of teams that can be observed in esports: general players who are randomly matched with strangers by the matching system of the game; players who play with their friends (online or offline); and on the higher end, professional or amateur teams who have fixed members with whom they play or practice regularly. Based on the context of the play, different patterns of communication behavior were found in these different groups.

The social aspect of esports was found to be very important among general players. In MOBA games, social relationships such as same-clan membership and friendship can improve the gameplay experience (Losup et al. 2014), and social interaction with familiar people is a core reason why players enjoy MOBA games (Johnson et al., 2015). In youthful stages of life, friendship is a natural outcome of esports practices like the formation of teams and gameplay behavior (Freeman & Wohn, 2018). Emotionally supportive communication often leads to more intimate or romantic relationships, but sometimes the high commitment to victory and the demand for skills can create feelings of frustration, make players feel like they are babysitting, or destroy the affiliated emotional satisfaction (Freeman & Wohn, 2017). Regardless of deviance or toxicity, playing with friends is predicted to increase the retention rate for play (both short and long term) at all levels of experience. Moreover, playing with friends was the only significant predictor of long-term retention for the most experienced players (Shores et al., 2014). In Johnson et al. (2015), participants showed a preference to play with "at least one friend on their team."

Compared to gameplay with friends, collaboration with strangers is usually lightweight and informal (Kou & Gui, 2014). But players still recognizes that collaboration is even more important than individual skill in the game. Players discipline themselves to keep a positive attitude and communicate in an appropriate way (Kou & Gui, 2014) as a common strategy for good performance. Even if they meet a teammate with lower skills, they help them and talk to them in a positive way (Kou & Gui, 2014). Interestingly, this cooperative behavior resembles that of permanent teams in other genre games. There is no designated leader in randomly matched temporary teams in esports, but leadership still emerges as people follow those who perform well, have positive attitudes, or make meaningful calls (Kou & Gui, 2014).

Unlike gameplay with friends or fixed team members, voice chat is used less often in communication among strangers. Using text chat can help task performance because it enhances more frequent communication, but players use text chat for socio-emotional rather than task-related chat (Leavitt et al, 2016). Using text chat is distracting within time-constrained and competitive gameplay (Innocent & Haines, 2007), so team coordination with strangers is limited compared to other groups. Thus, other types of nonverbal communication methods are provided by game developers to enable synchronous communication. A ping system is one of the nonverbal alerting signals that enables brief communication between users. Leavitt et al. (2016) examined the impact of pings on performance. There was mixed evidence of the effect (players who ping more tend to kill more but also die more), but junglers, a specific role that normally has more visibility than other teammates, used pings more frequently to warn of possible dangers to other teammates or to collaborate with other players to ambush the opponent (Leavitt et al., 2016). However, the ping system is sometimes misused to insult teammates: pinging multiple times (spam pinging), or pinging question marks on the spot where their teammates died are generally perceived as toxic behavior that abuses teammates (Kou & Gui, 2014).

In some cases, playing with strangers is preferred over playing with friends. Playing with strangers carries the risk of meeting disturbing people, but it also provides a chance to meet “amazing” people (Kou & Gui, 2014). Some players like the competitive atmosphere in a fair setting. Ranked games in LoL have a solo-only queue to avoid unfair matchmaking, and it offers the expectation of average teammates (Kou & Gui, 2014) with a similar level of skills.

Toxicity and Tilt

A problematic player behavior, toxicity, appears a lot in esports gameplay, and it is perceived as a prevalent culture in esports. Toxic behavior is a subset of deviant behavior that is considered “un-sportsmanlike” and includes sending negative messages or intentionally helping the opponent to make allies lose (Shores et al., 2014). Moeller et al. (2009) mention cheesers (players who exploit the weakness of the program and bend the rules in esports), pullers (players who intentionally disconnect to avoid losing), and glitchers (players who hit buttons rapidly in mashing combinations to exploit glitches to their advantage) as examples of unsportsmanlike behavior that negatively affects the system. But even in professional esports matches, mocking or provoking another player is partially allowed, depending on the severity. This can be a natural behavior that comes from the culture of sports. Conmy et al. (2013) measured the effect of trash talk in a competitive setting on self-efficacy and found higher self-efficacy and a positive effect when players were in an environment that allows trash-talking. Also, players in competitive settings (ranked games) exhibited more deviant behavior than players in normal-mode matches, and players with more knowledge showed more deviance (Shores et al., 2014).

In general, toxicity generates deviant play (or trolling) and it negatively affects gameplay. Players may intervene in other players’ toxicity to regain order and win the game back (Kou & Gui, 2014). In the long term, toxicity discourages players from playing, particularly by decreasing new player retention rates (Shores et al., 2014). Game developers see it as problematic and have proposed a set of community norms to prevent toxic behaviors from players. One such example was Riot Games’ implementation of a “summoner’s code” to list desirable and undesirable player behaviors (Riot Games, n.d.). Kou and Nardi (2016) defined the behavior that starts antisocial communication as “flaming” and found that Riot Games’ reputation record system (the Tribunal system) was effective in regulating toxic behaviors.

Another term that refers to this phenomenon is tilt, where “players are triggered by a person or event in the game which generates frustration and other negative emotions, and in turn starts to negatively impact decision-making and gameplay overall” (Wu et al., 2021). The term tilt originated from pinball, where the machine would flash, “tilt,” when a frustrated player hit the machine (Duncan, 2015). Another context where the term tilt is used is gambling, referring to poor money management and poor self-control (Browne, 1985), losing control of negative emotions (Wei et al., 2016), or letting any emotion (positive or negative) impact reasonable decision making (Schull, 2016).

Methods of Esports Player Experience Research

Ethnography/Interview

In the early stage, researchers from game studies and information science conducted ethnographic research to explore esports players and the structure of esports events. Chee (2006) went to Korea to explore PC Bang (an internet gaming cafe) culture and conversed with young players. Researchers attended early esports events and tournaments and interacted with players, spectators, and organizers (Reeves et al., 2009; Taylor & Witkowski, 2010; Taylor, 2012; Wimmer, 2012). Some researchers investigated players in virtual spaces, and they participated in online communities like developer communities or gaming clans (Moeller et al., 2011; Kou & Nardi, 2016; Witkowski & Manning, 2017) or Twitch chat rooms (Kow & Young, 2013). As esports player experience consists of diverse social contexts, ethnography methods are useful in studies that explore game-related activity in the real world.

Survey

A Game Experience Questionnaire (GEQ) has a modular structure comprised of the core questionnaire, the social presence module, and the post-game module (IJsselsteijn et al., 2013). The core module assesses game experience scores on seven components: immersion, flow, competence, positive and negative effect, tension, and challenge (IJsselsteijn et al., 2013). The social presence module and post-game module supplement the core module by including the peripheral context of playing games. A Game Engagement Questionnaire (GEnQ) is used to measure the engagement level of players from a psychological view. The engagement of players includes shared academic concepts of video game and psychology such as immersion, flow, dissociation, and presence (Brockmyer et al., 2009). These measures are often combined and modified to fill in the gap between gaming experience and esports experience (Nacke & Lindley, 2009; Gerling et al., 2011).

Lee and Schoenstedt's (2011) motivation study uses 14 sports consumption motivation scales from sports science; social interaction, fantasy, identification with the sport, diversion, competition, entertainment, sport knowledge application, arousal, design/graphics, to pass time, control, skill building for playing an actual sport, permanence, and peer pressure were brought from existing scale of sports science, while game participation, televised sports viewing, purchase of team merchandise, using the internet specific to the sport, using print media about the sport, listening to radio content specific to the sport, and game attendance were added to adapt the scale to esports players (Lee & Schoenstedt, 2011).

Core Elements of the Gaming Experience (CEGE) is a theory that identifies the necessary elements to provide a positive experience while playing video games (Calvillo-Gámez et al., 2015; Bernhaupt, 2015). The CEGE model presents two core elements of a gaming experience:

video game (gameplay and game environment) and puppetry (control and ownership) (Calvillo-Gámez & Cairns, 2008). The CEGE Questionnaire (CEGEQ) was developed to measure the behavior of players and capture the CEGE from their play. It provides 38 questions and seven different scores from them: enjoyment, frustration, CEGE, puppetry, video game, control, facilitators, ownership, environment, and gameplay (Calvillo-Gámez et al., 2015; Bernhaupt, 2015).

Nuyens et al. (2016) used three self-report questionnaires to measure impulsivity in MOBA players: the Problematic Online Game Questionnaire (preoccupation, overuse, immersion, social isolation, interpersonal conflicts, and withdrawal), a short version of UPPS-P (Urgency, Premeditation, Perseverance, and Sensation-seeking Positive urgency), and the Barratt Impulsiveness Scale (motor impulsiveness, cognitive impulsiveness, and non-planning impulsiveness).

Telemetry

Game telemetry is data logged from clients or servers about how players play games or about how the game client itself responds to player behavior (Drachen, 2015). Game telemetry is a relatively new trend in game user experience analytics (El-Nasr et al., 2013), which refers to all kinds of data collected about game development, production, post-launch management, and player behavior (Drachen, 2015). Such data can be collected from the back end of the game, through a client or a game server. Every single event in a game, such as using an item or firing a weapon, can be fetched on a large scale. Unlike a lab environment, the telemetry method allows an analysis of players in real-world interactions and of long-term player behavior that lasts weeks or even longer (Weber et al., 2011). Another advantage of behavioral metrics is that it does not disturb players during their actual play or during the test session. It fosters a natural environment for the users (Drachen, 2015). However, the usage of game telemetry data within the industry has been limited so far because the method of merging telemetry data and the player experience is not yet perfect (Drachen A., 2015). Also, since video games are often run by private businesses, many available datasets remain confidential, inaccessible by the public (Drachen et al., 2009; Drachen & Canossa, 2011; Weber et al., 2011).

Recently with the wide spread use of datamining and machine learning, the data science field uses esports data to build and validate predictive models. The prediction of player behavior is an important topic in data science in esports because interaction among people is more precarious than the interaction between a user and their system. Weber et al. (2011) built a regression model to predict the number of games a user played based on different situations in Madden NFL 11. It measures peer behavior's effect on user retention. For example, the opponent's action of disconnecting from the game is negatively correlated to that player's retention. Goyal et al. (2018) quantified the co-play performance of MOBA players and created a framework that recommends teammates, performing better than the linear model. Encounter detection is done in DotA matches to capture the most important moment of the match and even to predict the winner of the game (Schubert et al., 2016). Hodge et al. (2017) use in-game metrics data of DotA, such as the number of kills, amount of damage, total XP gained, and gold earned, to predict the game result in the MOBA genre using logistic regression and random forest method. Both methods were used because logistic regression estimates the importance of individual characters on the result of the match, and random forest considers combinations of characters (Hodge et al., 2017).

Natural Language Processing

Natural language processing is applied in communication research in esports. A large corpus is retrieved from a massive chat log of Twitch or even from the live speech of shoutcasters.

Barbieri et al. (2017) analyzed Twitch chat corpus using a long short-term memory bidirectional recurrent neural network (LSTM BRNN), a bag-of-words (BoW) classifier, and the skip-gram model to classify emotes and isolate interchangeable troll emotes from them. Musabirov et al. (2018) found temporal patterns of topic groups and topic inequality of viewer's voice by measuring the chat log during a series of esports events with the Gini coefficient. Olshefski (2015) built a model that detects the game-changing event by applying pattern analysis on shoutcasters' speech during a game.

Physiology

There are diverse types of physiological data that researchers can collect from players. Game developers frequently utilize eye trackers to collect visual attention and gaze movement, generating heat maps and gaze point maps (Sundstedt et al., 2016; in El-Nasr et al., 2016). Nacke (2015) recommends diverse physiological methods such as electromyography (which detects whether or not muscles are active and measures the activation and control part of the user's action), electrodermal activity and galvanic skin response (which measures the level of skin conductance), cardiovascular measures (which include electrocardiography, heart rate, heart rate interval, heart rate variability, blood volume pulse, and blood pressure), and electroencephalography (also known as EEG, which measures the frequencies and amplitudes of the user's brainwaves) (Nacke, 2015).

Heart rate variability (HRV) is widely used to measure stress level in many fields, including clinical situations, and assumes that HRV is a noninvasive and reliable index of stress (HG Kim et al., 2018), evaluating the sympathovagal balance—the autonomic state resulting from sympathetic and parasympathetic influences (Sztajzel, 2004). HRV displays the capacity of the heart to respond to internal or external stimuli, including physiological and environmental stimuli (Pollatos et al., 2017). Even without active body movement from the user, extrinsic factors adjust HR and HRV levels at rest and during times of stress (Anderson, 2020). Low HRV is associated with defective regulatory and homeostatic autonomic nervous system (ANS) functions, reducing the body's ability to recover from internal and external stress factors (Mccraty & Shaffer, 2015; HG Kim et al., 2018). An advantage of incorporating HRV is that measuring HRV is simple and affordable, and it is collected in real-time (Anderson, 2020).

Physiology measurement generates a huge set of data while users play a game in a lab setting, but it is hard to tie it to the actual evaluation of player experience. Also, the measurement method of player experience interrupts the interaction flow of the players and often takes them out of the present (Drachen, 2015). It is important to understand how to make this method valuable for the evaluation and improvement of player experience (Nacke, 2015). One good example of research concerning this problem is Mirza-Babaei et al.'s biometric storyboards. It visualizes the biometric data as a journey map, and it incorporates the user's comments on the journey map as a storyboard (Mirza-Babaei et al., 2012). The users do not need to be interrupted because the physiological metric data can be collected without disturbing users while they conduct the task, and the data can be correlated to the qualitative comments of the users after they finish the task.

Summary

Compared to the analytic research of esports in the past, this study provides several advantages in understanding esports player and team behaviors and performance. First, it enables tracking of data for selected users as opposed to relying on collecting enough data from enough players through purely remote methods to meaningfully analyze their behavior at different skill levels. Second, past studies collected the data of random users from open data sources such as application programming interfaces (APIs) (Sapienza et al., 2018). While that approach is suitable for collecting large amounts of data on which to train and test machine learning models, it does not consider the gameplay's context because the API data cannot capture fine-grained variables vital to understanding team communication, coordinated play, and physiological changes in behavior under stress. This study will provide a novel methodological example of a data-driven esports study that compiles various types of data, and it will help to create a comprehensive understanding of esports players.

Chapter 3: Methods

Participants

Recruitment Criteria and Eligibility

To document meaningful behaviors and response changes of players, participants were required to have a certain level of experience and understanding of the game. League of Legends has a ranking system for competitive games, and it has nine different ranks: Iron (~top 96.8%), Bronze (~top 82.3%), Silver (~top 46.7%), Gold (~top 15.3%), Platinum (~top 3.0%), Diamond (~top 1.0%), Master (~top .16%), Grandmaster (~top .042%), and Challenger (~top .013%) (Milella, 2021). For our study, only the players who were ranked above Bronze in League of Legends were selected because ranked games are only available to players who have reached level 30 in normal matches (determined by the number of matches played) and own at least 20 different champions (Juras & Lupasco, 2021). Also, Iron players were filtered out because they are at the bottom 5% of all ranked players and considered to not have enough experience and understanding of the game.

To compare changes across different player groups, participants from different levels of team cohesion and game skill were recruited. Participants were identified as "team" players if they registered as a full team of five players and they had played as a team of five more than 10 times before they registered. Participants who individually registered were identified as "solo" players. Criteria for the skill level was again their player rank in League of Legends. The Bronze to Gold 4 (top 95.7%~38.9%) (Juras & Lupasco, 2021) players were categorized as game novices in skill level, and Gold 3 and above (top 38.9% to .013%) (Juras & Lupasco, 2021) players were categorized as game experts in skill level.

Thus, participants were categorized into four groups, divided by the team expertise level and the game expertise level. A participant played with or against nine other participants from the same group. For example, “team experts” were a team of high-rankers who registered as a team of five players, and they were matched against another “team experts” by researchers. For solo groups, researchers manually selected 10 solo players to create two teams for a session, considering the balance of their game skill level.

In total, 120 players were recruited for 12 sessions for four player groups. Players were asked to play three matches during a session. One player did not show up at the session and was replaced by a substitute player with the same team and game expertise level but was not counted as a study subject and no data was collected from them ($N = 119$).

Recruitment

This study was approved by the University of California, Irvine Institutional Review Board. Institutional Review Board approval (Appendix A) was obtained prior to study recruitment.

Participants were recruited from nine University of California (UC) campuses and high schools that participate in a nationwide esports league (North America Scholastic Esports Federation, NASEF). All study sessions were conducted remotely during the pandemic era of 2020 to 2021, and the study participants were recruited via emails to relevant departments; online flyers on course learning management systems (i.e. Canvas) of classes within the Department of Informatics at the University of California, Irvine; emails to students who participate in NASEF league; and online flyers on social media (i.e. Discord) of esports-related groups at UC campuses (i.e. esports programs at different campuses and student gaming clubs).

When registering, participants were given the options of team or solo participation and informed of their eligibility based on their ranks in the League of Legends. As a reward, participants kept the heart rate monitor they used for the study session (worth $70) and a $20 Amazon gift card. To incentivize group participation, participants received an extra $25 Amazon gift card if they participated as a full team.

Demographics

Among 119 participants, 100 participants were male (84.0%), 15 were female (12.6%), and 4 were non-binary (3.4%). Although this study does not count gender as a variable, our participant pool is skewed with respect to gender due to the male-dominant pool of esports players in general. Our pool is found to be similar to the gender distribution from another study of this research group on over 400 participants in the NASEF population (male: 91%, female: 9%) (JS Lee et al., 2021). 29 participants (24.4%) were minors (under 18 years old), and 90 participants (75.6%) were adults (18 years and older).

Regarding their assignments to different groups, half of the participants were ranked between Bronze and Gold 4, and the other half were ranked between Gold 3 and Challenger. Figure 2 shows the age and rank distribution of the study participants.

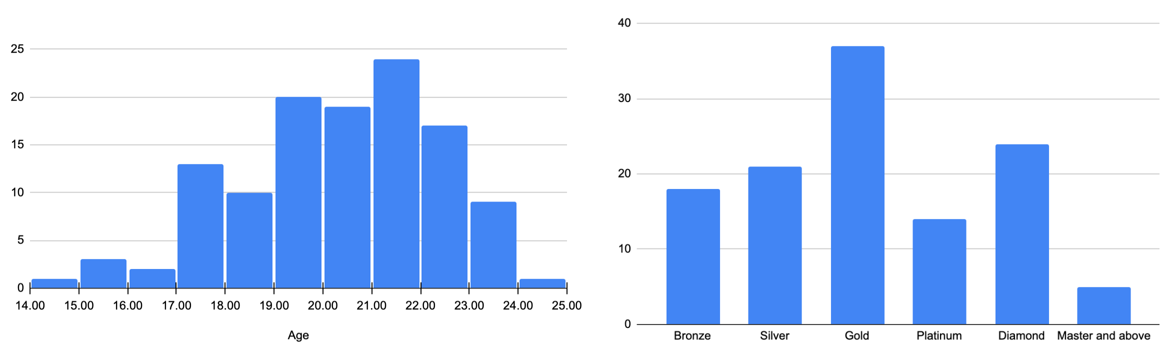

Figure 2. Age and Rank of Participants

Study Procedure

With COVID-19 restrictions in place, in-person study sessions were not allowed by the university. The entire study session procedure was conducted remotely, online. Figure 3 is a diagram that illustrates the entire study procedure.

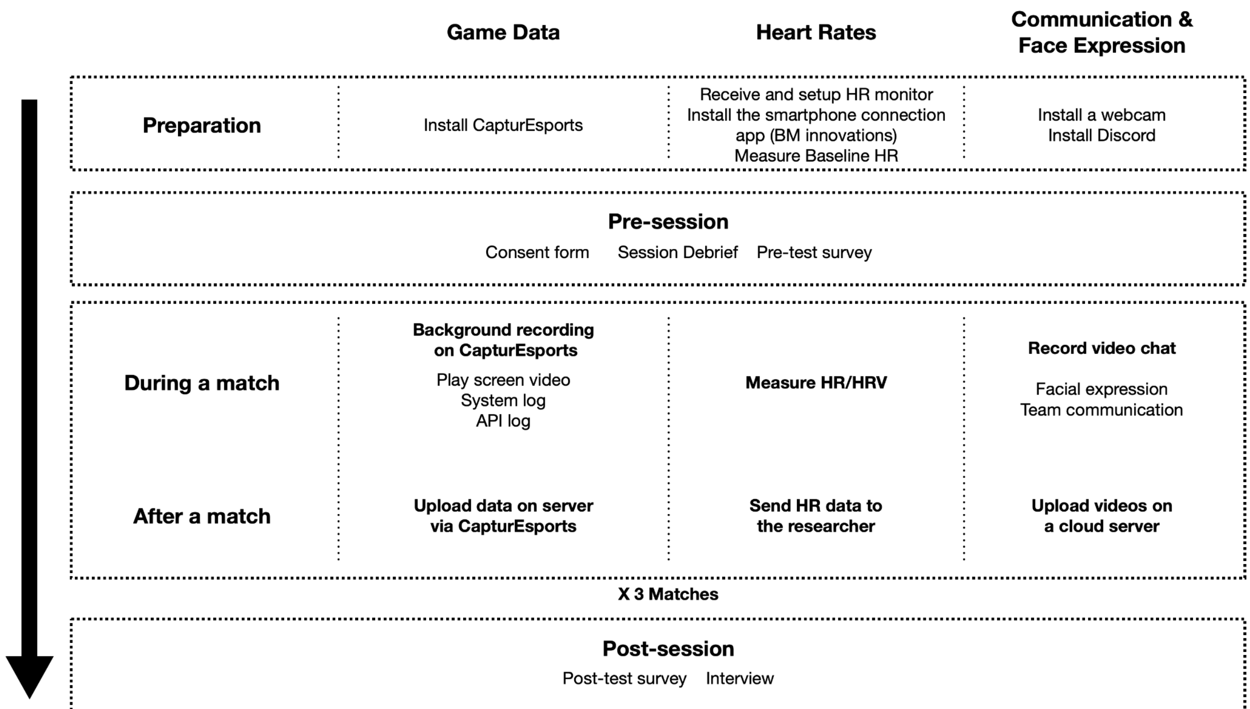

Figure 3. Diagram of the study procedure sorted by data types

Upon participants' consent (and parental consent for minor participants), researchers obtained participants' mailing addresses through emails and sent a wearable heart rate monitor, equipment required for the study session and the participation reward at the same time.

Prior to the session, researchers sent each participant instructions to install an in-game event-logging application (CapturEsports) on their PC, to set their webcam or smartphone to record facial images, and to install a heart rate tracking application (BM innovations GmbH) on their smartphone.

After setting up their devices, they were asked to measure their baseline heart rate for 5 min while in relaxation, export the heart rate data from the mobile application, and send it to researchers via email. This was intended to assist participants in learning how to use the gear and to troubleshoot any issues before the session date. It minimized any confusion during the actual study session that might affect the variability of the heart rate data. Researchers guided participants remotely but thoroughly to calibrate their devices at their own residences. For the accuracy of the data, participants were asked to not eat or drink food or beverages with caffeine on the day of heart rate measurement to relax for more than 15 min prior to beginning the measurement. Participants were given a pretest survey on Qualtrics asking for their demographic information.

As a study session started, all researchers and participants joined a voice chat server created by researchers using a Voice over Internet Protocol (VoIP) app (Discord). Researchers debriefed the entire study procedure to the participants over the voice chat. After the debrief, participants were assigned to two teams as determined beforehand by researchers if they were not naturally grouped as a participating team. The two teams were physically separated throughout the whole session to prevent any possible interaction between teams, including the inadvertent sharing of team-sensitive information. Participants then joined a video chat channel on Discord divided into two teams. Throughout the session, researchers recorded their communication and facial imagery simultaneously on a combined screen.

After checking the setups, participants were asked to play a series of three custom matches of League of Legends on a default map (Summoner’s Rift). Matches were made in a custom game, with the Tournament draft pick which has the same pick and ban system as solo-only ranked games.

Upon starting each match, participants were asked to start recording their game by using CapturEsports, a research-purpose application developed by researchers. While participants play games, CapturEsports records telemetry data, their gameplay screens, and the voice chat audio from players' computers. At the end of each match, participants finished recording under the direction of researchers, and the application fetched match summative data and match timeline data from Riot Games' API. Researchers advised participants how to upload all data files to the UC Irvine ICS server via the CapturEsports app.

During the session, participants were also asked to wear a chest band heart rate monitor (Garmin HRM Dual or Polar H10) to measure their heart rates throughout the game. Participants started heart rate tracking before and ended after each match under the direction of the researchers. Once a session finished, participants were guided to export the heart rate data using a smartphone application (BM innovations GmbH) and send it to a researcher via an encrypted email. The heart rate monitor and the post-test monitoring application measure and collect the participant's heart rate (BPM and Δ of R-R interval) every second.

Participants played three matches in a one-time session. To measure participants' emotional changes after successive matches, they were asked to play three back-to-back matches. They played with the same teammates throughout all three matches, regardless of their participation as a team or as a solo player. Players went through the tournament rule pick/ban draft which mimics the process of character selection in regular ranked games. The average length of a match was 28 min, 56 s (*SD* = 4 min, 53 s), and it varied from 19-39 min depending on participants' gameplay (see Figure 4 for the histogram of game length). After each match, participants were given a 5-min break. During the break, they could freely communicate with their teammates about the debrief of the last game and the game plan of the next game, but they could not communicate with the opposing team.

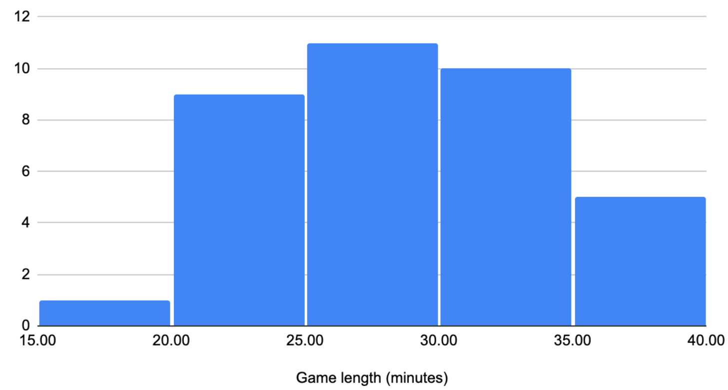

Figure 4. Length of Games

Immediately following the series of three matches, participants completed a post-test survey (5-7 min), and one player from each team was asked to participate in an interview for another study (20-30 min). The whole session procedure took 3 to 4 hours, depending on the length of the matches and the time to set up the participants' equipment. Participation rewards were distributed within a week after the session finished.

Measures and Data Points

Target Game: League of Legends

For the gameplay session, a MOBA esports title *League of Legends* (Riot Games, 2011) was selected. Apart from having the widest fan base in the world among all esports games (Webb, 2019), League of Legends was the most adequate title for the study because it has an organized API that is open to the public unlike other popular esports titles, such as Overwatch or Heroes of the Storm. This study also incorporated the LoL API and Software Development Kit (SDK) to develop an add-on app that collects participants' play data.

Data Collection Application: CaptureEsports

The research team developed a third-party application called CapturEsports. CapturEsports collects four types of telemetry data (event log, keyboard/mouse log, match summary, and match timeline log) in JSON format (see Appendix B for sample data) and records a gameplay video file from each participant (see Figure 5 for a screenshot of in-game video).

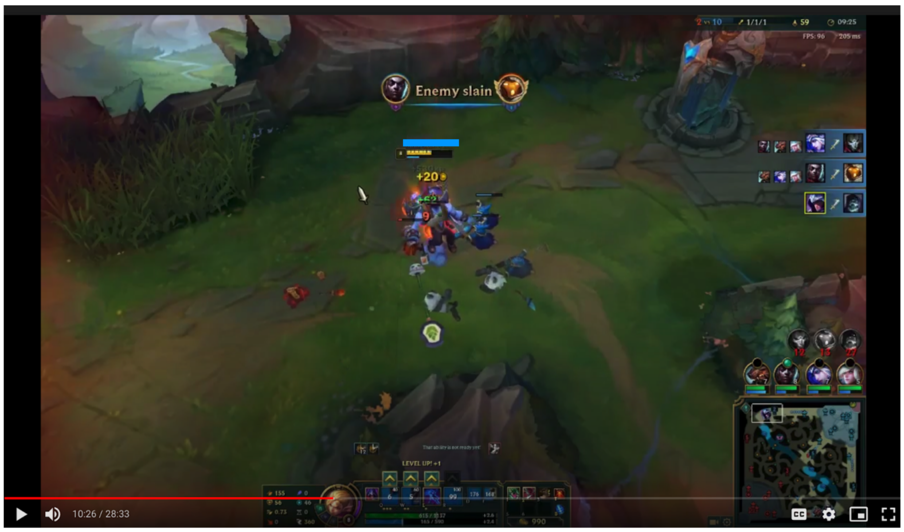

Figure 5. Screenshot of user-recorded video via CapturEsports (username is masked)

CapturEsports was developed as a data collection tool for esports research in general, and this study was the first research project that implemented the application for data collection. The design of CapturEsports reflected the particular needs of this study, such as synchronizing timelines of the logs from remote users' systems and monitoring study sessions from the researcher's view. It is designed to serve both user types (participants and researchers), and a user can select one of the user types when signing in. Installed on a participant's PC, the application records participant game telemetry data and uploads it to the researcher's server. For researchers, it supports session monitoring and database management.

CapturEsports is developed on Overwolf (Overwolf, n.d.), a third-party app platform for gamers. Overwolf supports SDK and development API (Overwolf., n.d.) for various esports games and gives developers access to game telemetry data and user logs. It has its own app store where developers can distribute their applications. CapturEsports is also registered on the Overwolf app store, but it was developed for a research purpose only and was not open for public download. Instead, participants were given a direct link to download and install the application.

Before each match, a session code is created by researchers and given to participants. A new Asterix database is created on the server with each new session code. While a participant is signed in with a session code, an ID number is assigned to the user, and their in-game data is saved on the database that matches the session code and ID number. A researcher can sign in under the researcher role, and they can manage session codes and monitor the recording status of the user logged in the session.

When a participant runs the application while playing a game, it records the game client screen, event logs of the game, and keystrokes in the background. While the application is active, an indicator (a small, blinking red dot with a timer) appears at the bottom left of the screen to inform the user that they are being recorded. In order to prevent an invasion of privacy, the recording function is active only when the game client window is in the foreground, and it is disabled when the match ends or the user switches to another window during a match. Users can start or cancel recording at any time, and the data is stored on the user's hard drive before they choose to upload it. Since each user is on a different system, their local system time may vary. CapturEsports synchronizes timestamps of all events across all users and converts them into in-game time.

After a match ends, the app fetches match log JSON files from the Riot API using the match ID created by the API. Two types of logs—match summary and match timeline—are requested from the API, and the application automatically fetches the responses and stores them on the user's hard drive. After all data files were saved on their hard drive, participants were asked to upload their data on the researcher's server via the application. All data files, including the game log JSON files and videos, are uploaded to an Asterix database hosted by the UC Irvine ICS server. In case the server was overloaded due to the large size of video files, participants were asked to browse and upload their video files manually on the research group's secured cloud storage.

In-Game Log Data

As described above, CapturEsports collects four types of in-game log data (event log, keyboard-mouse log, match summary, and match timeline log). This study did not incorporate keyboard-mouse log data because there was little connection between player input and the variables of interest.

The event log records game information (e.g., game start time), individual events (e.g., ability use, level up, and kill/assist/death events), and game-wide events (e.g., kill/death of other users, objectives, building kill). Individual events are logged through the game client, and the shared events are logged from the in-game announcer's comments which are delivered to all players during the game. All events are marked with a synced timestamp and an in-game timestamp so they can be incorporated with other types of data (e.g., heart rate and emotion).

While the event log was recorded directly from the game client, match summary and match timeline data were fetched from the Riot Games API. After each match, participants are asked to enter the match ID into CapturEsports. By using the given match ID, the application automatically requests and fetches response data from the match information API and the match timeline API. The match summary contains overall information and the result of the game (e.g., game duration, kill/death/assist of each user, and the number of buildings destroyed), and the match timeline contains the list of events and event information in temporal order (see appendix B for sample data).

Gameplay Video

CapturEsports captured individual user game client screens and voice chat audio input in 720p MP4 video format. Capturing individual screens allows researchers to conduct a quantitative analysis of the gameplay. It provides detailed information about the user's in-game behavior such as movement, skill combos, text chats, pings, and teamwork, which are difficult to explore with telemetry data. To supplement the areas of the map blinded from each participant's view, a spectator view of the game was recorded by a researcher in 1080p MP4 format. Researchers could either move freely around the map with a spectator view or let the automated spectator camera track the spots where an important event was happening (team fights or objective fights). It shows less information about the individual players (e.g., skill cooldown time and voice chat) but reveals the areas hidden from the player's view and helps the researcher understand the game in a wider context.

Physiological Data*: *Heart Rate and Heart Rate Variability

To measure participants' stress levels, their heart rate was measured during a match. Participants wore a chest band heart rate monitor during each session. Heart rate monitors were connected to participants' smartphones via Bluetooth, and a commercial application (Heart Rate Monitor by BM innovations GmbH) was used to record and export the data. Upon completion of the measurement, participants were asked to send the CSV files of heart rate data saved in the application to researchers.

From among the different models of commercial heart rate monitors, Garmin HRM Dual and Polar H10 were selected because they have been proven to be accurate for use in research by relevant past studies (Weaver et al., 2019; Portuese et al., 2020; Rothschild et al., 2021), and they are not obtrusive so as to interfere with participants' play activity. Both models are chest band heart rate monitors, which are highly reliable compared to the wristband heart rate monitors typically implemented in smartwatches (e.g., Apple Watch) (Weaver et al., 2019). Chest band monitors record the user's heart rate in more detail; while wristbands measure heart rates irregularly (every 5 to 8 seconds), chest band monitors measure heart rates consistently and show results every second. While wristband smartwatches are designed for everyday use, chest band monitors are designed for advanced activity tracking and provide more accurate data and are frequently used for clinical research (HG Kim et al., 2018).

Out of 12 sessions, Garmin HRM dual was used in the first six sessions, and Polar H10 was used in session 7 to 12. To find potential differences between two heart rate monitors, the researcher tested two monitors by wearing two models of monitors at the same time and measured while playing a match of League of Legends for five minutes respectively. To test the equivalence of two monitors, Welch's two one-sided t-test (TOST) was used to test the mean HR and HRV. In both HR and HRV, null hypotheses of statistical differences were rejected (see table 1) and the measurement of two monitors was found to be equivalent enough.

Table 1. T-test result between participants groups with different models of equipment

	Garmin HRM Dual	Polar H10	Epsilon	df	p-value
Mean HR	130.54	130.51	1	2398	0.019
Mean HRV	5.85	5.92	1	2397.8	<0.001

Both models of heart rate (HR) monitors used for the study measure heart rate in two ways: beats per minute (BPM) and R-R interval (the time elapsed between two successive heartbeats). In general, heart rates are displayed as beats per minute (BPM), calculated to the average number of heartbeats per minute. However, the mean value over time does not reveal that the behavior of the heartbeat is irregular when measured on a beat-to-beat basis (McCraty & Shaffer, 2015). Heart rate variability (HRV), is the fluctuation in the length of heartbeat intervals (HG Kim et al., 2018), and it shows the capacity of the heart to react to various physiological and environmental stimuli (HG Kim et al., 2018). Lower HRV correlates with impaired regulatory and homeostatic autonomic nervous system functions, which adjust an individual's physical ability to cope with stressors (HG Kim et al., 2018). This study incorporates the root mean square of successive differences between normal heartbeats (rMSSD) to measure HRV as past studies recommend (Task Force of the European Society of Cardiology the North American Society of Pacing Electrophysiology, 1996).

Facial Expressions and Emotion

Participants' emotions were measured by observing facial expressions during gameplay. Video of participants' face cam was recorded, and it was processed and analyzed by Microsoft Azure's Face API. Microsoft Azure's Face API is an AI service that analyzes faces in images (Microsoft Azure, n.d.). It has a range of possible usage scenarios (e.g., face verification and face detection), and this study incorporates the emotion recognition feature of the service. The Face API automatically locates human faces in an image and extracts eight different emotions from a face: neutral, happiness, surprise, sadness, anger, disgust, fear, and contempt. Multiple emotions can be extracted from one facial expression, and all present emotions are recorded as a ratio from .0 to 1.0 (the sum of all emotions is always 1.0). Figure 6 shows an example of a set of emotions extracted from a facial expression image.

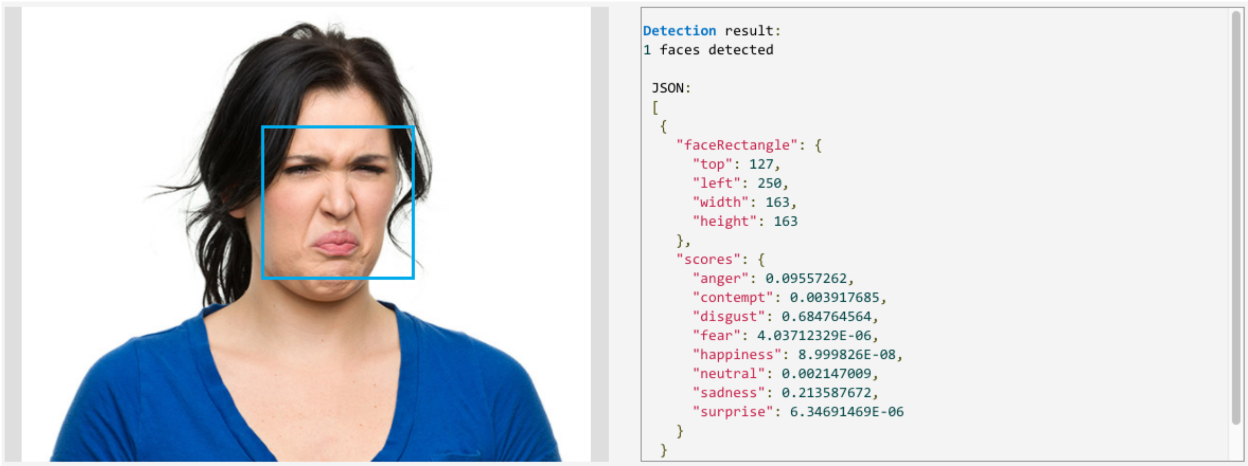

Figure 6. Example of a set of emotions detected from a facial expression (dakkusingh, 2017)

Participants used their own webcam or smartphone to join a video chat with their teammates on a VoIP application (Discord). Not only was it a channel to communicate with their teammates during the match but also a method for researchers to record participants' real-time face expressions. Participants were guided in correctly positioning their cameras to show the fronts of their faces under proper lighting to minimize noise and errors in the AI detection process. Two researchers joined each team's video chat room and recorded the participants' faces in MP4 formats (720p at 30 fps). One match session naturally generated two videos, and each video contained five faces (figure 7).

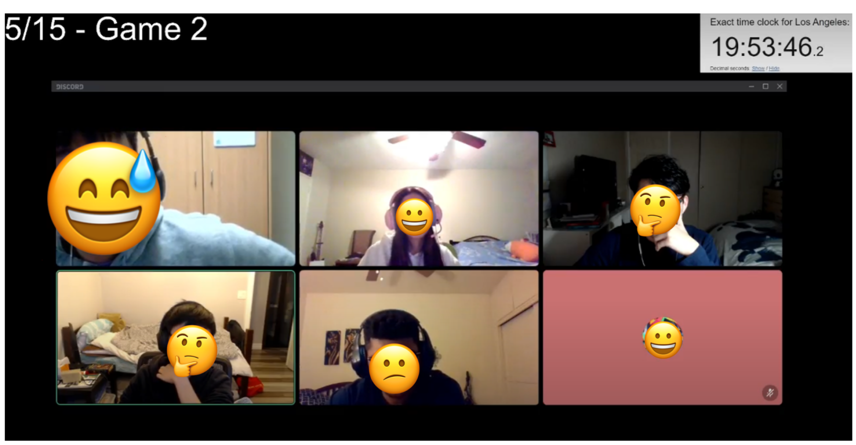

Figure 7. Screenshot of participants' face recordings (identifiable information is masked)

After a session, videos were manually trimmed and synchronized to match the in-game timeline. To process facial images with Azure Face API, each video was sliced into a set of images. A video was captured every 0.25 s, generating 4 images per second by using the OpenCV library in Python 3. A Python code developed by the research team automatically sent each image to Azure Face API, requested the analysis, and fetched relevant data (face location and emotion). The code automatically identifies each participant's face by their location in each image, selects dominant emotions (an emotion that comprises more than 40% of an instance of emotion and can be either a single emotion or mix of two emotions), and saves them in a CSV file.

Communication

Players' team voice chat and in-game text chat were recorded to investigate the verbal communication of the participants. As described above, participant's audio conversations with their teammates were recorded from the video chat. In-game screen recordings from individual and spectator views included in-game text chat. In addition, the usage of pings (a nonverbal in-game communication method used to make a signal to another player) was observed during the video observation.

Analysis

Data cleaning

Time Sync. This study required data collection from diverse sources of data points. Sources included telemetry data from game clients, observation from gameplay video, heart rate data measured from the human body, and AI recognition of emotions from face cam videos. Such data were collected from different devices and systems, which sometimes caused a dislocated timeline between different data types.

The start and end times of all types of data measures must be synchronized. Neither did the game telemetry data provide the exact game start time, nor could the researchers record the exact start time of each game during the session. In a custom game mode of League of Legends, a spectator view is streamed 3 minutes behind the players to prevent potential cheating in competition settings. Since researchers were not able to monitor the participants' screens in real time, the exact start time was calculated by syncing the audio from individual game recordings and the face cam video marked with the exact network time. The portion of the face video recorded before the game started was trimmed before processing for emotion analysis.

Heart rate measurement began when the user started recording on their smartphone app, so each user had a different start time. The CSV data file created by the app contains the measurement start time, and each row shows the heart rate of every second. Using the actual start time of the game, the unnecessary rows at the beginning of the heart rate data were removed.

The duration of each game was provided in seconds (i.e., 1,800 for a 30-min game) by the Riot Games API data. However, it disagrees with other data measures when a participant pauses the game during a match. Game pauses happened in 13 of the 36 matches, as players paused the game when they had a problem with their equipment setup or temporarily lost their internet connection. When a player pauses the game, the game becomes unplayable for all other players, and the in-game timeclock stops until the player unpauses the game. Timeline displacements happen because in-game event logs use the in-game timeclock while heart rate measurement and face recordings use human time. While a game is paused, HR and emotion measurement continue regardless of the game pause. Thus, the game pause durations must be removed from the HR and emotion data.

Missing or Bad Data. Unlike clinical or experimental settings, this study was done remotely from participants' residences. This fostered an environment similar to the actual setting of esports play where all players play and communicate from their homes over the internet. But researchers could not have full control over participants' equipment, which caused missing or bad data.

For HR and HRV analysis, out of 357 participants, 153 participants were removed because they contained missing or invald baseline data (abnormally high delta R-R intervals, HRV>150), and 204 participants were analyzed. Among successful cases, event periods with invalid HRV data were considered invalid data and filtered out. Those invalid HRV typically occurred by a participant's posture or movement that temporarily positioned the heart rate monitor in a wrong spot. After cleaning the entire dataset, 4979 data points were used for the final analysis.

For facial expressions, 30 participants were missing or dropped out of 357 participants (327 valid participants). Those were typically caused by bad positioning or angling of the camera, dark lighting of the participant's room, an unstable internet connection, or a lack of the user's system's graphic resources to handle both gaming and camera recording. In cases where the AI failed to recognize the face, the emotion was recorded as N/A and not counted in the analysis.

Variables of interest

Stressful Events. Among the events from the event log and match timeline log, events that would negatively affect the participants' emotions were selected as stressful events. Table 2 below is the list of all stress event types, categorized by different triggers of stress. The four categories were brought from the research team's past study on the "tilt" of esports players (Wu et al., 2021).

Table 2. List of event types and categories

Category	Event type	Data source	Description and criteria
Team	Building destroyed	Event logs	Ally's building (towers and inhibitors) is destroyed by the enemy.
	Monster stolen	Event logs	A neutral monster that gives advantages to allies is captured by the enemy.
	Teamfight Loss	Event logs & Human observation	The player's team lost in a team fight where more than 3 players from each team were involved, and more than 2 players from the player's team were dead within 30 seconds. In cases of teamfight loss, other deaths (teammate death and/or my death) involved in the fight were removed and only the teamfight loss was logged.
	Repeated Teamfight Loss	Event logs & Human observation	The player's team lost in a team fight more than 2 times in a row.
Teammate	Teammate Death	Event logs	A teammate is killed by the enemy.
	Silence	Human observation	No communication among teammates for more than a minute, or no response from other teammates after a player's call.
	Toxic Communication	Human observation	Offensive communication toward the teammates. Either verbal (i.e. text and voice chat) or non-verbal (i.e. repetitive ping to blame a player's mistake).
Enemy	Backdoor	Human observation	The enemy infiltrated to destroy the ally's building (inner tower or inhibitor) or nexus in the late phase of the game (after the 10th minute), without exposing their position to the allies.
	Ambush	Human observation	The enemy hid and waited in a bush to kill the player.
	Instant kill	Event logs & Human observation	The player knew that the enemy was near them (within sight for more than 5 seconds) but killed the player from full HP within 3 seconds.
	Gank	Event logs & Human observation	The enemy roamed from another lane and cooperated to kill the player.
Myself	My death	Event logs	The player died, either by an enemy or neutral objects, but did not fall under any of the other categories that involve the player's death.
	Solo-killed	Event logs & Human observation	The player was killed by an enemy player during a 1-on-1 line fight.

Not all events were able to be captured from only the event logs. For example, the system logs a player's death but does not automatically identify whether it is a solo-kill or a gank (an underhanded defeat). Thus, some events required human observation for an exact classification. The research team consisting of the author and an undergraduate level intern researcher separately observed the recorded video, comparing the human-identified events with the log data. For event coding, researchers created a manual that contains the description of events and criteria to classify the events. The same research team with knowledgeable experience in League of Legends and esports in general have coded the events separately. Cohen's kappa (κ) was run to determine if there was agreement between two researchers. There was substantial agreement between two researchers, $\kappa = 0.643$. For the 49 event types with disagreements, researchers discussed together to find a concession.

Dependent Measures: Emotional Change before, during, and after the Event

While heart rate and facial expression were measured throughout a game, the research question is associated with emotional change before, during, and after stressful events. Thus, physiological changes during a specific time window were selected and analyzed for a change. The following section explains how the time window for each variable was selected, and how emotional changes were analyzed.

Heart Rate (HR) and Heart Rate Variable (HRV) For HR and HRV, 30 seconds before-during and after stress events were selected, considering the time window that is used frequently in past heart rate studies of the physiology field (Notterman et al., 1953; Borst et al., 1982) and from the repeated observation of researchers during study sessions. The length of pre-event period time would vary by the type of event (i.e. a long teamfight would last 30 seconds and an instant kill happens within 3 seconds). Fifteen seconds was a typical length of an in-game event conceded among players, and 30 seconds was long enough time window to cover all types of stress events. The length of the post-event period was decided by the past finding that “HR peaks 3-5 s after a stimulus and rapidly decreases between 12-20 s after an event” (Borst et al., 1982). In recent studies on wearable heart rate monitors, the minimum time window for measuring valid ultra-short-term HR and HRV is found to be 10 seconds for HR and 30 seconds for rMSSD HRV (Baek et al., 2015; Salahuddin et al., 2007).

Unlike other past physiology studies in a lab environment, however, in-game stressful events in this study are neither instant nor equal in their duration across different occasions. This study was conducted within realistic play settings and naturally, the start time and duration of each event are all different from each other. Moreover, the telemetry data does not provide when each event starts, but instead, where each event ends is marked in the telemetry data. For example, if a player was involved in a fight during the in-game time of 1:30 to 1:45 and was killed at 1:45, 1:45 is marked as 0-second point of the event. Therefore, all events are anchored to end at the 0-second point, and 30 seconds before and after that point are selected for analysis.

During this 60 second window, players undergo a stressful event in the following order: Baseline - Anticipation - Action - Recovery. The concept of different periods refers to past studies in physiology; Notterman et al. (1953) distinguished HR measurement periods as Basal - Conditioning - Extinction - Spontaneous Recovery. The concept of anticipation was additionally adopted from Epstein & Roupenian (1970) which measured HR through the phase of Anticipatory - Impact - Recovery. After events are concluded, players recover from the stress after a few seconds (Borst et al., 1982) and stress levels would decrease spontaneously (Notterman et al., 1953; Borst et al., 1982) until a new stimulus appears.

From the heart rate data, 3 different variables were calculated: time length of HR increase from lowest HR level to the end of an event (T_{Inc}), HR level increase rate (HR_{Inc}), and HR level decrease rate (HR_{Dec}). To measure these variables, 3 points of inflection in HR level were identified for every stress events: Pre-event dip (HR_{Pre}), Peak (HR_{Peak}), and Post-event dip (HR_{Post}). Each variable is selected to show different types of the impact caused by the stress event trigger. Figure 8. illustrates all variables related to heart rates. The curve in the figure is the most representative shape of a stress event observed from the data.

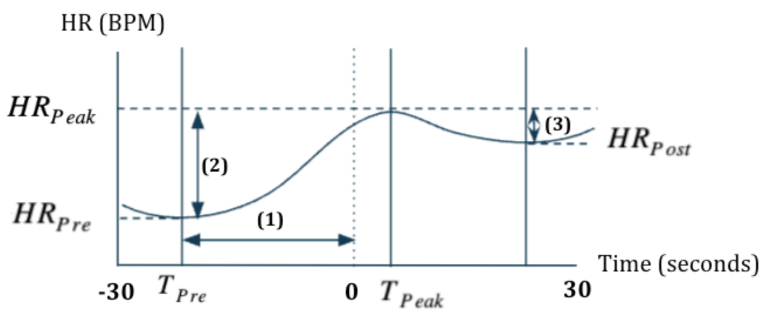

Figure 8. Variables of heart rates

(1) Time length of HR increase from the lowest HR to the end of an event (T_{Inc}): It is a time window where the participant's HR increased from the lowest HR level during the stress event. It was measured to identify how early the stress response started during or before an event. This can estimate the player's capacity of anticipating or recognizing an event to happen.

$$T_{Inc} = T_{0sec} - T_{Pre}$$

(2) HR increase rate (HR_{Inc}): HR level increase ratio from pre-dip to the peak level. The difference between peak and dip was divided by the baseline HR level (measured before the study session) of the participant to normalize the individual difference of HR level. It displays

how much the player's HR level increased by the stress event and explains the impact of the event on the stress level of a player.

$$HR_{Inc} = \frac{HR_{Peak} - HR_{Pre}}{HR_{Base}}$$

(3) HR decrease rate (HR_{Dec}): HR level decrease ratio from the peak to post-dip. Again, the difference between peak and dip was divided by baseline HR level of the participant to normalize the individual difference of HR level. It explains how much the player recovered from the peak stress level after a stress event ended.

$$HR_{Dec} = \frac{HR_{Peak} - HR_{Post}}{HR_{Base}}$$

From HRV data, 2 variables were calculated: HRV difference from baseline during an event(HRV_{Diff})and HRV change rate during and after an event(HRV_{Rate}). To measure these variables, HRV level during stress events, after stress events, and baseline HRV levels were measured. To calculate HRV variables, this study utilized the root mean square of successive differences between normal heartbeats (rMSSD) as past studies recommend (Task Force of the European Society of Cardiology the North American Society of Pacing Electrophysiology, 1996). See figure 9 for illustrations of HRV variables utilized in this study.

(4) HRV difference from baseline(HRV_{Diff}): The difference between HRV measured during the first 30 seconds of a stress event (HRV_{Pre}) and baseline HRV (HRV_{Base}). It suggests how much a player's stress level increases from their baseline level. Since lower HRV suggests higher mental stress, higher $HRV_{Diff}$is associated with higher negative changes in stress level.

$$HRV_{Diff} = HRV_{Base} - HRV_{Pre}$$

(5) HRV Change Rate (HRV_{Rate}): HRV was measured during the first 30 seconds and the second 30 seconds, and the change rate between HRV during two periods was calculated (HRV_{Rate}). A higher HRV_{Rate} implies that the player recovered better from the mental stress after a stress event ends.

$$HRV_{Rate} = \frac{HRV_{Post} - HRV_{Pre}}{HRV_{Pre}}$$

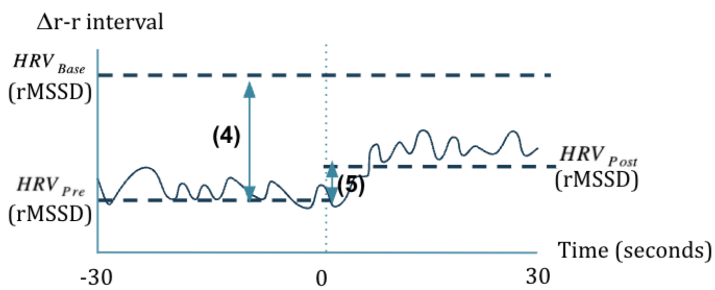

Figure 9. Variables associated with HRV

Statistical analysis of HR data Participants were repeatedly measured during a study session, and those observation cases violate the independence assumption. Thus, to perform linear mixed-effects analyses of the relationship between stress responses and events, R 4.1.0 (R Core Team, 2021), *lme4* package (Bates et al., 2015), and *lmerTest* package (Kuznetsova et al., 2017) were used. As fixed effects, game skill level, team cohesion level, match result, age, sex, in-game phase, and event category were commonly entered. Additionally, an interaction term between game skill level and team cohesion level was explored to find out if different team levels would generate opposite effects for different game skill levels, and tested for any significant gain to the model. As random effects, intercepts for subjects were entered. For the HRV change rate, the baseline HRV of the participant is added to the random effects because the dependent measure does not include the baseline HRV level. Visual inspection of residual plots did not reveal any obvious deviations from homoscedasticity or normality. P-values of models were obtained by likelihood ratio tests of the full model with the effect in question against the model without the effect in question.

Facial Expressions. Facial expressions of 3 seconds before and after events were selected (4 observations per second for 24 observations in total). Facial expressions were captured more frequently but for a shorter period of time because facial expression responses are much quicker and occur more frequently than HR and HRV. When more than one emotion is found in an image, only the top two emotions that comprise more than 10% of the facial expression were selected. To track emotional change before and after an event, emotions in the interest period were aggregated by seconds and counted by their frequency.

CHAPTER 4: Results

Descriptive Results of HR and HRV

Figure 10 and Table 3 show the average of all participants' HR and HRV at each second, from 30 seconds before to 30 seconds after all stress events (*n* = 10717). Mean HR (mean = 99.08) is above the baseline HR (81.53) and the in-game average level (97.81). Shortly after the moment of the stress event, the HR peaks (maximum = 99.62 at 3 second).

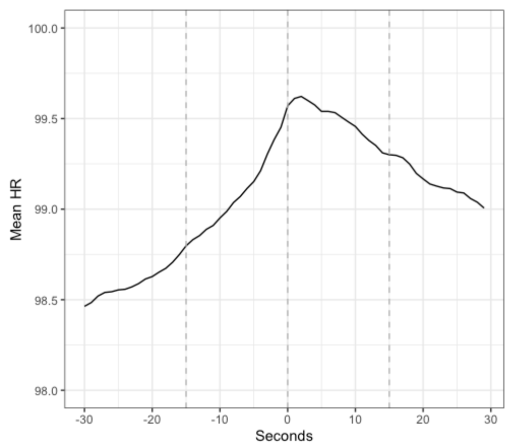

Figure 10. HR of 30 seconds before and after all stress event cases

Table 3. Descriptive statistics of overall mean HR

	N	Mean	SD
30 seconds before and after stress events	10717	99.08	17.06
In-game average	318	97.81	15.30
Baseline	106	81.53	12.94

The mean HRV around the stress event was 20.13 compared to 34.49 for the baseline and 22.78 for the overall in-game playing (See Table 4). When comparing the HRV (rMSSD) level before and after the stress event, HRV increased by 0.22 after an event ended. Based on observing both HR and HRV, players are more aroused during stress events compared to their relaxed baseline status and overall status while playing a game.

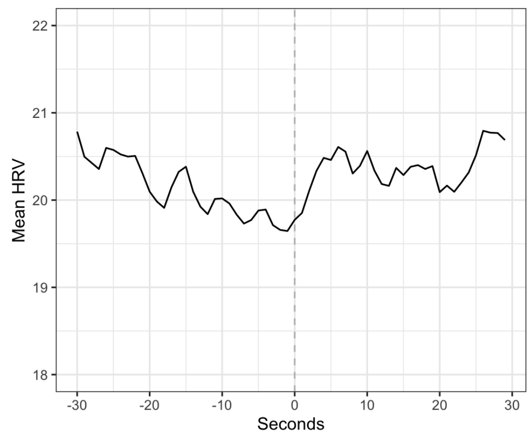

Figure 11. Descriptive statistics of overall mean HRV (rMSSD)

Table 4. Descriptive statistics of overall mean HRV (rMSSD)

	N	rMSSD
-30 second to 0 second	10717	20.13
0 second to 30 second	10717	20.35
In-game average	315	22.78
Baseline	105	34.49

Facial Expression

Table 5 shows participants' facial expression changes before and after stressful events. Overall, primarily neutral emotion was displayed, with happiness, surprise, and sadness comprising a smaller portion of the displayed emotions. Contempt, disgust, anger, and fear appeared to be marginal, constituting less than 1% of the entire emotional response dataset. The largest change was found in happiness (+3.2%p), constantly increasing during the 3 s before and after stress events. This result is different from our natural assumption and the result of HR and

HRV: players' negative emotions increase until a stress event happens and decrease after a stress event. However, it may not be appropriate to interpret happiness as a purely positive player emotion. Face API recognizes happiness by capturing a smile or a laughing face. In many cases, however, players' laughter shows mixed emotions of embarrassment, dismay, renouncement, relief, and absurdity.

Table 5. The ratio of emotion during 3 seconds before and after all stress events

(%)	-3~-2s	-2~-1s	-1~0s	0~1s	1~2s	2~3s
Neutral	80.8	81.1	80.8	79.8	78.8	78.3
Happiness	12.4	12.5	12.7	13.4	14.5	15.6
Surprise	4.5	4.3	4.3	4.5	4.1	3.7
Sadness	1.5	1.5	1.6	1.7	1.8	1.7
Contempt	0.5	0.4	0.4	0.4	0.5	0.5
Disgust	0.1	0.1	0.1	0.1	0.1	0.1
Anger	0.2	0.1	0.1	0.1	0.2	0.1
Fear	0.0	0.0	0.0	0.0	0.0	0.0
N of cases = 10717						

Linear Mixed-effects Models of HR and HRV Change

To investigate the impact of stress events on the stress response level of players, 5 different models of HR and HRV variables were fitted by using a series of linear mixed-effects models for each variable. Each model was predicted by game skill level, team cohesion level, match result, age, sex, in-game phase, and event category as fixed effects, and each participant as random effects. Estimate, t value, and p-value of each effect are reported, along with the 95% confidence interval of estimate.

Hypothesis 1 - HR response during the anticipation phase

Time from the lowest HR level to the end of a stress event (0-second point) was measured to identify how early the stress response started, which implies the better capability of anticipation and recognition for a stress event. Model 1 was fitted with the fixed effects and random effects, but did not yield a statistically significant gain in model fit over the null model, Likelihood ratio χ^2 (9)=11.655, p<0.234. In model #2, an interaction term between game skill level and team cohesion level was added as a fixed effect. This model yielded a statistically significant gain in model fit over model #1, Likelihood ratio χ^2 (1) = 5.893, $p < .05$, and a decrease in AIC from 36578 to 36574, indicating that this model is a better fit to the data without overfitting. Table 6 is the results for the fixed effects of the full model.

$$Model.null = T_{Inc} \sim (1 \mid ParticipantID)$$

$$Model\ \#1 = T_{Inc} \sim GameLevel + TeamLevel + Result + Age + Sex + Phase + EventCat + (1 \mid ParticipantID)$$

$$Model.full = T_{Inc} \sim GameLevel + TeamLevel + GameLevel * TeamLevel + Result + Age + Sex + Phase + EventCat + (1 \mid ParticipantID)$$

Table 6. Result of linear mixed models for time of increasing HR (T_{Inc})

Variable	Estimate	Std. Error	Lower Confidence Interval (Lower CI)	Upper Confidence Interval (Upper CI)	t	p
Intercept	21.450	2.311	17.100	25.751	9.281	<.001***
Game Level - Low	-1.689	0.650	-2.899	-0.479	-2.601	0.013*
Team Level - Low	-0.643	0.484	-1.547	0.260	-1.328	0.190
Result - Win	0.424	0.316	-0.167	1.044	1.341	0.181
Age	-0.088	0.101	-0.275	0.101	-0.874	0.387
Sex - Male	0.001	0.630	-1.168	1.171	0.001	0.999
Phase - Late	0.742	0.370	0.014	1.465	2.004	0.045*
Event Category - Myself	0.055	0.801	-1.515	1.622	0.068	0.946
Event Category - Team	-0.932	0.678	-2.254	0.401	-1.375	0.169
Event category - Teammate	-0.596	0.664	-1.889	0.710	-0.898	0.369
Game Level:Team Level	1.733	0.744	0.352	3.124	2.331	0.024*

In this model, higher game skill level, later in-game phase, and interaction between game skill level and team cohesion level were significant positive predictors of time to peak. Players with a higher game level started HR increase 1.689 [0.479, 2.899] seconds earlier than low game level players. Also, the model showed a statistically significant interaction between Game level and Team level, B=1.733, p<.05. The effect of team cohesion level on anticipation and recognition of an upcoming event was opposite for different game skill levels. Figure 12. provides a qualitative interpretation of this interaction: players with a higher skill level have an earlier HR response to an event when playing in a cohesive team (with teammates that they already know). On the other hand, players with a lower skill level showed a slower HR response to an event when playing in a cohesive team. Also, during the late phase of the game, players' HR increased 0.742 [0.014, 1.465] seconds earlier than during the early phase of the match.

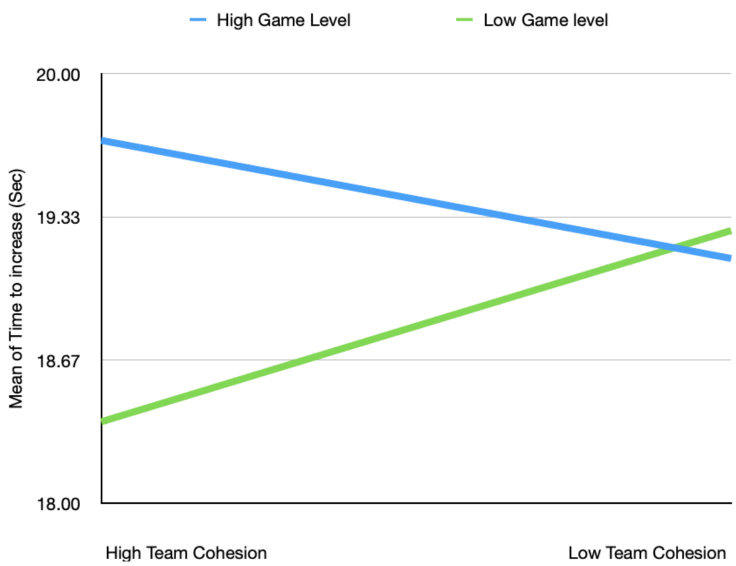

Figure 12. The mean time of HR increase for different team cohesion levels and game skill levels

Hypothesis 2.1 - HR Increase during the impact phase

HR increase rate during the stress event was calculated to measure the impact of the stress event on the increase of stress level. Model 1 was fitted with the fixed effects and random effects, and yielded a statistically significant gain in model fit over the null model, Likelihood ratio $\chi^2(9)=79.318$, $p<.001$, and a decrease in AIC from -10501 to -10563.

$$Model.null = HR_{Inc} \sim (1 \mid ParticipantID)$$

$$Model\ \#1 = HR_{Inc} \sim GameLevel + TeamLevel + Result + Age + Sex + Phase + EventCat + (1 \mid ParticipantID)$$

$$Model\ \#2 = HR_{Inc} \sim GameLevel + TeamLevel + GameLevel * TeamLevel + Result + Age + Sex + Phase + EventCat + (1 \mid ParticipantID)$$

In addition to the existing fixed effects, the interaction between game skill level and team cohesion level was explored (Model #2). However, Model #2 did not yield a statistically significant gain in model fit over the Model #1, Likelihood ratio χ^2 (1) = 0.418, p = .518 and increase in AIC from -10563 to -10561, indicating that Model #1 is a better fit to the data over Model #2 without overfitting. Table 7 is the results for the fixed effects of the selected model, Model #1.

Table 7. Result of linear mixed models for HR increase rate (HR_{Inc})

Variable	Estimate	Std. Error	Lower CI	Upper CI	t	p
Intercept	0.218	0.059	0.148	0.238	3.684	<.001***
Game Level - Low	0.008	0.012	-0.002	0.015	0.643	0.522
Team Level - Low	0.001	0.010	-0.000	0.015	0.059	0.953
Result - Win	0.008	0.004	0.006	0.017	2.264	0.024*
Age	-0.005	0.003	-0.007	-0.003	-1.970	0.053
Sex - Male	0.014	0.020	0.013	0.040	0.694	0.490
Phase - Late	0.009	0.003	0.003	0.016	2.901	0.004**
Event Category - Myself	-0.000	0.007	-0.017	0.011	-0.053	0.958
Event Category - Team	-0.028	0.006	-0.042	-0.018	-4.824	<0.001***
Event category - Teammate	-0.028	0.006	-0.040	-0.018	-4.788	<0.001***

In this model, winning match results, late in-game phase, Enemy, and Myself event categories were significant positive predictors of HR increase. During the stress event, the HR level of players who won the game increased 0.8% [0.6%, 1.7%] more than players who lost the game. In the later phase of the game, the HR level of players increased 0.9% [0.3%, 1.6%] more than in the early phase of the game. Events of the Enemy category and Myself category increased players' HR level 2.8% [1.8%, 4.2%] higher than events of Team and Teammate categories. Although not significant, age was negatively associated with the HR increase, indicating a 0.5% [0.3%, 0.7%] lower increase of HR by age increase of one year.

Hypothesis 2.2 - HRV difference from baseline level during the impact phase

The difference of HRV during the stress event from the baseline level was calculated to measure players' stress level during stress events compared to the baseline level. Model #1 was fitted with the fixed effects and random effects, and yielded a statistically significant gain in model fit over the null model, Likelihood ratio $\chi^2(9)=35.265$, $p<.001$, and a decrease in AIC from 34887 to 34869. In addition to the existing fixed effects, the interaction between game skill level and team cohesion level was explored (Model #2). Model #2 was fitted with an interaction term between Game level and Team level. It did not yield a statistically significant gain in model fit ($\chi^2(1)=2.915$, p=0.087), but AIC remained at the same number (AIC=34689), not overfitting the data. Also, even though Model #2 did not show a statistically significant interaction between Game level and Team level, it still showed an effect of the interaction term (B=-13.323, t=-1.714, p=.09). Thus, Model #2 was considered to be more appropriate as a model over the null model and Model #1. Table 8 is the results for the fixed effects of the selected model, Model #2.

Model.null: $HRV_{Diff} \sim (1 \mid ParticipantID)$

Model #1: $HRV_{Diff} \sim GameLevel + TeamLevel + Result + Age + Sex + Phase + EventCat + (1 \mid ParticipantID)$

Model #2: $HRV_{Diff} \sim GameLevel + TeamLevel + GameLevel * TeamLevel + Result + Age + Sex + Phase + EventCat + (1 \mid ParticipantID)$

In this model, game level, age, and in-game phase were significant positive predictors of HRV difference from the baseline level. A higher difference means a bigger drop of HRV during stress events, which implies a higher level of stress. Lower game level players showed higher

HRV differences by 15.23 [2.14, 28.66] during stress events. HRV difference increases by 3.50 [1.67, 5.43] as age increases by one year. Events in the later phase of the game increased the HRV difference by 1.36 [0.77, 1.96].

When exploring the interaction term between team cohesion level and game skill level, the effect of team cohesion level on HRV difference during stress events was opposite for different game skill levels. Figure 13 provides a qualitative interpretation of this interaction: players with a higher skill level showed smaller differences of HRV level (lower stress level) when playing with a team of higher cohesion level. On the other hand, players with a lower skill level showed bigger differences in HRV level (higher stress level) when playing with a cohesive team.

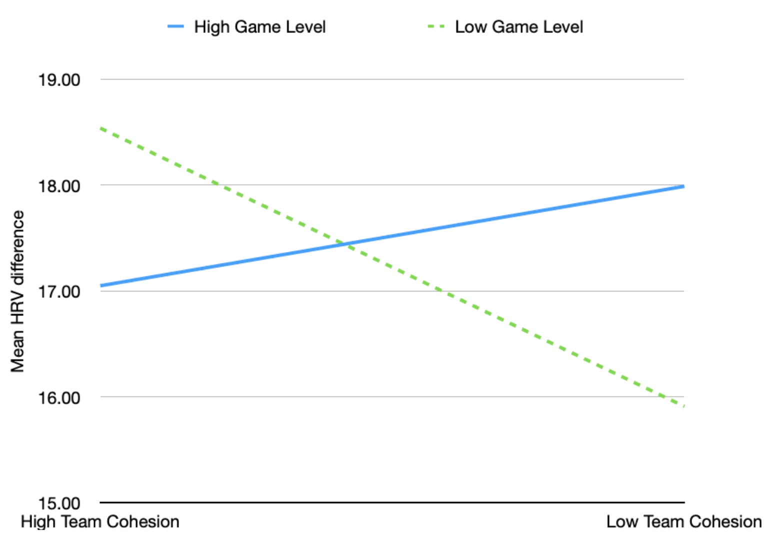

Figure 13. Mean difference of HRV level by different game levels and team levels

Table 8. Result of linear mixed models for HRV difference (HRV_{Diff})

Variable	Estimate	Std. Error	Lower CI	Upper CI	t	p
Intercept	-52.744	21.280	-95.91	-11.02	-2.479	0.015*
Game Level - Low	15.237	6.659	2.146	28.660	2.288	0.025*
Team Level - Low	2.416	4.946	-7.391	12.278	0.488	0.627
Result - Win	0.012	0.362	-0.698	0.722	0.033	0.974
Age	3.497	0.949	1.637	5.425	3.685	<0.001***
Sex - Male	-4.027	7.137	-18.233	10.147	-0.564	0.574
Phase - Late	1.364	0.302	0.773	1.956	4.520	<0.001***
Event Category - Myself	0.279	0.656	-1.007	1.564	0.425	0.671
Event Category - Team	-0.255	0.554	-1.341	0.831	-0.461	0.645
Event category - Teammate	-0.387	0.543	-1.450	0.677	-0.712	0.476
Game Level:Team Level	-13.324	7.772	-28.917	2.003	-1.714	0.091

Hypothesis 3.1 - HR decrease during the recovery phase

HR decrease rate during the stress event was calculated to measure how a player could recover from the peak stress level after a stress event. Model 1 was fitted with the fixed effects and random effects, and yielded a statistically significant gain in model fit over the null model, Likelihood ratio $\chi^2(9)=43.241$, $p<.001$, and a decrease in AIC from -11196 to -11221. In addition to the existing fixed effects, the interaction between game skill level and team cohesion level was explored (Model #2).

Model.null = HR_{Dec} *~ (1 | ParticipantID)*

Model #1 = HR_{Dec} *~ GameLevel + TeamLevel + Result + Age + Sex + Phase + EventCat + (1 | ParticipantID)*

Model #2 = HR_{Dec} ~ *GameLevel + TeamLevel + GameLevel * TeamLevel + Result + Age + Sex + Phase + EventCat + (1 | ParticipantID)*

However, Model #2 did not yield a statistically significant gain in model fit over the Model #1, Likelihood ratio $\chi^2(1) = 0.346$, $p = .557$ and increase in AIC from -11221 to -11219, indicating that Model #1 is a better fit to the data over Model #2 without overfitting. Table 9 is the results for the fixed effects of the selected model, Model #1.

Table 9. Result of linear mixed models for HR decrease rate (HR_{Dec})

Variable	Estimate	Std. Error	Lower CI	Upper CI	t	p
Intercept	0.207	0.058	0.095	0.318	3.554	0.001***
Game Level - Low	0.017	0.012	-0.006	0.040	1.401	0.166
Team Level - Low	0.006	0.010	-0.014	0.025	0.585	0.560
Result - Win	0.003	0.003	-0.004	0.010	0.933	0.351
Age	-0.005	0.003	-0.010	-0.000	-2.050	0.044*
Sex - Male	0.019	0.020	-0.018	0.057	0.971	0.335
Phase - Late	-0.005	0.003	-0.011	0.001	-1.673	0.094
Event Category - Myself	-0.009	0.007	-0.021	0.004	-1.317	0.188
Event Category - Team	-0.014	0.006	-0.025	-0.003	-2.523	0.012*
Event category - Teammate	-0.022	0.005	-0.033	-0.012	-4.091	<0.001***

In this model, age, Enemy, and Myself event categories were significant positive predictors of HR decrease. As age increases by one year, the HR decrease rate decreases by 0.5% [0.0%, 1.0%], which means a lower capacity to recover from stress after an event. HR decrease rate after Enemy category events was 1.4% [0.3%, 2.5%] higher than Team category events and 2.2% [1.2%, 3.3%] higher than Teammate category events. Also, the HR decrease rate after Myself category events was 1.3% [0.8%, 1.2%] higher than Teammate category events.

Hypothesis 3.2 - HRV increase during the recovery phase

HRV change rate during and after stress events was measured to find out how much players could recover from a stress event. Model #1 was fitted with the same fixed effects and random effects, but did not yield a statistically significant gain in model fit over the null model, Likelihood ratio $\chi^2(9)=11.782$, $p=.226$, and an increase in AIC from 10416 to 10422. Model #2 added Base HRV as another random effect because the dependent variable did not include different effects of baseline HRV, but the model obtained singular fit, indicating that the model is overfitting. Thus, HRV change rates during and after stress events were not able to be fitted with the fixed effects used in this study.

Model.null: HRV_{Rate} ~ (1|ParticipantID)

Model #1: HRV_{Rate} ~ GameLevel + TeamLevel + Result + Age + Sex+ Phase + EventCat + (1|ParticipantID)

Model #2: HRV_{Rate} ~ GameLevel + TeamLevel + Result + Age + Sex+ Phase + EventCat + (1|ParticipantID)+(1|BaseHRV)

Facial Expression Changes

Hypothesis 4 - Facial expressions

Facial expressions of players were analyzed to find out if stress events affected the emotional change of players. Facial expressions are displayed as a mean ratio at each second to show the change of emotion, but not statistically tested for significance. The result of this analysis can be understood as supplement findings to interpret the result from linear mixed models tested above.

Team Cohesion Level Table 10 and Figure 14 show the facial expressions of solo players (low team cohesion) and team players (high team cohesion) before and after stressful events. Contempt, disgust, anger, and fear were left out from this table and below because they comprised less than 1% of the entire emotional response dataset. For Figure 14, only Neutral and Happiness emotions were included because they comprised most part of the emotion, and show the biggest change before and after events. Overall, team players showed less neutral emotion and more happiness compared to solo players. Team players were more comfortable expressing their emotions because they have been playing as a team for a certain period and they know each other better than the other group. They could "laugh it off" when they encounter negative events.

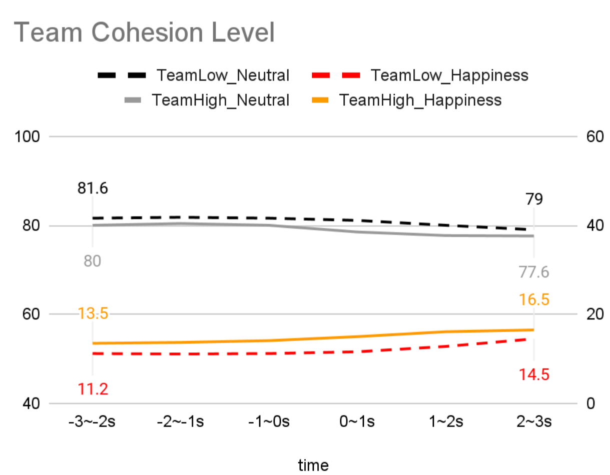

Figure 14. The ratio of Neutral and Happiness emotion by team cohesion levels

Table 10. Ratio of emotion before and after stress events by team cohesion levels

Solo (Case N=5152)						
(%)	-3s	-2s	-1s	0s	1s	2s
Neutral	81.6	81.8	81.6	81.1	80.0	79.0
Happiness	11.2	11.1	11.2	11.6	12.8	14.5
Surprise	5.0	4.8	4.8	4.8	4.4	3.9
Sadness	1.5	1.6	1.7	1.8	2.0	2.0

Team (Case N=5565)						
(%)	-3~-2s	-2~-1s	-1~0s	0~1s	1~2s	2~3s
Neutral	80.0	80.4	80.0	78.5	77.7	77.6
Happiness	13.5	13.7	14.1	15.0	16.1	16.5
Surprise	4.2	3.8	3.7	4.3	3.9	3.5
Sadness	1.4	1.4	1.5	1.5	1.6	1.5

Game Skill Level Table 11 and Figure 15 show the facial expressions of game experts (high skill level) and novices (low skill level) before and after stressful events. Overall, experts actively showed the emotions of happiness and surprise. Novices showed more “dull faces” compared to the experts. This implies that the experts understood what had happened and reacted more emotionally while novices did not perfectly perceive what was happening, resulting in less variability in their emotions.

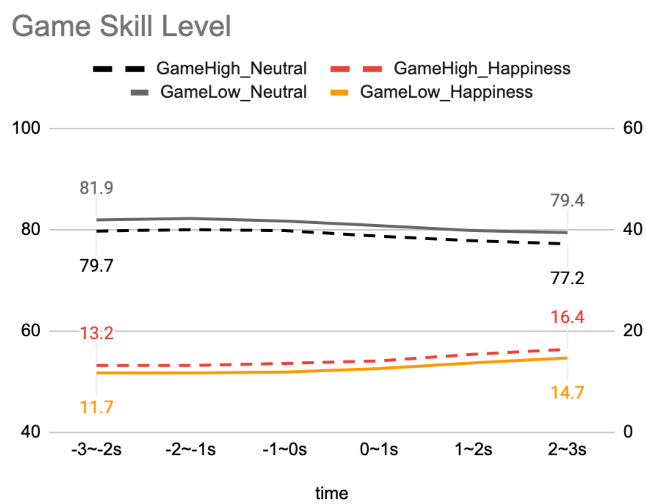

Figure 15. The ratio of Neutral and Happiness emotion by game skill levels

Table 11. Ratio of emotion before and after stress events by game skill levels

Expert (Case N=5202)						
(%)	-3~-2s	-2~-1s	-1~0s	0~1s	1~2s	2~3s
Neutral	79.7	80.0	79.8	78.7	77.8	77.2
Happiness	13.2	13.2	13.6	14.1	15.4	16.4
Surprise	5.7	5.4	5.1	5.5	5.1	4.7
Sadness	0.8	0.9	1.0	1.1	1.0	1.1

Novice (Case N=5515)						
(%)	-3~-2s	-2~-1s	-1~0s	0~1s	1~2s	2~3s
Neutral	81.9	82.2	81.7	80.8	79.8	79.4
Happiness	11.7	11.7	11.9	12.6	13.7	14.7
Surprise	3.5	3.3	3.4	3.6	3.2	2.8
Sadness	2.1	2.1	2.3	2.2	2.5	2.4

In-game Phase Players' facial expressions show similar trends as HR and HRV (see Table 12 and Figure 16). Players remained calm in the early game phase (higher neutral and lower happiness), and in the later phase, players were bolder in expressing their emotions (higher happiness).

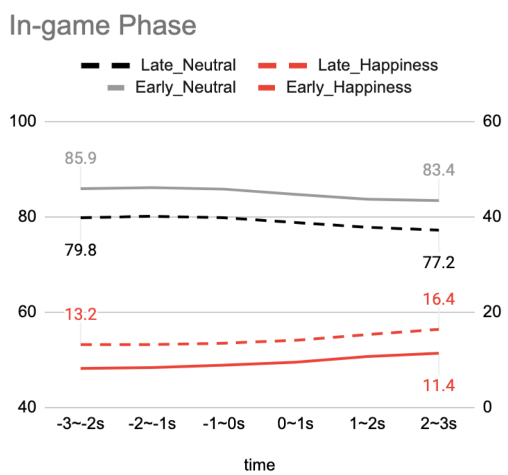

Figure 16. The ratio of emotion before and after stress events by in-game phases

Table 12. Ratio of emotion before and after stress events by in-game phases

Late (Case N=8984)						
(%)	-3~-2s	-2~-1s	-1~0s	0~1s	1~2s	2~3s
Neutral	79.8	80.1	79.8	78.8	77.8	77.2
Happiness	13.2	13.2	13.5	14.1	15.3	16.4
Surprise	4.6	4.4	4.3	4.6	4.2	3.8
Sadness	1.5	1.6	1.7	1.8	2.0	1.9

Early (Case N=1733)						
(%)	-3~-2s	-2~-1s	-1~0s	0~1s	1~2s	2~3s
Neutral	85.9	86.1	85.8	84.7	83.7	83.4
Happiness	8.2	8.4	8.9	9.5	10.7	11.4
Surprise	4.2	3.9	3.8	4.4	3.9	3.5
Sadness	1.2	1.2	1.1	0.9	1.0	1.1

Match Result In Figure 17, Happiness increased to a higher degree in winning games (4.1%p) than in losing games (2.5%p). Sadness trended in a different direction: while it shortly increased and then decreased back to its previous level in winning games, it constantly increased in losing games (Table 13). Players in a winning game could easily laugh off stress events. Thus, this confirms the finding from the HR and HRV differences that winning players can quickly recover from stress events.

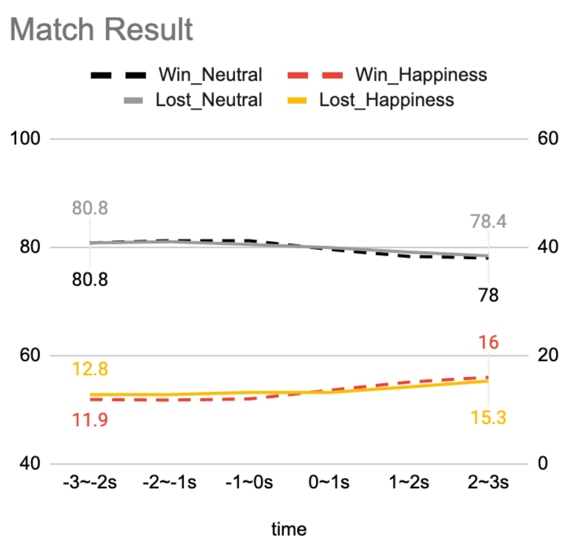

Figure 17. The ratio of Neutral and Happiness emotion by match results

Table 13. Ratio of emotion before and after stress events by match results

Win (Case N=3693)						
(%)	-3~-2s	-2~-1s	-1~0s	0~1s	1~2s	2~3s
Neutral	80.8	81.2	81.2	79.6	78.3	78.0
Happiness	11.9	11.8	12.0	13.6	15.1	16.0
Surprise	5.0	4.8	4.6	4.6	4.3	3.7
Sadness	1.4	1.3	1.5	1.6	1.4	1.3

Lost (Case N=7024)						
(%)	-3~-2s	-2~-1s	-1~0s	0~1s	1~2s	2~3s
Neutral	80.8	81.0	80.5	79.9	79.1	78.4
Happiness	12.8	12.8	13.2	13.2	14.2	15.3
Surprise	4.3	4.0	4.0	4.5	4.0	3.7
Sadness	1.5	1.6	1.7	1.8	2.0	2.0

Event Categories Patterns in players' emotional changes are largely differentiated by the event category (see Table 14 and Figure 18). After enemy and myself events, which showed earlier change and higher stress levels in HR, the ratio of happiness increased dramatically (12.3%p and 18.6%p, respectively) during the 3 s before and after events. As explained in the above section, happiness is derived from players' laughing in dismay or embarrassment. Events in the enemy and myself categories are more directly linked to a player's death, which causes a more drastic emotional change.

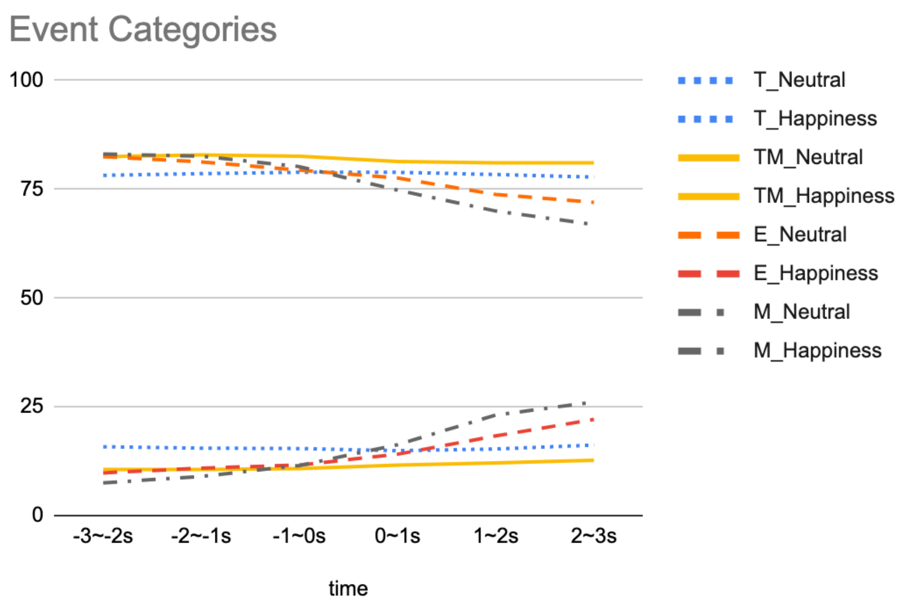

Figure 18. The ratio of Neutral and Happiness emotion by event categories

Table 14. The ratio of emotion during 3 seconds before and after stress events, separated by the event categories

Team (Case N=4393)						
(%)	-3~-2s	-2~-1s	-1~0s	0~1s	1~2s	2~3s
Neutral	78.2	78.6	78.9	78.9	78.4	77.8
Happiness	15.8	15.5	15.4	14.9	15.3	16.2
Surprise	3.9	3.7	3.5	3.9	3.7	3.6
Sadness	1.5	1.7	1.7	1.7	1.9	1.8

Teammates (Case N=5048)						
(%)	-3~-2s	-2~-1s	-1~0s	0~1s	1~2s	2~3s
Neutral	82.5	82.9	82.6	81.4	81.1	81.1
Happiness	10.6	10.6	10.8	11.6	12.1	12.7
Surprise	4.5	4.2	4.3	4.6	4.3	3.8
Sadness	1.6	1.5	1.6	1.7	1.7	1.7

Enemy (Case N=490)						
(%)	-3~-2s	-2~-1s	-1~0s	0~1s	1~2s	2~3s
Neutral	82.5	81.3	79.4	77.6	73.8	72.0
Happiness	9.8	10.9	11.6	14.1	18.3	22.1
Surprise	6.1	6.7	7.4	6.4	5.5	3.5
Sadness	1.0	0.9	1.3	1.5	1.9	1.6

Myself (Case N=785)						
(%)	-3~-2s	-2~-1s	-1~0s	0~1s	1~2s	2~3s
Neutral	83.1	82.6	80.2	74.8	70.0	66.9
Happiness	7.5	9.0	11.5	16.3	23.1	26.1
Surprise	7.3	6.8	6.2	6.4	4.3	3.8
Sadness	1.3	1.0	1.6	1.5	1.6	2.0

Chapter 5: Discussion

The primary goal of the present study is to assess the effect of diverse traits of players and in-game contexts on the stress level of competitive game players. This chapter will review and discuss significant factors found in the analysis, and propose potential directions for future research.

Game skill levels and team cohesion levels

In the current study, a higher game skill level of players was identified as a significant factor in deciding the time length of HR increase and HRV difference from baseline during stress events. The results indicate that players with a higher game skill level had a longer time length of HR increase, which implies earlier anticipation or recognition when an event occurs. Also, players with a higher game skill level showed a smaller drop of HRV during stress events, which implies a lower stress level. In other words, they were more prepared and could remain calm during stressful situations.

Shores et al. (2014) state, "players in the more competitive ranked matches were associated with higher toxicity indexes than players in normal matches." However, the present study results suggest an opposite finding that expert players are less likely to show higher levels of stress (measured by HRV) than novice players. But this study limits the time window of measurement within each stress event, and it does not represent the stress level from overall gaming activity. If the stress level throughout a match, or a series of matches were measured, it would show a different result that is aligned with Shores et al..

More importantly, an interaction effect between game level and team level was found to be significant in both models. There was an opposite effect of game skill level by different team cohesion levels on how early HR response started and how much HRV decreased during stress events. Players with a higher skill level could anticipate an upcoming event earlier when they played with teammates they used to play with frequently. On the other hand, players with a lower skill level responded slowly when they played with their regular teammates or friends. Also, players with a higher skill level could remain at a lower stress level when they played with familiar teammates. Contrarily, players with a lower skill level were under a higher stress level when they played with their regular teammates.

An assumption derived from this finding is that quality of communication matters more than the frequency of communication. During study sessions, the biggest difference between teams of high and low cohesion levels was the frequency of verbal communication; a much higher frequency of verbal communication was observed in a team of high cohesion levels. The exact frequency and content of the communication need to be further analyzed to verify this qualitative observation, but a higher frequency of communication does not always positively affect the gameplay. Highly skilled players benefitted from playing with their teammates by anticipating an upcoming event earlier and suppressing the increase of stress level (smaller HRV decrease). With their rich background knowledge and sensibility, high-level game players were able to share essential in-game information in a timely manner, which built constructive communication among teammates. For lower-level players, on the other hand, even if the frequency of communication was high, the quality of their communication made it ineffective in delivering information and controlling their emotions.

It echoes the past studies on the social aspect of esports that have pointed out the importance of team cohesion for play experience in some points. Having a regular team with friends or teammates to play as a team improves the gameplay experience (Losup et al. 2014), and social interaction with friends is a core reason to enjoy MOBA games (Johnson et al., 2015).

Regardless of deviance or toxicity, playing with friends is predicted to increase the retention rate for play (both short and long term) at all levels of experience. Moreover, playing with friends was the only significant predictor of long-term retention for the most experienced players (Shores et al., 2014). However, let alone that these are not directly related to the stress level during in-game events, current research could not find a significant effect of team cohesion on stress levels.

Players' Age and Stress Responses

This study found that age is associated with a significantly smaller decrease in HR after an event (poorer recovery), a bigger difference of HRV during an event (higher stress), and a marginally significant smaller increase in HR during an event (lower arousal). Considering the symmetric pattern of HR increase and decrease, the smaller decrease is related to maintaining homeostasis after a smaller HR increase. Thus, HR and HRV show opposite evidence of stress affected by age. Presumably, there are contradictory effects of age on the physiological stress response. Older players would be more capable of controlling their emotions compared to younger players because they have mature personalities, are more socialized in communication, and are less immersed in video games in general. On the other hand, aging is associated with a bad physiological capacity, resulting in lower HRV and higher HR. Plus, this study is conducted on players of ages between 15-24, which is a representative age for video gamers, but not a broad enough age range to decide the difference among age groups. To conclude the effect of age, an alternate study design with a wider age range would be needed.

Match Result

Match results were found to be a significant factor of HR increase. Players who won the match showed higher increases during stress events. It suggests that players with a pre-existing advantage would feel higher stress of losing what they own at that point. Contrarily, losing players who already expect their loss would experience a smaller fluctuation of emotion during an event. An alternative explanation would be, winning players are more likely to be excited during a match and overall arousal level is higher than losing players, and this higher arousal would be displayed as a higher HR level. A further study would be needed to validate the interpretation of the result.

Effects of late-game events

Among all fixed effects of linear mixed-effects models, events in the later phase of a match were found to be significantly associated with the stress level. During the later phase of a match, players were able to anticipate earlier, HR increased more, and HRV dropped more. Unlike other factors that showed symmetric patterns of increase and decrease, HR in the late game events decreased less than the early game events. Therefore, it is implied that player's tension goes higher in the latter part of a game. This could be further investigated through visualizing and analyzing the overall HR trend within a full match.

Events of Different Categories

For both HR increase and decrease, event categories of Enemy and Myself, and Team and Teammate showed similar patterns, respectively. HR arose significantly higher during events triggered by enemies and myself than events triggered by their team and teammates. Players have to confront Enemy and Myself events more immediately, and the result of the event directly affects the players by leading to a death or a critical loss of advantage. Events of those categories are more likely to occur within the player's vision and do not require much attention to recognize them. Team and Teammate events sometimes affect the result more critically because more critical events like teamfight loss or objective loss are included. However, the result is shared with the whole team, which ameliorates the negative emotion after those events. Also, events like teammate death are sometimes not recognized by a player if they are engaged in another important event, resulting in less impact on physiological response changes.

The present study also demonstrated the physiological influences of tilt triggers (i.e., teammate, myself, enemy, and other players) that Wu et al. (2021) presented. However, the ranking of the impact of the triggers was different between the two studies, as the present study analyzed emotional responses in a more specific period (a single stress event), and Wu et al. (2021) asked participants about their general experiences while gaming. Our study also echoes Kou and Gui's (2020) finding that "personal performances lower than expectation could trigger negative emotions such as frustration and anger" by replicating the highest stress response during Myself events among the different categories of stress events.

Application for Healthier Gaming Behavior

This study explores different conditions that may cause varying stress levels for esports players. Although these conditions have different effects in different contexts and sometimes interact in complex ways, this study offers insights below into what fosters a less stressful gaming environment.

The results support the assumed relationship by showing that players react differently to the same types of stress events by different match outcomes. This variable was presumed to affect not only a player's stress level but also their inability to stop playing, causing streakiness of play (Kou et al., 2020). However, the study design limited the number of matches and this study could not determine how likely players were to continue playing after a loss.

As Wu et al. (2021) suggest, "tilt is an important construct to understand because it represents the esports version of self-management." The present study tested how possible causes of tilt impact players' emotions using physiological methods, and the results offer insights into fostering a healthy gaming environment, a fundamental solution for problematic gaming behaviors. For example, with the understanding that a match's outcome would negatively affect their emotions and performance capability, players may be able to avoid becoming tunnel-visioned. Alternatively, having a regular team with constructive communication may help decrease stress levels and provide moderated play with a specific goal, opposed to simply spending time.

Limitations and Future Work

While this study incorporates physiological measurements such as heart rate, the study environment was not under the researcher's complete control because study sessions were conducted remotely at participants' residences. Although the participants were guided by instructions, some variables were unable to be controlled. For example, clinical physiological studies control the air temperature in the study room and diet before the experiment session as it might affect the heart rate of a participant. Our research team could not control the study room's air temperature or diet instructions strictly for this study. Additionally, changes in body posture often caused detachment of the heart rate monitor from participants' skin and delivered invalid data. Also, unstable network connections from some participants interfered with the study procedure and paused the process, which possibly affected the arousal levels of the other participants.

However, this setting resembles the real-world settings of playing esports. By letting participants play in familiar spaces, we could foster a realistic setting for esports players. If players were to have been invited to the institution's experiment lab, they would have felt less comfortable than if they were to play in their own settings. Participants could play at their best with their own gaming gear (e.g., a computer mouse with a familiar size, weight, and sensitivity) and in their favored position. If they were in a lab setting, it might have affected their emotions, and they might not have been able to perform at their best.

One limitation in measuring facial expressions is that the AI's classification of emotion is not perfect because it does not include context when interpreting faces. For example, happiness, the most frequently shown emotion among the participants, was recognized by a laugh or a smile, but those expressions could be interpreted in various ways based on their context. This method could be misleading if it were to be used without human observation and consideration of the context.

Even in this quasi-experimental setting, it is still uncertain if participants played as seriously as they play in a ranked mode. The results of the sessions did not affect their rank and there was no prize pool for winners. In addition, to collect team communication data, individual participants were asked to join a video chat while playing. Although participants played from remote places, they were less blunt with their teammates compared to players in general ranked games who cannot see each other's faces. Also, players played only three games for a session, but more games in a single session may be required to observe emotional changes in repeated games, especially during a losing streak that triggers the tilt phenomenon.

The raw dataset of this study includes various in-game data, but only a subset of data (i.e., stress events) was used for this study. There is much more left to explore in this dataset in the future to study other aspects of a player's experience with esports. For example, similar to the way this study investigated tilt by linking negative in-game events with player stress response, the flow of gameplay could be probed by selecting positive in-game events.

This study focused on 10 players at a time and generated a huge dataset from which player patterns were observed. For a future study, an alternative study design could be employed to observe only one player at a time, but much more closely. This design would include an extensive review of the gameplay with the participant, scrutinizing their emotional change after each event in a qualitative way. While this study investigated the impact of tilt different triggers by measuring biological changes, the alternative study would be able to explore players' mental models both while they are tilted and while they attempt to overcome tilt.

This study could be further developed into a design study that moderates the behavior of players. Tilt is related to the loss of self-control, and self-awareness is important in regulating one's behavior. An assistive application that presents a user's emotion as an in-game status during a match would increase the user's self-awareness. By incorporating different datasets, the application might suggest tips for users to play better, calm down, or even quit playing to overcome tilt. This could be practically incorporated into professional players' training programs or used by general players who need help with self-regulation during gameplay.

Conclusion

The present research investigated players' stress levels and emotions around in-game stress events by combining game telemetry data, physiological measures, and communication data. Compared to the past studies that incorporated self-reported indices or surveys, the novel method of this study enabled a direct observation on players' behavior and response in an unobtrusive way. This study found physiological evidence that negative in-game events would impact players' stress levels, possibly trigger deviant behaviors so-called tilt. This study also compared different player groups, categories of stressful events, and different conditions within a game to investigate possible variables that would affect the stress level.

The method used in this study is novel but widely available for user application due to the accessible technologies of commercial self-tracking products. For example, measures used in this study (wearable heart rate monitors and AI face recognition systems) could be implemented by professional or amateur players' training process to enhance their socio-emotional skills that would maintain gaming performances at their best level. It could be applied by education institutes or within a family for a better self-regulation strategy and healthier gaming behavior. Moreover, the findings of this study include different contexts of gaming that would provoke stress levels.

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Appendix A. Institutional Review Board Approval

UCI University of California, Irvine

OFFICE OF RESEARCH
INSTITUTIONAL REVIEW BOARD
PAGE 1 OF 4

October 16, 2020

Constance Squire
INFORMATICS

RE: UCI IRB HS# 2020-5976 *Measuring Performance and Communication of Esports Players*

The above-referenced human-subjects research project has been approved by the University of California, Irvine Institutional Review Board (UCI IRB). This approval is limited to the activities described in the approved Protocol Narrative, and extends to the performance of these activities at each respective site identified in the Application for IRB Review. In accordance with this approval, the specific conditions for the conduct of this research are listed below, and informed consent from subjects must be obtained unless otherwise indicated below. Additional conditions for the general conduct of human-subjects research are detailed on the attached sheet.

NOTE: Approval by the Institutional Review Board does not, in and of itself, constitute approval for the implementation of this research. Other institutional clearances and approvals may be required (e.g., EH&S, Radiation Safety, School Dean, other institutional IRBs). Research undertaken in conjunction with outside entities, such as drug or device companies, are typically contractual in nature and require an agreement between the University and the entity. Such agreements must be executed by an institutional official in Sponsored Projects, a division in the UCI Office of Research. The University is not obligated to legally defend or indemnify an employee who individually enters into these agreements and investigators are personally liable for contracts they sign. **Accordingly, the project should not begin until all required approvals have been obtained.**

Questions concerning the approval of this research project may be directed to the Office of Research, 141 Innovation Drive, Suite 250, Irvine, CA 92697-7600; 949-824-6068, 949-824-2125, or 949-824-0665 (biomedical committee) or 949-824-6662 (social-behavioral committee).

Expedited Review: Category(ies) 3,6,7

Susan Turner, Ph.D.,
Vice-Chair, Institutional Review Board

Approval Issued: 10/16/2020
Expiration Date: 10/15/2023
UCI (FWA) 00004071, Approved: January 31, 2003

Appendix B. Sample Log Data

Events log

```
{
      "events":[
         {
            "name":"announcer",
            "data":"{\r\n  \"name\":
\"slain\",\r\n  \"data\":
\"enemy\"\r\n}"
         }
      ],
      "localTimestamp":1607824691325,
      "syncedTimestamp":1607824661128,
      "syncedInGameTime":"04:53:94"
   },
   {
      "events":[
         {
            "name":"ability",
            "data":"1"
         }
      ],
      "localTimestamp":1607824692885,
```

Key/Mouse log

```
[{'keyValue': 0, 'keyName': 'MOUSE
left', 'press': 'keyDown', 'mouseX':
907, 'mouseY': 300, 'localTimestamp':
1611458112535, 'syncedTimestamp':
1611458082377, 'syncedInGameTime':
'00:00:00'},
{'keyValue': 0, 'keyName': 'MOUSE
left', 'press': 'keyUp', 'mouseX':
907, 'mouseY': 300, 'localTimestamp':
1611458112566, 'syncedTimestamp':
1611458082408, 'syncedInGameTime':
'00:00:00'},
{'keyValue': 0, 'keyName': 'MOUSE
left', 'press': 'keyDown', 'mouseX':
717, 'mouseY': 336, 'localTimestamp':
1611458112718, 'syncedTimestamp':
1611458082560, 'syncedInGameTime':
'00:00:00'}
```

Match timeline log

```
{
"type":"CHAMPION_KILL",
                  "timestamp":160980,
                  "position":{
                     "x":6415,
                     "y":6904
                  },
                  "killerId":10,
                  "victimId":3,

"assistingParticipantIds":[
                     9
                  ]
               },
               {

"type":"SKILL_LEVEL_UP",
                  "timestamp":161707,
                  "participantId":1,
                  "skillSlot":3,
```

Match summary log

```
"participantId":1,
            "teamId":100,
            "championId":28,
            "spell1Id":4,
            "spell2Id":11,
            "stats":{
               "participantId":1,
               "win":false,
               "kills":5,
               "deaths":6,
               "assists":4,

"largestKillingSpree":2,
               "largestMultiKill":2,
               "killingSprees":1,

"totalDamageDealt":97072,

"magicDamageDealt":78226,

"physicalDamageDealt":10079,
```