Electrodermal Activity Evaluation of Player Experience in Virtual Reality Games: A Phasic Component Analysis

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Abstract: Electrodermal activity (EDA) is considered to be an effective metric for measuring changes in the arousal level of people. In this paper, the phasic component of EDA data from players is analyzed in relation to their reported experience from a standardized questionnaire, when interacting with a couple of virtual reality games that featured two different input devices: the HTC Vive and Leap Motion controllers. Initial results show that there are no significant differences in the phasic component data, despite having significant differences in their respective player experience. Furthermore, no linear correlations are found between the phasic component data and the evaluated experience variables, with the only exception of negative affect which features a weak positive correlation. In conclusion, the phasic component of EDA data has here shown a limited correlation with player experience and should be further explored in combination with other psychophysiological signals.

1 INTRODUCTION

Electrodermal activity (EDA) is considered a very efficient methodology for measuring the changes in arousal levels of players when playing video games (Navarro et al., 2021). Because of this, several publications have used EDA measurements in the assessment of different variables in game research, such as the emotional responses (Bontchev, 2016; Moghimi et al., 2017) or the cognitive loads (Buchwald et al., 2019) of players.

A predominant area in which EDA data has been analyzed in previous publications is the assessment of player experience. Multiple studies have used EDA data to quantitatively evaluate different experience variables in game research (Drachen et al., 2010; Martey et al., 2014; Ang, 2017). However, the majority of those studies have focused on games played on regular 2D screens. With the introduction of virtual reality (VR) technologies into the consumer market, novel interaction techniques have emerged, affecting the manner in which players experience video games. Few publications have explored the effects that these novel interaction techniques may have in the EDA data from players and their respective experiences (Egan et al., 2016), offering the opportunity to further explore the relationship that may exist between these variables.

Therefore, this study presents the following research question: *How may the differences in player experience relate to the variations of their respective EDA data in VR games?*. In particular, this study focuses on analyzing the *phasic component* (see Section 2) from players' EDA data, gathered in a previous experimentation. We hypothesize that there is a strong relationship between the EDA data from players and their respective game experience: significant differences in the arousal level of players during gameplay, and consequently significant differences over the phasic component of EDA data, may be an indicator of significant differences in the reported player experience.

2 BACKGROUND

Electrodermal activity, also known as galvanic skin response (GSR), is defined as the measurement of the variations in the electrical conductivity on the skin, due to Eccrine sweat glands activity (Boucsein, 2012; Tasooji et al., 2019). EDA measurements focus on applying an imperceptible amount of electric voltage on the skin and measure the variation of the speed in which this voltage travels trough it. When strong

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emotional reactions are experienced by people (i.e. increase in their arousal levels), the body increases the levels of perspiration on the skin and, consequently, its electrical conductivity. Therefore, increases in the EDA signal are often associated with increases in the arousal level of people (Boucsein, 2012).

EDA signals have two main components called tonic and phasic. The *tonic component* describes the slow and gradual changes in the EDA signal over time, establishing a baseline for the EDA signal called skin conductance level (SCL). The *phasic component* focuses on identifying quick and abrupt changes in the EDA signal, commonly referred to as a skin conductance response (SCR) (Boucsein, 2012; Navarro et al., 2021).

3 RELATED WORK

Several publications have explored EDA data and their potential relationship with multiple variables from the player experience. An initial study by Ravaja et al. (2006) focused on analyzing the changes of the phasic component data during gameplay, combining data from electromyography, heart rate, and EDA; and showing a strong positive relationship between phasic increases of arousal and in-game rewards. A further study from Drachen et al. (2010) aimed to generate a quantitative understanding of player experience by analyzing its potential correlation with EDA and heart rate data. A set of first-person shooting games were used in this paper, showing significant correlations between EDA data and reported player experience, despite having limited covariance between the physiological metrics. Another study using first-person shooting games was presented by Nacke et al. (2010), exploring the effects of turning on and off the sound effects and music on the arousal responses from players. The results showed that changes in sonic stimuli had little effect on players' EDA data, despite showing significant effects over reported player experience. In (Klarkowski et al., 2016, 2018) challenge, and the relationship with EDA signals, were analyzed. Despite discrepancies with extant literature, results from these studies show a directly proportional relation between player arousal and game challenge. Few articles, however, have explored the variation of EDA data in VR games. One such study compared the effects of VR and non-VR environments in players' EDA and heart rate data (Egan et al., 2016), finding significant differences between the gathered physiological metrics.

The analysis presented in this paper is based on additional EDA data gathered in an earlier experiment that evaluated player performance and experience when manipulating objects in two virtual reality games (a pentomino puzzle and a ball throwing task) with two different interaction devices: the HTC Vive controller and the Leap Motion Controller. More details on the earlier experiment design and procedure that is the basis for the EDA data gathering can be found in (Navarro and Sundstedt, 2019). The performance evaluation was carried out by analyzing the amount of piece grabs require to complete the puzzle in the pentomino game, and the number of throws required to hit all targets in the ball throwing game. Additionally, completion times were included in this part of the analysis. The experience evaluation was done through a set of three questionnaires, two applied after completing the games with each respective interaction device, and one at the end of the experiment. The questionnaires where a modified version of the Game Experience Questionnaire (GEQ), a standardized survey to evaluate player experience (IJsselsteijn et al., 2013).

As an outcome of the previous work, the HTC Vive was reported to offer an improved overall subjective experience. The performance was reported to decrease when using the Leap Motion controller and gesturing with the hands was not perceived as reliable as when using the HTC Vive for input control. However, the earlier work also showed potential in terms of positive responses for both controllers, in particular relating to enjoyment. Since there was a previous significant difference reported in the player performance it was considered relevant to also analyze the gathered EDA data collected during the experiment in further detail.

4 METHODOLOGY

A statistical evaluation between player EDA signals and the reported experience results was established as the main methodology for this study. Specifically, an analysis of the phasic component of the EDA data and its potential relationship with player experience variables.

4.1 Phasic Component Analysis

For the phasic component analysis, the metric *peaks per minute* was used. Peaks per minute highlight the ratio in which EDA signal peaks occurred within the time required by players to complete each game. This metric aims to compare how the different input devices featured in each game might have affected the arousal levels of players and, subsequently, their respective perceived experience results. The process used to calculate the peaks per minute (P_{min}) is shown in Equation 1, where P represents the total number of peaks (automatically detected by iMotions) between the initial exposure time (t_o in ms) and the completion time (t_f in ms), over the completion time divided by $6*10^4$ ms.

$$P_{min} = \frac{\sum_{t_o}^{t_f} P}{\frac{t_f}{6*10^4}} \quad (1)$$

Peaks per minute were calculated for each game (pentomino and ball throwing), and for each input device (HTC Vive controller and the Leap Motion controller). A third measurement was done over the entire exposure with each input modality, adding the peaks from both games together.

4.2 Statistical Analysis

Several statistical analyses were carried out with the calculated peaks per minute, and the reported player experience results from the GEQ. First, the ANOVA assumptions were tested for all the data sets using the Shapiro-Wilk test for normality, and the Levene's test for homoscedasticity. Only the data sets that satisfied the ANOVA assumptions were later compared using a paired t-test, while all others were compared by using a Wilcoxon signed-rank test. Lastly, to evaluate any potential correlation that might exist between the calculated peaks per minute and the variables tested in the GEQ, a Pearson correlation coefficient was calculated with the data from the pentomino game, the ball throwing game, and the overall experience.

4.3 Software Tools

To capture the participants' EDA data, the iMotions platform (iMotions, 2021) and the Shimmer3 GSR+ sensor were used. IMotions recorded and processed the raw data captured by the GSR sensor, allowing us to directly export the phasic component data. These phasic data were later imported, processed, and analyzed using a script developed in Python (version 3.8). The script used three main libraries to carry out the analyses: Pandas (Pandas, 2021) was used to read, store, and manipulate data frames; ScyPy (Virtanen et al., 2020) was used to carry out the statistical significance analyses; and Matplotlib (Matplotlib, 2021) was used to plot the calculated data.

4.4 Ethical Considerations

The EDA data can be considered a sensitive metric since it allows to identify when and how much the arousal levels of a person change, when exposed to a specific stimulus. Therefore, this study made the identity of the players confidential, and made no direct links between the participants and the gathered EDA data. The study was submitted to a regional ethics board in Sweden for its evaluation, and was granted ethical approval (dnr: 2018/624).

5 RESULTS

A total of 20 participants volunteered for the experiment. However, only data from 18 of them were analyzed and reported in this study. The EDA data from participants 15 and 20 were affected by noise at the end of the exposure with the Leap Motion controller, which generated incomplete data sets when exported from iMotions. Therefore, data from these participants were excluded from the analysis.

5.1 Peaks per Minute

For each game, two different peaks per minute data sets were calculated, one for each input device. Moreover, we computed also two additional peaks per minute data sets for the entire stimuli exposure, adding together the peaks per minute from the pentomino and the ball throwing games for each interaction device. An overview of the distribution of the calculated peaks per minute is shown in Figure 1.

5.1.1 Pentomino Game

Both peaks per minute data sets for the pentomino games passed the normality and homoscedasticity tests, allowing the use of the paired sample t-test to compare the data. Results from the test showed that there was not a statistically significant difference in the peaks per minute from players when playing the pentomino game:

$$t-test_{(1,n=18)} = 0.89, p > 0.05$$

5.1.2 Ball Throwing Game

The peaks per minute data set for the Leap Motion passed the normality test, while the one for the HTC Vive controller failed it. Therefore, a Wilcoxon signed-rank test was used to compare these data sets, showing that there was not a statistically significant difference in the peaks per minute from players when playing the ball game:

$$WSR_{(1,n=18)} = 48, p > 0.05$$

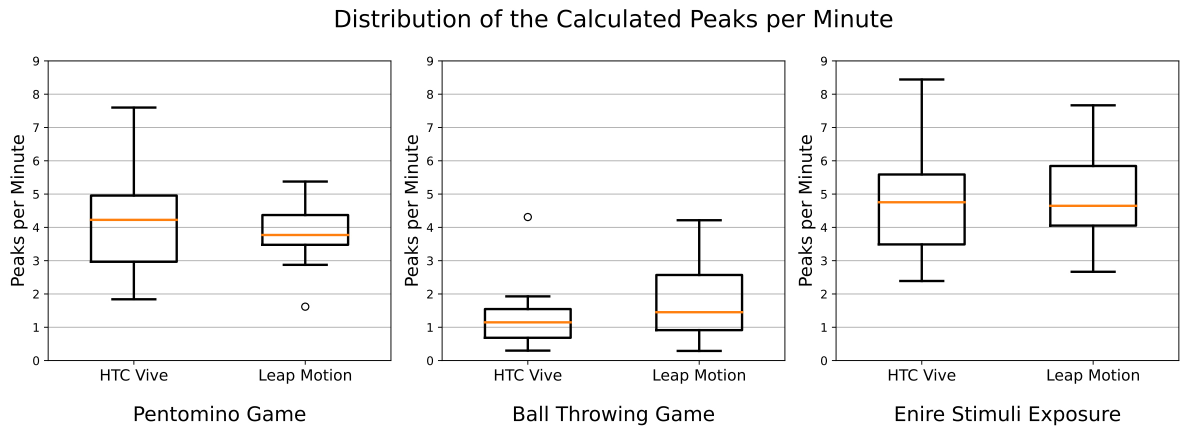

Figure 1: Calculated peaks per minute for the pentomino game, ball throwing game, and the entire stimuli exposure, between the HTC Vive controller and the Leap Motion controller.

5.1.3 Entire Stimuli Exposure

The entire stimuli exposure data sets added the peaks per minute from both games that used the same input device. Both data sets that were calculated this way passed the normality and homoscedasticity tests and were compared using a t-test. Results from the test showed that there was not a statistically significant difference in the players' peaks per minute when using the HTC Vive and the Leap Motion:

$$t-test_{(1,n=18)} = 0.10, p > 0.05$$

5.2 GEQ Results

Six different data sets (one per input device) were created from the answers gathered in the GEQ: two for the pentomino game experience, two for the ball throwing game experience, and two for the overall experience reported by players.

In the GEQ, two different sets of variables were used to evaluate player experience. The first set was used to evaluate the experience when playing each of the games, exploring the perceived *competence, level of challenge, tension, positive affect*, and *negative affect* from players. The second set explored the overall experience of using each input device in terms of the perceived *enjoyment, ease of use, sense of control,* and *preference* from players[CITE].

5.2.1 Pentomino Game

All experience variables failed the normality test for the pentomino game. Therefore, the Wilcoxon signed-rank test was used to evaluate the perceived player experience. An overview of the distributions from the results obtained in the GEQ for the pentomino game is shown in Figure 2 . These results from the test showed that there was a statistically significant difference among all evaluated variables, with the exception of the perceived negative affect:

- Competence: $WSR_{(1,n=18)} = 1, p < 0.05$
- Level of challenge: $WSR_{(1,n=18)} = 3.5, p < 0.05$
- Tension: $WSR_{(1,n=18)} = 8, p < 0.05$
- Positive affect: $WSR_{(1,n=18)} = 10.5, p < 0.05$
- Negative affect: $WSR_{(1,n=18)} = 8, p > 0.05$

5.2.2 Ball Throwing Game

All experience variables failed the normality test for the ball throwing game. The only exception occurred with the perceived competence, which also passed the homoscedasticity test. Given this, a t-test was used to evaluate the perceived competence, while all other variables were evaluated with the Wilcoxon signed-rank test. An overview of the distributions from the results obtained in the GEQ for the ball throwing game is shown in Figure 3. Results from these tests showed that there was a statistically significant difference between all evaluated experience variables:

- Competence: $t-test_{(1,n=18)} = 3.05, p < 0.05$
- Level of challenge: $WSR_{(1,n=18)} = 9, p < 0.05$
- Tension: $WSR_{(1,n=18)} = 20.5, p < 0.05$
- Positive affect: $WSR_{(1,n=18)} = 12, p < 0.05$
- Negative affect: $WSR_{(1,n=18)} = 11, p < 0.05$

5.2.3 Overall Experience

An overview of the distributions from the results obtained in the GEQ for the overall experience is shown in Figure 4. The variables used to assess the overall

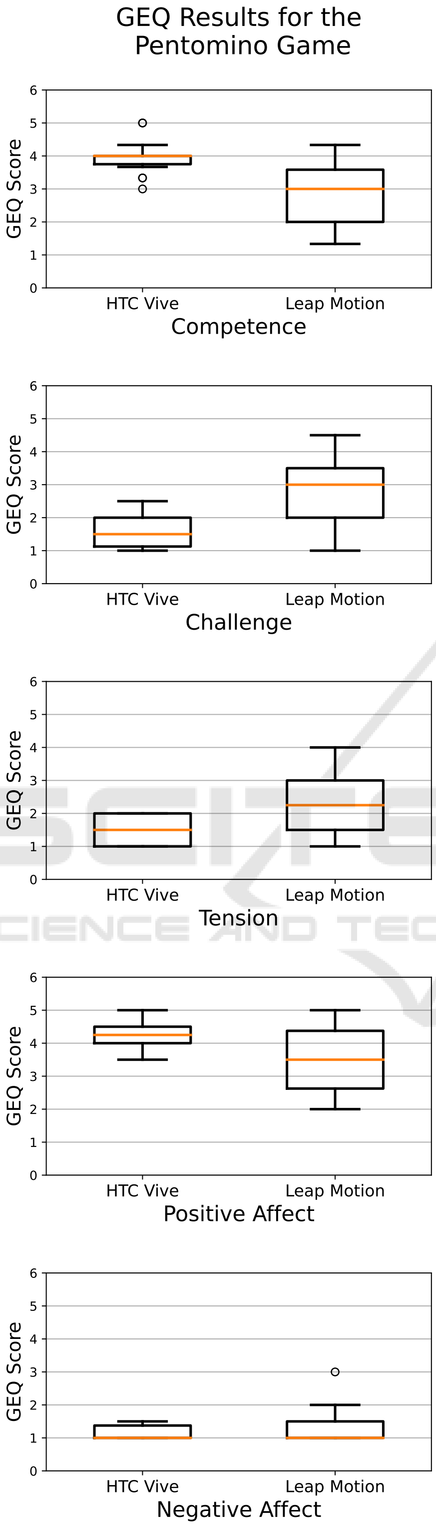

Figure 2: Results of each variable evaluated with the GEQ in the pentomino game, for the HTC Vive controller and the Leap Motion controller.

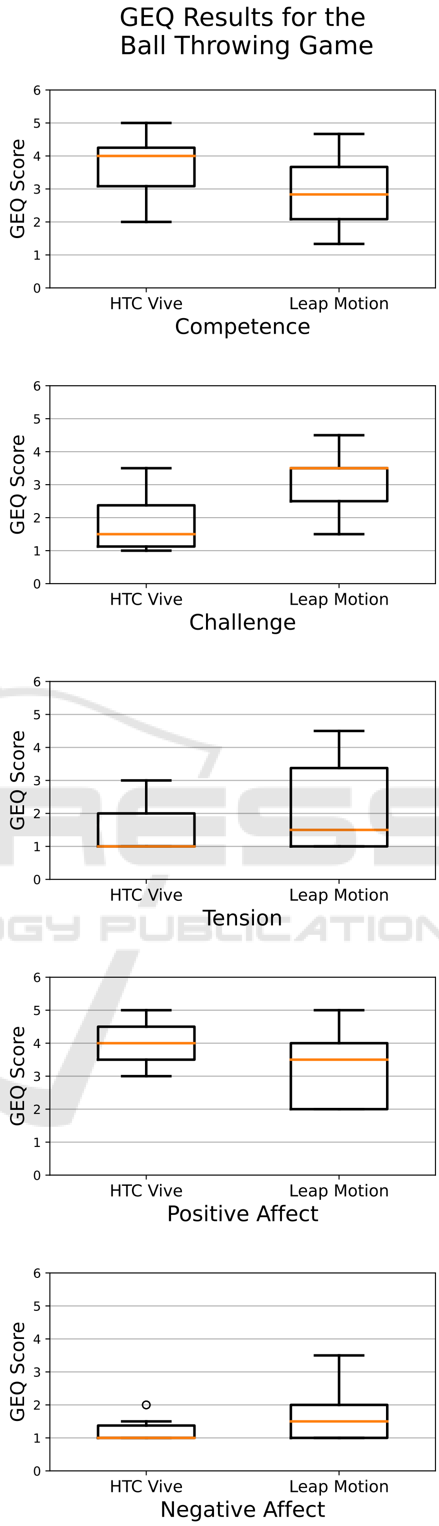

Figure 3: Results of each variable evaluated with the GEQ in the ball game, for the HTC Vive controller and the Leap Motion controller.

experience failed the normality test, and were evaluated using the Wilcoxon signed-rank test. The results of these tests showed that all variables had a statistical significant difference, with the exception of enjoyment:

- Enjoyment: $WSR_{(1,n=18)} = 9, p > 0.05$
- Ease of use: $WSR_{(1,n=18)} = 3.5, p < 0.05$
- Sense of control: $WSR_{(1,n=18)} = 4, p < 0.05$
- Preference: $WSR_{(1,n=18)} = 18.5, p < 0.05$

5.3 Correlation Analysis

The correlation analysis evaluated the potential linear correlation between the peaks per minute and GEQ Scores. Results from this analysis were classified into five different categories, based on the results obtained in the Pearson coefficient (ρ) (Shevlyakov and Oja, 2016):

- A *strong positive* correlation when ρ was greater than 0.8.
- A *weak positive* correlation when ρ was greater than 0.4 but lesser than 0.8.
- *No correlation* when ρ was between the values of 0.4 and -0.4.
- A *weak negative* correlation when ρ was lesser than -0.4 but greater than -0.8.
- A *strong negative* correlation when ρ was lesser than -0.8.

Lastly, this analysis should be understood as exploratory and no correction for multiple comparisons was performed on it.

5.3.1 Pentomino Game

For the HTC Vive controller, only the negative affect showed a weak positive correlation with the peaks per minute. All other GEQ variables showed no correlation:

- Competence: $\rho_{(1,n=18)} = 0.017, p > 0.05$
- Challenge: $\rho_{(1,n=18)} = -0.039, p > 0.05$
- Tension: $\rho_{(1,n=18)} = 0.048, p > 0.05$
- Positive affect: $\rho_{(1,n=18)} = -0.26, p > 0.05$
- Negative affect: $\rho_{(1,n=18)} = 0.516, p < 0.05$

For the Leap Motion controller, all GEQ variables showed no correlation with the peaks per minute:

- Competence: $\rho_{(1,n=18)} = -0.057, p > 0.05$
- Challenge: $\rho_{(1,n=18)} = -0.202, p > 0.05$
- Tension: $\rho_{(1,n=18)} = -0.280, p > 0.05$
- Positive affect: $\rho_{(1,n=18)} = -0.278, p > 0.05$
- Negative affect: $\rho_{(1,n=18)} = -0.104, p > 0.05$

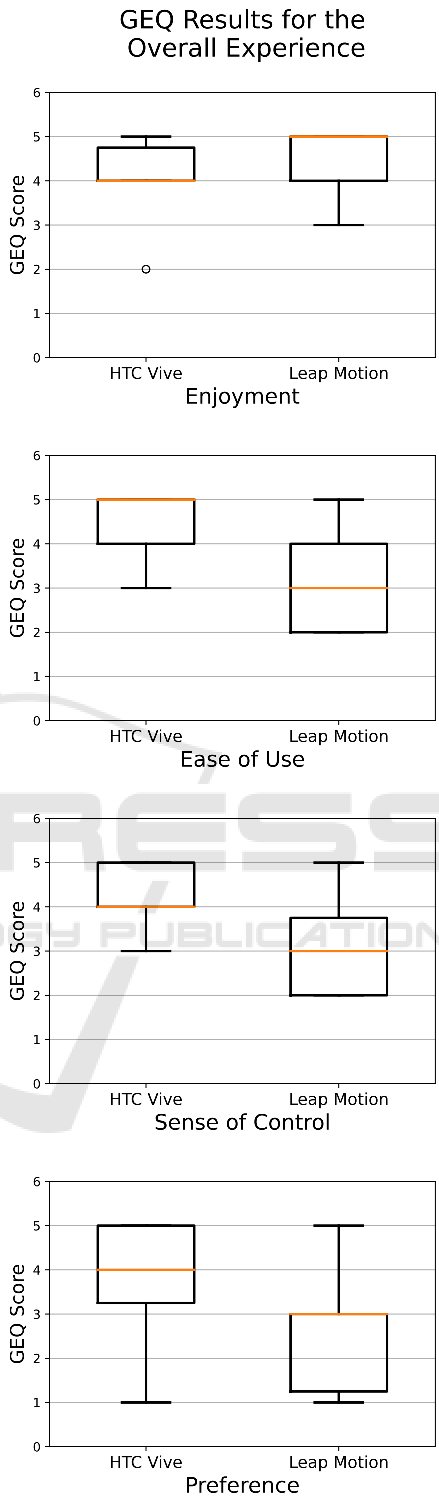

Figure 4: Box plots from the results of each evaluated variable with the GEQ for the overall player experience with each input device.

5.3.2 Ball Throwing Game

For the HTC Vive controller, the variables of challenge, tension, and negative affect showed a weak positive correlation with the peaks per minute. All other GEQ variables showed no correlation:

- Competence: $\rho_{(1,n=18)} = -0.259, p > 0.05$
- Challenge: $\rho_{(1,n=18)} = 0.487, p < 0.05$
- Tension: $\rho_{(1,n=18)} = 0.568, p < 0.05$
- Positive affect: $\rho_{(1,n=18)} = 0.063, p > 0.05$
- Negative affect: $\rho_{(1,n=18)} = 0.683, p < 0.05$

In the case of the Leap motion controller, all GEQ variables show no correlation with the peaks per minute:

- Competence: $\rho_{(1,n=18)} = -0.329, p > 0.05$
- Challenge: $\rho_{(1,n=18)} = 0.346, p > 0.05$
- Tension: $\rho_{(1,n=18)} = -0.125, p > 0.05$
- Positive affect: $\rho_{(1,n=18)} = -0.233, p > 0.05$
- Negative affect: $\rho_{(1,n=18)} = 0.230, p > 0.05$

5.3.3 Overall Experience

For both, the HTC Vive controller and the Leap Motion controller, all GEQ variables evaluated in the overall experience showed no correlation with the calculated peaks per minute for the entire stimuli exposure. The results for the HTC Vive were:

- Enjoyment: $\rho_{(1,n=18)} = -0.094, p > 0.05$
- Ease of use: $\rho_{(1,n=18)} = -0.127, p > 0.05$
- Sense of control: $\rho_{(1,n=18)} = -0.001, p > 0.05$
- Preference: $\rho_{(1,n=18)} = -0.154, p > 0.05$

Similarly, the results obtained for the Leap Motion controller were:

- Enjoyment: $\rho_{(1,n=18)} = -0.203, p > 0.05$
- Ease of use: $\rho_{(1,n=18)} = -0.137, p > 0.05$
- Sense of control: $\rho_{(1,n=18)} = -0.073, p > 0.05$
- Preference: $\rho_{(1,n=18)} = -0.228, p > 0.05$

6 DISCUSSION

The results from this study showed that there were no significant statistical differences in the peaks per minute within the players in the evaluated games. However, the reported player experience did show a significant statistical difference in the majority of variables evaluated with the GEQ. In addition to this, no strong correlation between the peaks per minute and the evaluated experience variables was found in the analysis.

These results show an initial discrepancy with our proposed hypothesis. Nevertheless, this is not enough evidence to propose its rejection with certainty. This study should be interpreted as a work in progress and reports only on the initial results from the phasic component analysis. Previous publications that showed a correlation between player experience and EDA data focused on analyzing the tonic component (Drachen et al., 2010), suggesting that variations in the skin conductance level may display a stronger relationship with the differences in the player experience, than the variations of the peaks per minute.

Despite this, the results obtained in the phasic component analysis showed an interesting consistency with previous publications that proposed alike methodologies, showing that positive correlations have only been found between EDA data and negative affects of player experience (Drachen et al., 2010). Furthermore, the peaks per minute seemed to be affected by the different game genres. An initial evaluation of the peaks per minute showed statistically significant differences between the pentomino and ball throwing games for both, the HTC Vive controller ($WSR_{(1,n=18)} = 0.0, p < 0.05$) and the Leap Motion controller ($t-test_{(1,n=18)} = 9.41, p < 0.05$). Analyzing the changes that different game genres may generate in players' phasic component data is beyond the scope established for this paper, but the results obtained for the peaks per minute suggest that this could be a potential relationship to further explore.

It has been suggested that the correlation between experience variables and EDA data can be limited, since the game genres and experimental approach can affect the measurements (Martey et al., 2014; Egan et al., 2016). Therefore, the use of multiple methodologies for relating player experience with EDA data is recommended (Navarro et al., 2021).

7 CONCLUSION AND FUTURE WORK

This article has presented an initial analysis of the phasic component of EDA data gathered from players and evaluated its potential relationship with their respective player experience. Initial results show that there were no statistically significant differences in the calculated peaks per minute within players, while having statistically significant differences in their respective experience; suggesting that phasic component data captured during gameplay does not vary significantly in terms of the player experience. However, a weak positive linear correlation was evidenced between the peaks per minute and the negative affect of players, which is consistent with the results disclosed in other publications.

Future work should focus on continuing this evaluation, expanding over the analysis of the tonic component of EDA data. In addition to this, other evaluation metrics, such as heart rates, should also be considered when analyzing the potential relationships between player physiology and player experience, due to the limited correlation that may exist with EDA data alone.

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