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# Comparing the Applicability of Pressure as a Game Metric to Self-Assessment and Physiological Metrics

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**Abstract.** Recently, the amount of pressure that is exerted on an input device during a gaming session has been shown to correlate with several aspects of the game experience. While studies have used this metric in a game analysis perspective with promising results, there is still a lack of comparison between the performance of this metric compared to physiological metrics or self-assessment method. Therefore, we conduct an experiment in which we compare exerted pressure against the electrodermal activity (EDA), heart rate (HR) and self-assessment of a subject during a gaming session. Our results indicate that pressure can be used to assess the perceived game difficulty, possibly even better than EDA and HR.

**Keywords:** Game Metrics · Pressure · Self-Assessment · Physiological Metrics.

## 1 Introduction

In recent years, a variety of approaches have explored how to measure and analyze game experiences, especially in relation to different methods and types of data to use, which has given rise to a plethora of options. Recently, pressure exerted on an input device - which can be categorized as behavioural data - has been shown to be a promising measurement of arousal [27, 13], as well as possibly indicating levels of immersion, types of frustration and different player actions [30, 19, 31]. However, there's a lack of research on how well this metric performs against other metrics such as physiological and self-assessment methods. This is important to understand, as it can help to make an informed choice on which metrics to use in a game analysis context. Furthermore, pressure is an attractive metric to use, as some devices such as newer smartphones (e.g. Apple iPhone 6s) are already able to measure different levels of applied pressure. This would mean that a game analysis based on pressure would not necessarily require additional equipment, allowing for data collection on a larger scale without having to spend additional time or effort. In comparison, physiological metrics require external sensors to be attached to the player, which is both obtrusive to the player and

limits how much data can be collected within a time frame based on how many sensors and test facilitators are available. In the case of self-assessment metrics, the collection and analysis of qualitative data is a very time-consuming process compared to the alternatives. This paper aims to compare the performance of exerted pressure against electrodermal activity (EDA), heart rate (HR) and self-assessment as metrics for measuring game experiences. To this end, we conduct an experiment in which all four metrics are used, and follow up with a discussion of the possibilities and limitations of pressure as a game metric.

## 2 Related work

In order to properly compare pressure against other metrics, it is important to first understand the different methods that exist for analyzing game experiences. One such validated method is through self-assessment. To this end, various questionnaires have been developed. The Game Experience Questionnaire (GEQ) [14] and its associated modules, used in several previous studies [20, 7, 13, 28, 1]. The Self-Assessment Manikin (SAM) [2] was developed to measure a person’s affective reactions to stimuli. Previous studies have used SAM in conjunction with other methods to form a coherent understanding of the game experience [25, 9, 21, 30]. Another self-assessment method is think-aloud protocols [5, 6, 12]. However, these self-assessment methods have previously been criticized as being too disruptive or inhibiting the experience [11, 18]. Players may have to pause mid-game to answer questions, or they have to focus on the task of thinking aloud while simultaneously playing the game. Post-game questionnaires or retrospective video-cued think-aloud sessions also present the issue of being reflective rather than reactive, and players may not remember all details after the game has ended [29]. The issues with self-assessment methods caused researchers to look into the use of physiological metrics as a possible supplement or alternative to self-assessment data [18, 16, 7]. While several different physiological metrics have been explored, the most popular metrics appear to be electrodermal activity (EDA) and facial electromyography (fEMG), followed by heart rate (HR) [29]. These metrics relate well to the emotional dimensions defined by J.A. Russell [24], as EDA and HR has previously been linked to arousal, while fEMG has been linked to valence [26, 15, 23]. However, while physiological data is objective and has a high temporal precision, it lacks the contexts that self-assessment data may provide [29]. This shortcoming can be made up for through triangulation, i.e. combining the physiological metrics with other metrics (such as self-assessment [22], logging player behaviour [10] or analyzing video recordings [28]).

In recent years, there has also been an increasing interest in using exerted pressure as a possible game metric. Sykes & Brown [27] found that there was a significant difference in the mean pressure exerted on a gamepad when subjects played *Space Invaders* at varying difficulties, which suggests a connection between pressure and arousal. This finding was supported by van den Hoogen et al. [13], who found a connection between the game difficulty and the max pressure exerted on a mouse button when subjects played three levels of varying

difficulty in *Half-Life 2*. In another study by van den Hoogen et al. [30], aside from finding a connection between pressure and arousal, it was also suggested that there is a connection between the pressure and the level of presence and dominance felt by the player. It was found that when playing levels of varying difficulty in the racing game *Need for Speed: Pro Street*, the pressure was higher in the cases where self-report measures also indicated a higher feeling of arousal, presence and dominance. Furthermore, using an adapted version of a basic infinite runner game, Miller & Mandryk [19] found a connection between the pressure exerted on a touch surface and the type of frustration the player was feeling (in-game frustration versus at-game frustration). Finally, van den Hoogen et al. [31] did a study that suggests that there is a connection between the exerted pressure and the type of player action (avoidance versus approach) in racing car games (*Colin McRae, Trackmania*) and shooter games (*Battlefield 1942, Hitman Contracts*).

As evident from the research, the applicability of pressure as a game metric has been studied and validated in several contexts. However, there are still aspects to explore. Current research has considered pressure in relation to behavioural metrics or self-assessment data, but have failed to include physiological metrics. Comparing pressure in relation to multiple metrics at a time may provide insight on previously unknown correlations, or could aid in giving a better overview of pros and cons of pressure as a game metric.

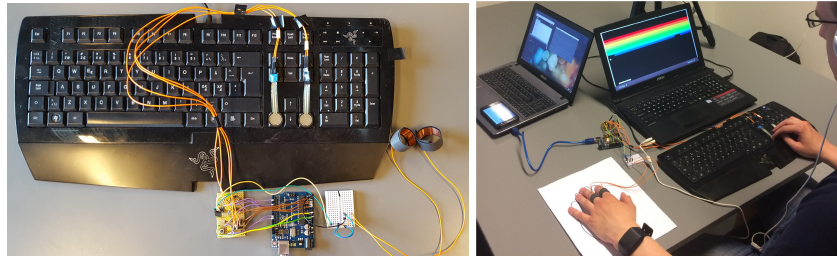
### 3 Evaluation

The purpose of the experiment was to collect data to be used to explore the eventual connections and correlations between the different types of metrics.

#### 3.1 Materials and setup

The game used in the main experiment was an adapted version of the arcade game *Breakout*. The game follows the design and rules of the original *Breakout* from 1976 by Atari Inc.. However, the game was adapted to easily switch between two different difficulties. This could be done at the start of a level, and it changed the amount of speed the ball have. It was decided to use *Breakout* for the experiment as the arcade game genre has been used in previous studies on pressure as a game metric [27]. Furthermore, the game has simple controls and the difficulty could easily be changed.

Fig. 1 shows the custom reader that was built to measure EDA and the exerted pressure using an Arduino. The pressure was measured through two Force Sensitive Resistors (FSR) attached to the left and right arrow keys, and the EDA was measured through two copper bands made of copper tape with velcro on the back (seen to the right of the keyboard), which were to be worn around two fingers on the hand. Both signals are sampled at 20 Hz. The Empatica E4 wristband was used to obtain the blood volume pulse (BVP) sampled at 64 Hz. While the E4 is technically also able to measure EDA, in preliminary test it



**Fig. 1.** Left: The custom reader that was used to obtain pressure and EDA signals during the test. Right: The subject can be seen wearing the E4 wristband and the copper bands for the EDA reader. FSRs were attached to the left and right arrow key. The screen shows *Breakout*.

proved to be less reliable than our custom-built reader due to a faulty sensor in the wristband. Self-assessment data was collected by distributing the iGEQ and SAM questionnaires to the subjects. The statements for the immersion aspects ('I was interested in the game's story' and 'I found it impressive') were excluded from the iGEQ as the statements did not seem relevant in this particular game. Furthermore, video recordings of the game and the subject's face while playing were also collected. To assess the difficulty of the levels that the subjects played, a difficulty questionnaire by van den Hoogen et al. [13] was also distributed. It consists of the single item 'How difficult did you find it to play the level?', which is rated on a scale from -2 ('too easy') to 2 ('too hard'), with 0 being 'optimal'. Furthermore, a camera was angled to record the subject's left hand (which wore the E4 wristband and the copper bands). These recordings could be used during data analysis to assess whether noise or artifacts in the physiological signals were generated by hand movement. Fig. 1 shows a photo of the setup of the experiment.

### 3.2 Subjects and procedure

The results of the experiment consist of data from 25 tests. The subjects were University students aged 20-25 years old (18 males and 7 females). At the beginning of each test, the subject was briefed about the test procedure and asked to sign a consent form. They were then asked to rate how often they play games on a scale from 0 ('never') to 5 ('daily'). One participant reported 'never' (4%), one reported 'less than once a year' (4%), one reported 'monthly' (4%), seven reported 'weekly' (28%) and 15 reported 'daily' (60%). The E4 wristband and the copper bands for the EDA readings were attached to their left hand, and they were asked to place their hand within a hand-shaped outline on the table and keep it still for the remainder of the test. Before playing, they watched a calming video with nature sounds for 3 minutes to allow for their physiological signals to fall to an acceptable base level. The subject was then asked to play two levels of *Breakout*, one of an easy difficulty and one of a hard difficulty. The

order of the given difficulty was counterbalanced. After each level, they were asked to fill out the iGEQ, SAM and difficulty questionnaire. Furthermore, after filling out the questionnaires between the two levels, they watched 1 minute of the calming video to reduce carry-over effects for the second playthrough.

## 4 Results

It should be noted that while pressure sensors were attached to both the left and right arrow keys on the keyboard, only the data from the FSR on the left arrow key is used during the following data analysis due to some issues with the readings of the right FSR. In regards to calculating the mean pressure, datapoints that were not connected to a keypress were excluded from the calculations. This ensures that readings that did not contain user input would not influence the calculated mean pressure, even when slight noise in the FSRs was recorded. Prior to data analysis, the EDA signal (measured at 20 Hz) was denoised by calculating the centered moving average with a window of 21 (i.e. calculating the centered moving average over 1 second). The HR was calculated from the interbeat interval (IBI) signal provided by the E4 wristband, which calculates the IBI signal from the BVP. Wrong peaks, i.e. noise in the BVP, are automatically removed by algorithms in the E4 wristband software. As a final pre-processing step, the EDA, HR and pressure signals were normalized (min-max) per subject. This meant that rather than finding a minimum and maximum value per playthrough for a given signal, a minimum and maximum value was found per subject (i.e. in each subject’s easy and hard playthroughs combined). This ensured that the individual differences between subjects were removed, while each subject’s difference between the easy and hard playthrough was preserved. To determine which statistical tests to use, a series of Lilliefors tests were performed to assess whether the obtained data come from a normal distribution. Table 1 shows the resulting p-values of performing Lilliefors tests on the mean (and max) values of the different signals in each difficulty, as well as the difficulty ratings ( $n=25$  for each test). The data that were found to come from a normal distribution (i.e. when the p-value was above a significance level of 0.05) have been emboldened in the table.

**Table 1.** Lilliefors p-values

	Easy	Hard
Max pressure	0.024	<0.001
<b>Mean pressure</b>	<b>0.272</b>	<b>&gt;0.5</b>
Mean EDA	0.034	0.003
<b>Mean HR</b>	<b>0.356</b>	<b>&gt;0.5</b>
Difficulty ratings	0.001	0.001

**Table 2.** T-test and Wilcoxon

Variable	Test	p-value	Effect size $r$
Max pressure	Wilcoxon	<0.001	-0.546
Mean pressure	t-test	<0.001	0.852
Mean EDA	Wilcoxon	0.367	0.127
Mean HR	t-test	0.557	0.121
Difficulty rating	Wilcoxon	<0.001	-0.470

Two-tailed Student’s t-tests or Wilcoxon signed-rank tests were then performed with the different variables ( $n=25$  for each test). In the case of normally

distributed interval data, a Student’s t-test was used, while in the case of ordinal data or data that was not normally distributed a Wilcoxon signed-rank test was used. Table 2 shows the resulting p-values of the student’s t-tests and Wilcoxon signed-rank tests, with the independent variable being the difficulty (easy/hard), and the dependent variable being specified in each row.

With a significance level of 0.05, we can interpret these results as that the difficulty ratings, max pressure and mean pressure are significantly different between the easy and the hard difficulty. By inspecting the max and mean pressure values in the easy and hard difficulty, it can specifically be determined that the harder difficulty resulted in a higher max and mean pressure. As for the effect size, following the general guidelines by Cohen [3], an  $r$  of 0.1 is considered small, 0.3 is considered medium and 0.5 is considered large. Thus, the  $r$  of the differences in max and mean pressures can be considered large, while the  $r$  for the difference in difficulty ratings can be considered medium, but on the verge of being large. Thus, the magnitude of the the difference in the mentioned variables can for the most part be interpreted as being large.

To explore any eventual linear relationships between variables, it was furthermore decided to calculate a set of Spearman’s and Pearson’s correlation coefficients (depending on whether ordinal data, i.e. answers to the iGEQ, were included in the calculations). The variables consist of the difference between the easy and hard difficulty. Calculating correlation coefficients using the differences between the difficulties rather than the raw values ensures that the correlation coefficients are based on the *change* that was experienced between the difficulties. As an example, a subject rating tension as ‘2’ and ‘3’ in the easy and hard difficulty respectively will have a tension difference of ‘1’, which would also be the case if they had instead rated it ‘4’ and ‘5’. The correlations that were found to be significant are listed in table 3. Following general guidelines [8], it can

**Table 3.** Significant correlation coefficients between variables

Variable 1	Variable 2	Correlation coefficient	P-value
Max pressure	Mean pressure	0.469*	0.017
Max pressure	Flow	-0.465	0.018
EDA	Negative affection	-0.447	0.018
EDA	Flow	0.370**	0.068
HR	Competence	0.423	0.034
HR	Positive affection	0.559	0.003
Difficulty	Tension	0.467	0.018
Difficulty	Challenge	0.529	0.006

\*Pearson’s correlation coefficient

\*\*p-value above 0.05

be said that all relationships listed in the table are moderate, with the exception of the relationship marked with a double-asterisk which is mild or weak. As expected, the difficulty correlates positively with the tension and challenge.

Furthermore, the EDA can be said to correlate with whether the player was in their optimal flow. The reason for this is it correlates positively with flow (consisting of the statement ‘I forgot everything around me’ and ‘I felt completely absorbed’), while correlating negatively with the negative affection (consisting of the statements ‘I felt bored’ and ‘I found it tiresome’). Following the definition of flow by Csikszentmihalyi [4], the negative affection seems to describe ‘boredom’ which is outside of the flow channel. Finally, looking at table 3, it also seems that HR correlates with how good the player felt. The reason for this is that HR correlates positively with both the positive affection (consisting of the statements ‘I felt good’ and ‘I felt content’) and the competence (consisting of the statements ‘I felt succesful’ and ‘I felt skillful’).

## 5 Discussion

The performed Student’s t-tests and Wilcoxon signed-rank tests indicate that the pressure exerted while gaming was affected by how difficult the game was, and more specifically, that a harder difficulty resulted in a higher mean and max pressure. Furthermore, looking at the calculated correlation coefficients, it has been found that difficulty relates with tension and challenge, i.e. the arousal of the subject. This finding - that pressure relates to difficulty and arousal - is also backed by previous research [27, 13, 30] in which different games and lengths of play sessions were used. Notably, as opposed to max and mean pressure, no significant difference could be found in the mean EDA and HR between the difficulties. This may indicate that pressure can be a better metric for measuring game difficulty than EDA and HR, at least in the case of short play sessions.

In contrast to findings by van den Hoogen et al. [13], we have not been able to find any significant correlations between pressure and the different player experience aspects covered in the iGEQ. This may be explained by the fact that the experiment designs were not similar and different games were used in the tests. In their experiment the subject played Half-Life 2 in three 10-minute sessions, and the pressure on the left mouse button was measured. In our experiment the subject played Breakout in two 5-minute sessions, and the pressure on the left and right arrow keys was measured. This dissimilarity in findings suggests that pressure is not necessarily indicative of player experience aspects. For a more conclusive discussion on this, further research would be required.

The calculated correlation coefficients indicate that the mean HR correlates positively with competence and positive affection, which can be summarized as emotional valence. This correlation is not backed by previous research, and while there is most likely an underlying cause of the correlation, it is currently not possible to pinpoint the exact explanation. Therefore, this result of the data analysis will be disregarded.

The correlation coefficients related to the mean EDA can be interpreted as that the mean EDA rose the more excited the subject felt, which has also been found in previous research [7, 17]. Firstly, the mean EDA correlated negatively with



negative affection (which describes how bored or disinterested the subject felt) and, secondly, it correlated positively with flow.

### 5.1 Impact for practitioners

Our results indicate that pressure relates to the arousal of the player and the perceived difficulty of the game. This in turn suggests that pressure can be used to create adaptive games that alter the difficulty to better fit the player’s skill level based on the amount of pressure they apply to the input device. This application has multiple benefits compared to using self-assessment or physiological metrics:

- Pressure is a non-obtrusive metric as opposed to physiological metrics that require sensors to be attached to the body.
- Pressure data is real-time compared to self-assessment data that is typically obtained during or after a game session through interviews or questionnaires.
- Some devices (e.g. styluses, trackpads, phones and tablets) have in-built technology that is able to detect different levels of pressure. This means that using it as a game metric does not necessarily acquire additional equipment for these platforms.

### 5.2 Limitations

It should be noted that the obtained results are based on subjects within a narrow age range that can be considered to be at least fairly experienced with games (88 % reported ‘weekly’ or ‘daily’ gaming). This may have had an effect on the results. The strength of the calculated correlation coefficients can be interpreted as ‘moderate’, or in one case ‘weak’. It is possible that play sessions longer than 5 minutes could increase the strength of the correlation coefficients, but this is a matter for further research. Finally, the game used for the experiment was specifically chosen due to being action-focused which is in line with prior work [13, 30, 19, 31]. Performing a similar experiment with other games may not produce the same results.

## 6 Conclusion

With this paper, we set out to explore the possibilities and limitations of pressure as a game metric in relation to other widely used game metrics. The results of the experiment firstly indicate that pressure relates to arousal, which means it can be used as an indication of the perceived difficulty of a game. As pressure is unobtrusive compared to physiological metrics and real-time compared to subjective metrics it enables developers to use it easily. Secondly, pressure has been better at indicating arousal in our experiment setup compared to the physiological metrics. Thirdly, we have not found any significant correlations between pressure and player experience aspects like others before us. We would advise that further research on this subject is conducted before anything conclusive can be said on the matter.

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