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EXPLORING PEAK-END EFFECTS IN PLAYER AFFECT THROUGH HEARTHSTONE

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KEYWORDS
Peak-end theory, player emotions, affective games, facial expression analysis

ABSTRACT

Peak-end theory suggests that when remembering an experience, people tend to focus on the moments of highest emotional variance and the last moments of the experience. In this paper, we study whether peak-end effects occur in gaming experiences, by comparing real-time to retrospective measurements of player affect. We ran an experiment where each of 26 participants played two games of Hearthstone while their affective state was monitored in real time through self-reporting and facial expression recognition. Additionally, participants submitted a retrospective report on their emotions 24 hours after the experiment took place. Strong correlation was found between the self-reported peak-end and retrospective emotion values, while no correlation was found between the retrospective self-reports and player facial expressions. The results of this study validate that the peak-end rule can be leveraged in order to identify players' retrospective emotions towards a game experience.

INTRODUCTION

The vast variety in video game players' personalities makes it impossible to guarantee that a game will be considered entertaining by every single player. People perceive in-game experiences in a unique way, leading to different individual responses (Kosinski et al. 2018). In the last decade, technological advances have enabled the obtaining of player feedback through consumer-level devices capable of monitoring player behaviour in real-time. A review by Peake et al. (2018) describes more than 100 devices able to measure humans' physiological, motor and cognitive functions.

One of the most popular biofeedback methods in affective computing research is facial expression recognition (Cohn et al. 2007). Players' facial expressions may provide accurate indicators of their affective state, translated into six basic universal emotion expressions (happiness, anger, fear, disgust, sadness and surprise) (Ekman and Friesen 1978). However, the search for a satisfactory experience goes beyond the sheer measurement of different emotions during a task. Gent et al. (2013) state that retrospective hedonic evaluations play a major role when people decide whether they are willing to repeat a certain experience or not.

Among the several tools that psychology has developed to try to understand what leads to a positive or negative retrospective memory, there is the peak-end rule (Kahneman et al. 1993). The peak-end rule states that people's judgement of an experience is highly associated with the emotions they felt at its peak and at its end (Kahneman et al. 1993; Do et al. 2008). Although the peak-end rule has been validated in different areas of science, its application in the gaming domain is still scarce (Gutwin et al. 2016).

In this paper, we use Hearthstone, an online collectible card game (Blizzard Entertainment 2013), to observe correlation between real-time player emotions and the retrospective hedonic memory of players' experiences. We run an experiment where player affective state is monitored during gameplay through self-reports and facial expression analysis. After 24 hours, players submitted a retrospective assessment of their emotions during the games played. Our main contribution is a multi-modal study of the applicability of the peak-end rule in online gaming scenarios.

RELATED WORK

In this section, we describe relevant studies conducted in the fields of facial expression analysis and human memory. Moreover, we describe the peak-end rule and its effect on retrospective memory.

Facial Expression Analysis

Facial expression analysis can be used to infer emotions, intentions and other internal indicators (Zhang et al. 2015). Although there is vast literature about recognizing emotions from facial expressions, it was Ekman and Friesen (1978) who defined the standard and most broadly accepted method of recognizing emotions by introducing the Facial Action Coding System (FACS)(Cohn et al. 2007). FACS defines 44 specific facial muscle movements (Action Units) that can be activated either individually or in combination, resulting in more than 7000 different facial expressions (Tian et al. 2001).

Ekman and Friesen (1978) define six basic emotions, namely happiness, sadness, anger, fear, disgust and surprise. These emotions can be identified through facial expressions, using the FACS. Multiple approaches have been presented (Amini et al. 2015; Ekman and Friesen 1982; Scherer et al. 2019; Zhang et al. 2015), each using a different mapping of facial Action Units (AUs) to specific emotions. It is important to note that the FACS is a descriptive system, excluding the subjectivity factor that is often connected to emotion expressions.

Facial expression analysis has been previously employed in game-related studies, including player experience assessment (Tan et al. 2014), avatar control (Zhan et al. 2008) or dynamic game difficulty adjustment (Blom et al. 2020). Compared to other biofeedback methods, facial expression analysis provides a cost-efficient non-intrusive solution, as it can be applied through any consumer level webcam. Furthermore, open source state-of-the-art software such as OpenFace (Baltrusaitis et al. 2018) can provide accurate detection of facial AUs in real-time. In the present paper, we employ OpenFace in order to detect player facial expressions during gaming experiences. The extracted facial expressions will be mapped to Ekman and Friesen's six basic emotions, and tested for correlation with peak-end effects of players' retrospective memory.

Memory Bias

The success of a video game highly depends on how much people are willing to repeat the experience that the game offers. A determinant factor in making this decision, is players' retrospective hedonic memory of an experience. In other words, how they remember they felt during the experience (Ariely and Carmon 2000).
Scientific studies point out a difference between how people feel during an experience and how people remember they felt during that experience. Due to memory limitations, the human brain is not able to recall everything that it has experienced in detail. Therefore, the brain selects to record certain features of a specific experience, and based on those, it reconstructs the retrospective summary of the experience (Geng et al. 2013). As this process does not take every event of an experience into consideration, the selection of such features may be biased. The result is that the actual experience and the retrospective memory of it may not be exactly similar (Kahneman 2000).

The Peak-End Rule

The Peak-End rule was first proposed by Kahneman et al. (1993). His hypothesis was that because of memory bias towards emotional factors, people are unable to accurately judge their own experiences in retrospect. This hypothesis was validated through a user study, where between two painful experiences, participants showed preference towards the one that lasted longer but was slightly less painful towards the end. Kahneman et al. proposed that participants' retrospective evaluation of the experience was not a time continuum, but a collection of moments. The selection of those moments to construct a retrospective evaluation were biased towards those with an emotional peak and the emotions perceived at the end of the experiment, regardless of the duration of the experience. The base of this theory is that situations that evoke high emotional valence are more remembered than situations that evoke low emotional valence (Kahneman et al. 1997; Kensinger 2009).
In the context of video games, studies regarding the Peak-End rule are scarce, even though players' retrospective affective memory of a game experience is a determinant factor in player retention. In addition, games provide highly immersive experiences and usually generate more intense momentary emotions than daily tasks (Gutwin et al. 2016).
Gutwin et al. (2016) explored this domain by testing for Peak-End effects in three games where in-game difficulty was manipulated to induce positive, negative and neutral peak-end effects. The results showed positive correlation between players' recollection of in-game challenge and peak-end effects. Furthermore, in one of the games, peak-end effects were also correlated to players' higher perception of interest, fun and desire to play the game again. In this study, we aim to further investigate the applicability of the peak-end rule, as we expand into the domain of online games played in a home environment.

METHODOLOGY

The goal of this study is to explore whether the peak-end rule can be applied to online games, played in a home environment. To that end, we ran an experiment where player affective state was monitored during gameplay through self-reports and facial expression analysis. Peak-end scores of player emotions were tested for correlation against retrospective emotion scores submitted by the participants.

Experimental Setup

During the experiment, participants played two online (non-competitive) games of Hearthstone against random opponents. We chose to use Hearthstone for three main reasons: (1) It is a widely popular game, which facilitates obtaining participants; (2) the average duration of a game of Hearthstone is approximately 10 to 15 minutes, which is enough time to collect an adequate amount of data for player emotion analysis; (3) most important, the game is played in turns, which provides researchers with enough idle game time during which participants may provide self-reports. Brief interruptions should not interfere with the participants' game immersion and consequently, their enjoyment of the experience (Brown and Cairns 2004).
This study was originally designed to take place in a University laboratory space, under controlled lighting, recording and computer hardware conditions. Due to the COVID-19 pandemic, social distancing regulations made physical data collection impossible. For that reason, this experiment was run remotely, using participants' home computers and peripheral devices. Even though the remote experimental setup deviates from our initial planning, we believe that it closely resembles a real-life gaming situation. In that sense, we expect recordings of players' facial expressions to be more spontaneous at home than in a lab environment. However, external distractions and uncontrolled lighting conditions may cause noise in the recorded data.
In this experiment, we attempt to validate the peak-end rule through two separate methods: we extract scores on player emotions through facial expression analysis and real-time self reports. Both input channels are tested for correlation with retrospective self-reports of emotions submitted by the players 24 hours after the experiment took place.

Figure 1: Snapshot of the Hearthstone Game. Each Player Uses a Deck of 30 Cards and Aims to Win by Reducing their Opponents' Health Points to 0

Data Collection

Participants were recruited by Convenience and Snowball Sampling during the months of April and May of 2020. A total of 26 (7 female) players participated in this experiment (mean age 24.8 years, sd=5.21). All participants had played Hearthstone at least once before.
Hearthstone is a single player online game, where one's goal is to bring their opponent's health points to 0 using a deck of 30 cards (see Figure 1). The game is played in alternating turns, each of which lasts a maximum of 75 seconds (Blizzard Entertainment 2013). Players have the option to end their turn prematurely, by pressing an "end turn" button. In this study, no game-related data was collected as it falls out of the scope of this research.
OpenFace was used in order to analyze player facial expressions (see Figure 2). OpenFace is an open-source, state-of-the-art facial behavior analysis tool that is capable of detecting facial landmark location, eye gaze, head pose and facial action unit estimations in real-time (Baltrusaitis et al. 2018).
Prior to participating in the experiment, participants received an email containing a consent form and an explanation of the experimental procedures. They were prompted with a link to an online video call with the experimenters which they joined after initiating Hearthstone on their computers. Through screen sharing, participants provided visual access to the Hearthstone game window and their webcam footage. Both the participant's face and game window were recorded throughout the experiment.
Participants played two games of hearthstone each. For every game, starting at the second turn and every three turns after that (including the last turn of the game), participants were signalized to answer the following question: "How would you rate your feelings this moment concerning this experience, on a scale from -5 (extremely unpleasant) to 5 (extremely pleasant), 0 being neutral?".
The question was adopted from Kahneman et al. (1997), aiming to obtain the maximum amount of information with the minimum amount of questions.

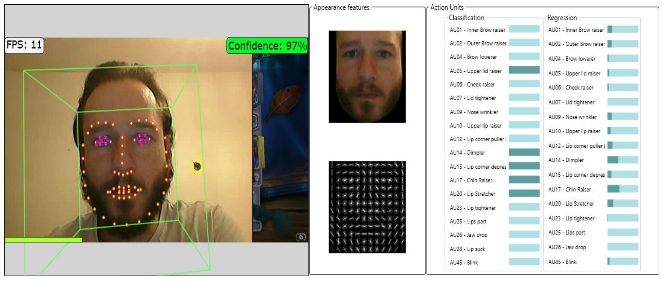

Figure 2: Snapshot of the OpenFace Software. On the Left, the Player's Webcam Recording with Facial Landmark Annotations. On the Right, Real-Time Estimations of Action Unit Intensity

This method was used in order to minimize gameplay disruption. The experimenters also avoided speaking with the participants during the games, doing so only to say the word "rate", which was the signal for participants to answer the previously described question. The three turn interval between participant ratings assured the collection of data alternating between the participant turn and the opponent's turn. Furthermore, it decreased the predictability as to when the assessment would be made, which could decrease the players' level of immersion (Brown and Cairns 2004).
An intermission of a few minutes was made between the two games and was used to ask participants to report on demographic questions (age, experience in Hearthstone). This intermission was intentionally designed to create a perception of finalizing one task (game 1) before starting game 2.
Regarding retrospective affective memory, 24 hours after the experiment took place, participants were contacted to answer the following question: "How would you rate your feelings at this moment concerning the experience of game 1, in a scale from -5 (extremely unpleasant) to 5 (extremely pleasant), 0 being neutral?" The same question applied for game 2. Participants were not informed about the content of the experiment's questions beforehand, to avoid influencing their answer.

Data Processing

From player self-report ratings collected during gameplay, two variables were extracted: (1) *Average emotion* was measured as the arithmetical average of all the ratings participants gave during the experiment. (2) *Peak-end emotion* was measured as the arithmetical average between the rating with the highest absolute value (peak) and the last rating given (end). The last rating was excluded from the peak value calculation. In cases of two peaks of similar absolute value but opposite sign (e.g. -4 and 4), the peak of opposite sign to the end rating was selected as *peak emotion*.
From the collected facial expression footage, per-frame AU intensity estimations were extracted using OpenFace. These intensity estimations are calculated in a continuous scale from 0 (no activation) to 5 (strong activation). OpenFace also provides a per-frame estimation confidence interval, and frames with a confidence value below 80% were discarded from the dataset. From AU intensity estimations, six basic

Table 1: Action Unit Configurations for Calculation of Basic Emotions, Based on Different Studies. Basic Emotions are Derived as the Aggregation of the Mentioned Action Unit Values

Basic Emotion	Action Units per study			
	Ekman and Friesen (1982)	Zhang et al. (2015)	Amini et al. (2015)	Scherer et al. (2019)
Happiness	6,12	6,12	6,12,25	6,7,12,25
Sadness	1,4,15	1,4,15,17	1,4,15	1,4,15,45
Anger	4,5,7,23	4,5,17,23	5,7,9,10,15,17	4,5
Fear	1,2,4,5,7,20,26	1,4,10,20,26	1,2,4,5,20,26	1,4,5,25,26
Disgust	9,15	4,10,17	9,15	4,7,9,10,17,20

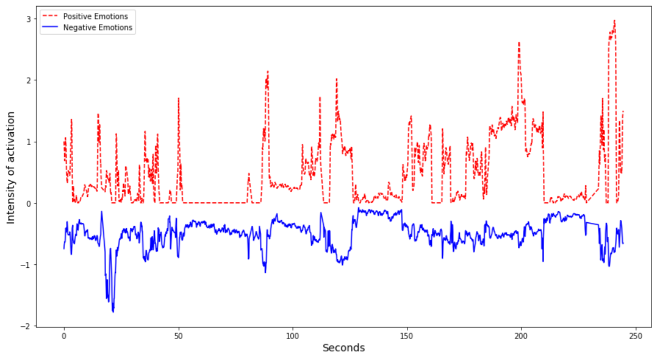

Figure 3: Time Series of One Participant's Activation of Average Positive and Negative Emotions During Gameplay

emotion intensity values were extracted, as defined by Ekman and Friesen (1978). To perform this transformation, four different mappings were used (see Table 1). Subsequently, the extracted emotions were divided into positive (happiness) and negative (sadness, anger, fear, and disgust) emotions. Surprise was discarded from the dataset, as we considered it to be a neutral emotion, yielding little information about player valence. The above methods resulted in a new facial emotion scale, from -5 (highly negative emotions) to +5 (highly positive emotions). Figure 3 illustrates a player's per-frame emotion estimations throughout the course of one game after the calculation of average positive and negative emotions.

In order to translate per-frame facial emotion estimations into per-game descriptors of overall player emotional state, the exact assessment moments (submitting ratings to the experimenters) were annotated. Around these moments, eight different time window configurations were applied. For each time window configuration, three emotion calculation methods were used. The above calculations resulted in a total of *3 x 8* overall emotion variables, for each moment of assessment. A summary of the different configurations used is shown in Table 2. The different configurations used aim to explore (1) whether different time intervals influence the assessment of player emotions and (2) whether negative emotions should be calculated individually or as a group.

Every per-game emotion value calculated through facial expression analysis was tested for correlation against the retrospective emotion value submitted by the players.

Table 2: Description of Per-game Emotion Calculation Parameters

Parameter	Configuration
Time window	1 second before assessment 1 second before and after assessment 3 seconds before assessment 3 seconds before and after assessment 10 seconds before assessment 30 seconds before assessment period between consecutive assessments peak-end values for entire game
Emotion calculation	Average positive & negative emotions Maximum mean value of 5 basic emotions Maximum absolute value of 5 basic emotions

RESULTS

In this section, we present the results obtained from experimentation, divided in two parts: results regarding player self-reports, and results regarding player facial expressions.

Results of the Self-Reported Assessment

Participants' submitted self-reports during the matches played were used to calculate the *average emotion* and the *peak-end emotion* variables. A statistical Shapiro test indicated that the collected data was not normally distributed, therefore the nonparametric spearman test was used to measure correlation between the retrospective affective memory and the extracted emotion variables. The spearman correlation between the retrospective affective memory and the *average emotion* was 0.725 ($p<0.01$, moderate correlation), and the spearman correlation between the retrospective affective memory and the *peak-end emotion* was 0.866 ($p<0.01$, strong correlation).

In order to test whether the correlation scores between *average* and *peak-end emotion* differ significantly, spearman rho scores were transformed to z-scores, using Fisher's ρ to z transformation. The *average emotion* z-score was 0.919 and the *peak-end emotion* z-score was 1.319. The Fisher coefficients comparison formula produced a z value of 1.98, which exceeds the critical value of 1.96 ($p<0.05$). Therefore, we identify that the *peak-end emotion*'s correlation is statistically superior to the *average emotion*'s correlation.

Results of the Facial Expression Analysis Assessment

We explore whether player emotions, as estimated through facial expressions, validate the peak-end rule. Our approach is to test for correlation between the extracted facial expression recognition variables and the self-reported retrospective affective memory variable. We used 4 different mappings of facial AUs into emotions, with 24 possible configurations.

None of the extracted per-game emotion values showed correlation with the retrospective player emotion rating. While real-time player emotion reports validate the peak-end rule, the same conclusion cannot be drawn for players' emotions extracted through analysing their facial expressions.

DISCUSSION

In this section, we discuss the results obtained, while we also point out the limitations and future studies that derive from the present study.

Self-reports

Regarding real-time player self reports, results showed correlation between both peak-end and average emotion ratings and the retrospective evaluations submitted 24 hours after the experience. Moreover, we found that the peak-end emotions' correlation to the retrospective reports was significantly superior to the average emotions' correlation to the retrospective reports.

The above findings are aligned with Kahneman's peak-end rule, which states that when remembering an experience, people tend to focus on the moment of highest emotional variance and the last moment of the experience. Furthermore, they also validate Geng et al. (2013): a characteristic of the peak-end rule is that it can be applied for a short period after the experience; in the case of this study, 24 hours after the experiment took place.

From the above observations, we may conclude that the results of this study validate the applicability of the peak-end rule in the discussed context. In other words, in online Hearthstone sessions, players tend to keep memory of the peak and end emotions they felt during gameplay. As the retrospective hedonic memory of an experience is a determinant factor for people to decide if they want to repeat an experience or not (Ariely and Carmon 2000), these findings can be used to improve the adherence to a game, which is crucial to its success.

Facial Expression Analysis

Additional to player self-reports, player facial expressions were monitored and analysed in order to to identify their emotions during gameplay. A combination of 4 different configurations of facial AUs (Amini et al. 2015; Ekman and Friesen 1982; Scherer et al. 2019; Zhang et al. 2015) were tested using 3 different emotion extraction procedures and 8 different time window settings. None of the combinations showed significant correlation to the retrospective emotion self-reports. In the context of this study and through the facial expression analysis methods selected, player facial expressions failed to validate the peak-end rule.

An underlying reason why this result is observed might be the experimental setup. Due to the COVID-19 pandemic, data collection was performed using participants' hardware, in their home environment. This may have caused noise in the collected facial expression data, mainly due to sharp changes in lighting conditions, face occlusion, poor hardware performance or external distractions. A more robust dataset would have been collected if participants played the games in a University laboratory space, where the experimental conditions could be controlled.

Furthermore, studies have shown that players' intrinsic emotions do not always comply with their facial expressions (Blom et al. 2020). We have observed instances where participants would smile when feeling frustrated, leading to negative emotions being falsely identified as positive. In order to obtain more accurate results, facial expressions should be mapped into more descriptive emotions, e.g. "happy smile" vs. "frustrated smile".

Limitations and Future Work

Certain limitations can be applied to this study. Following Geng et al. (2013), this study was conducted by getting the retrospective affective memory of participants 24 hours after the experiment. As a consequence, the obtained results are limited to this time specific interval. In future studies, it would be insightful to verify whether the results obtained hold true for various (larger) time intervals.

Lastly, the relatively small sample size (26 participants and 52 games played) and the use of a specific online game harms the generalizability of the results presented to the entirety of the online game industry. However, since most online card games are played in a turn-based fashion, we believe that the results of this study may still apply in other online card games. To generalise these results over other game genres, separate studies need to be conducted.

CONCLUSION

In this study, we present an experiment where participants play two games of Hearthstone while ratings of their emotions are retrieved in real-time, through self-reports and facial expression analysis. 24 hours after the experiment took place, participants submitted a retrospective self-report rating their emotions during gameplay. Our main goal is to test the applicability of the peak-end rule (Kahneman et al. 1997) in the context of online card games played from a home environment. To that end, we ran correlation tests between real-time player emotions (extracted through self-reports and facial expression analysis) and retrospective player emotion ratings.

Results indicate that our calculations of peak-end player emotions extracted through player self-reports are strongly

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correlated to the retrospective player emotion ratings. However, no correlation was found between peak-end player emotions extracted through facial expressions and the retrospective player emotion ratings.

Through the above results, we validate the applicability of the peak-end rule in the context of this study. It seems that in retrospect, players keep memory of the peak and end emotions felt during the game experience. In future studies, we aim to increase the generalisability of these results into other game genres, while at the same time, developing robust algorithms to accurately recognize player emotions through players' facial expressions.

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BIOGRAPHY

AGNER PITON, was born in Brazil, where he graduated in business administration and worked 10 years in the field. After realizing he wanted a career where he could have more impact in people's lives, he started to learn Neuroscience and became a master's student in Cognitive Science and Artificial Intelligence at Tilburg University.