Towards Player Health Analytics in Overwatch

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***Abstract*— Overwatch is a competitive, team-based first-person shooter game, with a professional eSports league supporting competitive play. Player mental health has been an issue in eSports, and in Overwatch multiple players have quit playing professionally and cited mental health concerns. Player physiology during gameplay presents an opportunity to understand stressors during gameplay that may affect individual performance and health. This paper presents the collection of physiological data from Overwatch players and overlays it with data from the video game. This method, demonstrated in a pilot study could be used to learn more about how in game events affect player mental health, and lead to the development of resilience building approaches for eSports athletes.**

Keywords—eSports, Overwatch, mental health, Big Data

I. Introduction

Overwatch is a team-based, first-person shooter game developed by Blizzard Entertainment that debuted in May 2016 [1]. In Overwatch, twelve individuals play concurrently in six versus six competitive matches online [2]. The Overwatch League (OWL) is a 20-team international eSports league that features teams and players from around the world. OWL games occur weekly over a six-month season in front of thousands of fans at live arenas [3]. The games are also broadcast on YouTube to tens of thousands of viewers. OWL professional players practice frequently to improve their hand-eye coordination, in-game decision making, and reaction time [4]. These skills are especially relevant in team-based, first-person shooter games.

Combat tactical training utilizing virtual reality environments like first-person shooter games, are being used to promote resilience against stressors. Resilience is an important component for mental health [5]. Mental health issues have led to multiple professional players taking leaves or quitting the OWL in its first two seasons [6].

In prior research, McGregor extended her Artemis Platform to create Athena, a Big Data analytics platform for the collection, analysis, and storage of physiological and game data for tactical operator resilience training and health analytics [7]. Artemis is a Big Data analytics platform that has been used to support clinical research in the neonatal population [8].

This paper presents an extension to McGregor et al.'s. research using ArmA 3, ARAIG, and Athena [5] to enable similar resilience and physiological assessment of non-tactical operators playing Overwatch.

Derived signals such as heart rate variability can be used as a proxy for player stress [9]. The method will be usable for consistent player-monitoring during multi-hour gaming sessions and could inform future studies on the impact of resilience training in competitive gaming.

II. Related Work

In their systematic review, Pedraza-Ramirez et. al describe the potential in developing a greater knowledge of eSports athletes through the use of biological markers. They suggest that using interrelated biological markers like heart rate variability, eye tracking, and brain activation is an appealing avenue for eSports research [10]. Grossman and Siddle proposed in military and tactical operator research that at different heart rate thresholds, certain motor skills and cognitive function deteriorate [11]. However, the impact of heart rate changes when sitting and playing competitive video games is different than that of military and other tactical personnel.

Using the Athena Platform, McGregor et al. demonstrated a new approach to the assessment of resilience and psychological trajectories by assessing physiological responses to events during a virtual reality video game simulation for tactical operator training using the first-person shooter game ArmA3. McGregor et al. collected ECG data and derived heart rate and respiratory rate from participants. In that research, participants wore the ARAIG haptic garment which enabled them to feel events (like shooting or being shot) that occurred in the VR environment [5]. However, that study did not consider a population of participants who were not professionally trained in tactical officer domain specific training.

Ding et al. collected ECG and EEG data from participants playing League of Legends. They grouped participants by their skill level, and included professional players. They extracted five-minute video segments and annotated key events manually for the purpose of comparing between participants in each skill level bracket. Their study objective was to determine which factors were most relevant in separating professional gamers from amateurs [12].

In Pedraza-Ramirez et al.'s research, they suggest considering homogeneous sample issues when designing studies [10]; however, in McGregor et al. and Ding et al.'s studies, stratifying by biological sex was not feasible as they did not include a representative sample of female participants [5], [12].

III. METHODS

A. Objectives

The objective of the study was to determine the feasibility of developing health analytics for Overwatch eSports players by combining player physiological data with game feed data. This extends McGregor's prior work with ArmA 3, ARAIG and Athena to measure how in-game events impact player physiology as demonstrated through player physiological change.

B. Ethics

This research study was approved by the Ontario Tech Research Board (#15746).

C. Recruitment

Undergraduate students from Game Development Program at Ontario Tech University were recruited via an advertisement in the Game Development Laboratory Discord Server. Students were asked to provide their age, biological sex, and experience playing Overwatch. Only students that had self-reported having played Overwatch in the past were recruited for the study.

D. Gaming Session

Students attended as many as two ninety-minute sessions at the Game Development Laboratory to play Overwatch. This included three or four games of Overwatch being played, the limiting factor being lab time availability. During of each game varied based on game play. Students were asked to wear a Zephyr Bioharness Strap directly on their skin. The Bioharness transmits physiological signals such as heart rate, respiratory rate, and body temperature via Bluetooth to a study laptop. Students were asked to play games of Overwatch against each other and computer-generated characters (Bots). Bots were used because there were fewer than twelve participants in each session. The gameplay from each participants gaming session was recorded using Open Broadcast Software. Players used Overwatch accounts purchased and created by the Ontario Tech Health Informatics Research Lab division of the Joint Research Centre in AI for Health and Wellness for the purpose of the study.

During the gaming session, key markers were recorded using the Zephyr Bioharness software. The beginning and end of each game were timestamped for the purpose of allowing each individual game to be viewed separately during analysis.

IV. RESULTS

Nine (2 female) unique participants attended one or two sessions each. No session had more than five participants, and two of the four sessions had only two participants. This meant that anywhere from seven to ten bots were included in games. Participants commented that playing with bots did not mimic normal game conditions and that it did not invoke the same stress during gameplay that they would feed when playing against all human participants. Gameplay and physiological signals were recorded for an hour.

Individual player videos for reviewed independently, with gameplay timestamps added for specific in-game events including team fights (when multiple players are shooting each other), player deaths, and the end of rounds within games.

A. Analysis

Participant heart rate data with timestamps was saved as a csv file and uploaded in to PowerBI. Timestamped in-game events were then added as an overlay for the purpose of depicting the change in heart rate during gameplay.

Table 1 includes the aggregations of each participant's minimum, maximum, average, and standard deviation heart rate values for both the pre-gameplay session used for baseline, as well as the gameplay session. Overall, seven of the nine participants had an increase in heart rate during gameplay; however, there was large variation in the changes in heart rate for each participant.

Similarly, Table 2 includes the aggregations of each participant's minimum, maximum, average, and standard deviation respiratory rate values for both the pre-gameplay session used for baseline, and the gameplay session. The respiratory rate was 18.6 in both time periods; however, four participants had a change in respiratory rate greater than one standard deviation.

Fig. 1 depicts a gameplay session where two participants played four separate games of Overwatch. In this figure, the yellow background depicts gameplay while the white background depicts breaks between games. In this gameplay session, the participant's heart rate (coloured red) has lower variability than that of the gameplay participant (coloured purple).

Fig. 2 depicts a single round, within a single game, of a gameplay session for a single participant. In this figure, the grey bars represent times when the participant's team was involved in a team fight with the opposing team. The red lines represent when the participant's character was killed in the game (the character respawns after 10 seconds). The participant's heart rate is depicted in blue.

In both Figures, using timestamp markers allows for visual depictions of changes in heart rate during gaming session events. Markers like deaths and team fights exist for all participants, allowing for comparison of physiology during similarly classified events.

V. DISCUSSION

A. Limitations

While physiological data collected from multiple Zephyr Bioharnesses were time-synced in the Zephyr software, it was not possible to sync video feed data in this study as no real-time outputs of the game play were available within Overwatch and modificiation of Overwatch to enable this by a user was not possible. To remedy this, the first game marker in each video was matched with the first game marker annotated in the Zephyr Bioharness software, allowing for video feed data to be synced with physiological data to within a second.

There were also some artifacts found in the data, which was attributed to issues with participants positioning the wearable. This was especially relevant in the baseline period, where participants were adjusting the Bioharness strap to ensure it was transmitting properly.

TABLE I. HEART RATE PARTICIPANT AGGREGATES

Heart Rate (HR) Participant Aggregates	**Aggregates**			
	Minimum	*Maximum*	*Average*	*Standard Deviation*
HR Baseline Minimum	45	112	71.7	20.9
HR Baseline Maximum	83	122	105.6	11.4
HR Baseline Average	71	116	88.6	22.6
HR Baseline Standard Deviation	2	22	8.1	6.0
HR Gameplay Minimum	56	105	72.6	15.2
HR Gameplay Maximum	107	141	120.3	13.2
HR Gameplay Average	76	114	94.5	13.6
HR Gameplay Standard Deviation	3	12	8.2	2.6

TABLE II. RESPIRATORY RATE PARTICIPANT AGGREGATES

Respiratory Rate (RR) Participant Aggregates	**Aggregates**			
	Minimum	*Maximum*	*Average*	*Standard Deviation*
RR Baseline Minimum	6	19	13	4.0
RR Baseline Maximum	15	31	24	5.0
RR Baseline Average	10	25	18.6	4.3
RR Baseline Standard Deviation	1.6	5.3	2.9	1.0
RR Gameplay Minimum	7	13	10.2	1.8
RR Gameplay Maximum	20	38	27.6	5.8
RR Gameplay Average	12	23	18.6	3.7
RR Gameplay Standard Deviation	1.9	6.1	3.8	1.4

Managing video feed data would have been more effective had the Overwatch client's spectator system been used. The spectator system saves replays, and allows for an observer to switch between player views. The challenge with using the client spectator system is that the game data must then be viewed in the Overwatch client, instead of in other video software. Saved replays also are deleted if there is a game patch, meaning they may not be reviewable at a later time [13]. A game patch occurred during the study. Events like team fights were difficult to view from a single character's viewpoint, especially if that character died.

A more effective solution would have been to export game-feed data in a quantitative format. Timestamped game events from the game, which the OWL uses to create advanced analytics for its OWL Stats Lab [14], was not available for this study, but represents an exciting opportunity for syncing with physiological data and other data sources for health analytics. In McGregor et al.'s [SEGAH 2017] prior research study using Athena, ARAIG and ArmA 3 they were able to demonstrate real-time game activity feeds through use of an ArmA3 mod developed by the research for the study that supported feeding game data to ARAIG to enable the haptic feedback and game play to Athena for real-time synchonisation with physiological data by Athena. The ability to perform this real-time synchronization is dependent on the ability of the game to output game play data in real-time.

Another limitation was the lack of participants involved in the study. A normal game of Overwatch includes twelve players; however, the most players involved in a session of the study was five. This meant that the gameplay was not consistent with normal Overwatch games, and any derived analysis would exist with the caveat that it was not a proper representation of gameplay. Player skill level also needed to be considered, as the sample included players with varying skill levels. In competitive Overwatch, players are generally matched against others within the same skill level. The OWL is generally representative of the most skilled players. An assumption is that participants playing in a non-competitive game due to mismatched skill levels will not have the same physiological response as if they were matched with those of equal skill levels in a more balanced game.

B. *Future Research*

In Pedraza-Ramirez et. al's systematic review, they recommended that future gaming psychology research should focus on singular games instead of genres, use machine learning, and develop knowledge from biological markers [10]. This research demonstrated the ability to collect biological markers during games of Overwatch, while McGregor et al. have demonstrated the ability to use machine learning with biological markers for the development of health analytics [5]. By including a live data stream from a video game, as well as eye tracking data, there is an opportunity to develop more detailed health analytics that demonstrate how in game events in Overwatch affect an individual's biological markers.

Future research should also look to involve the developers of games, for the purpose of accessing game data feeds. These data feeds are especially relevant in machine learning, and would also remove some of the objectivity of selecting and annotating moments via a video feed of the gameplay. If data being stored by the game was made available for research, more in-depth machine learning could be completed

eSports are not the only avenue where this research can be applied. According to a 2018 survey of Canadians conducted by the Entertainment Software Association of Canada, 61 percent of Canadians defined themselves as a gamer, with over 90 percent of teens reporting that they play video games [15]. Health analytics in gaming can be applied to younger and more casual gamers, not just eSport athletes. These analytics are essential in developing an understanding of the impact of gaming on physiology and mental health.

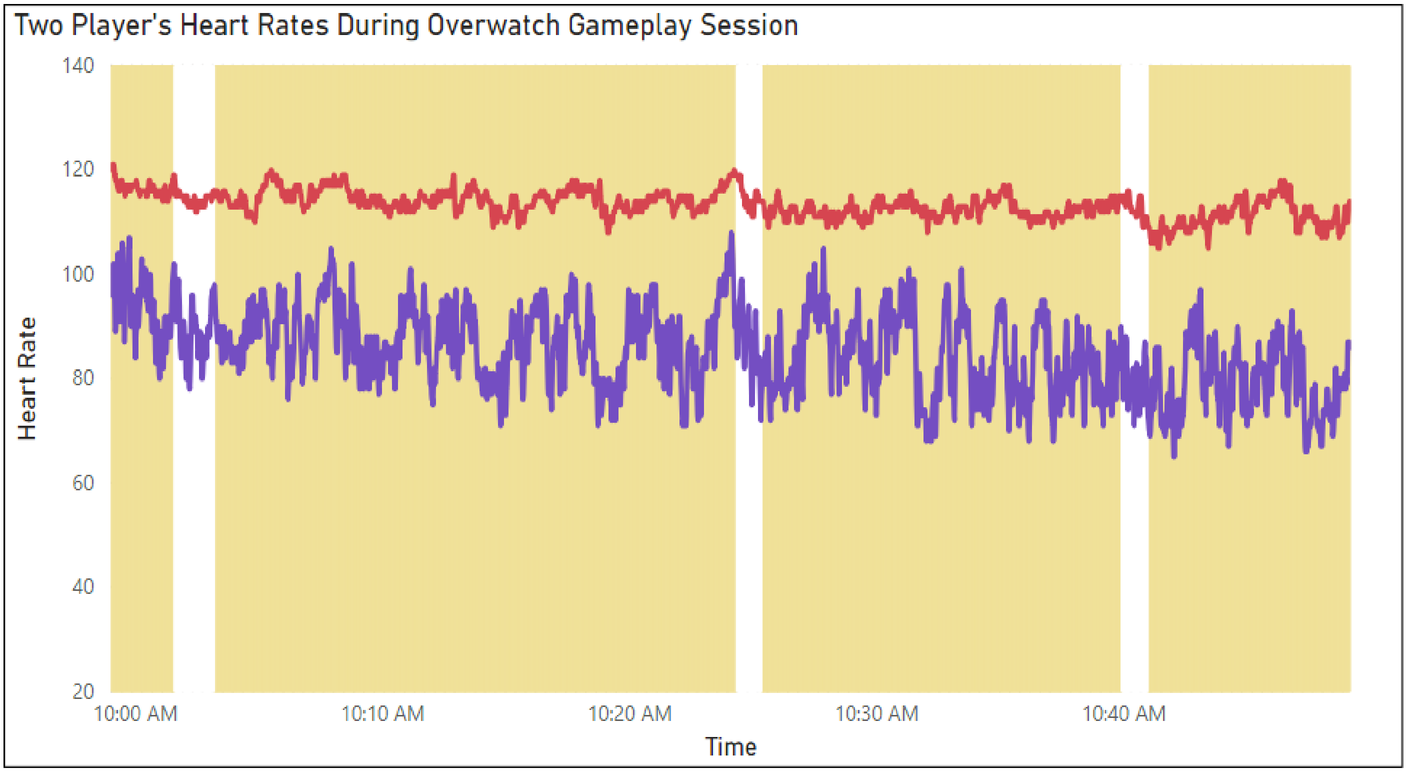

Fig. 1 Two Player's Heart Rates During Overwatch Gameplay Session

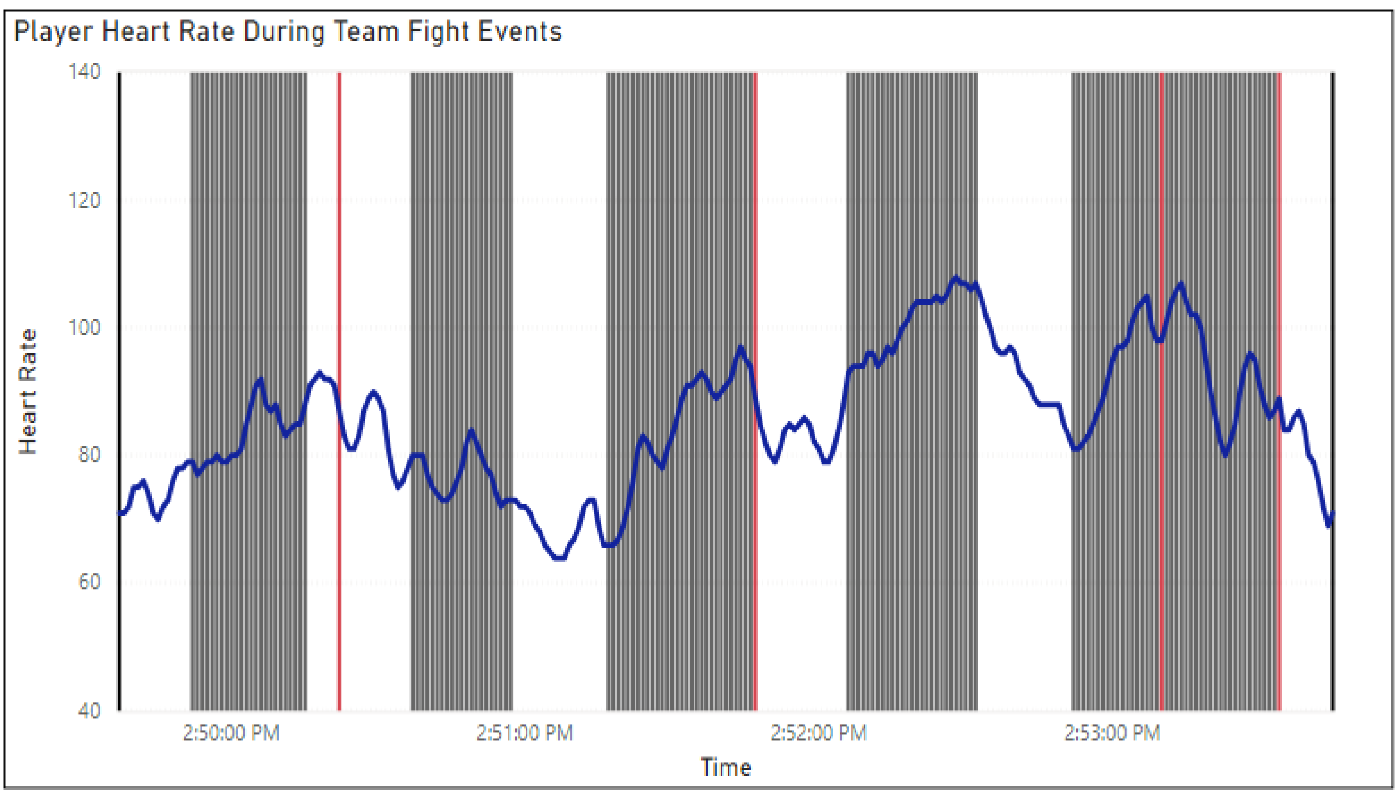

Fig. 2 Single Player's Heart Rate During Single Round of Gameplay Session

VI. Conclusion

This paper presents a research study for the collection of physiological data during Overwatch gameplay. The physiological data was matched with in-game events using an annotated review of gameplay video. This process could be used to develop health analytics matched with video game events through machine learning. These analytics could be used by eSports athletes and casual gamers to develop an understanding of how gaming affects physiology and mental health.

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