# The Pace of Fear: Temporal and Contextual Dynamics on Physiological Responses to Scary Videos

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## 1. Introduction

The horror genre has witnessed a significant increase in popularity over the past few years [1]. For younger viewers, in particular, horror ranks as the third favorite genre, just behind comedy and action, with 28 % of Gen Z members in the U.S. favoring horror [2]. But, why do we like scary movies?

The allure of horror media lies primarily in the complex interplay between fear and enjoyment [3]. The key to recreational horror is achieving an optimal level of physiological arousal: too low, and it is not thrilling enough; too high, and it becomes unpleasant [4]. This effective mix of suspense, shock, fear, and excitement is observable at the physiological level and can be measured using signals of arousal, such as heart rate and skin conductance metrics [5]. Understanding the factors that determine physiological reactions to fear-inducing stimuli allows for the design of effective horror experiences in media and games. Proper intensity, duration, and pacing of horror content ensure effective exposure to fear in a controlled environment that feels safe and fun. It provides the desired "cathartic experience" [6], without causing lasting anxiety or avoidance behaviors, which can damage viewer engagement and retention [7].

To contextualize the aim of the present study, it is important to consider the distinction between acute and sustained fear. The former, triggered by "jump scares", involves immediate, reactive mechanisms to unconditioned stimuli. The latter engages networks that prepare the organism for potential threats through increased sensory vigilance. Research indicates that although the relevant neural pathways for these fear responses may be distinct, they are interconnected [8]. Moreover, both types of fear relate to physiological arousal responses and can interact in controlled settings where fear anticipation is deliberately or inadvertently manipulated. For example, Bruckbauer et al. [9] found statistically significant increases in blood pressure, heart rate, and electrodermal activity (EDA) before an anticipated frightening stimulus. On the other hand, a phenomenon known as Stimulus-Preceding Negativity (SPN) predicts the opposite, that is greater heart rate deceleration before anticipated high-arousal stimuli [10].

Given the complexity of these effects and the nuanced relationship between acute and sustained fear, this study aims to examine how the temporal spacing and arousal content between presentations of fear-inducing stimuli influence physiological responses. Understanding this dynamic is crucial for designing balanced and engaging horror experiences. Moreover, the relevance of these insights extends beyond the entertainment industry. Considering the shared neural mechanisms between fear and anxiety, as well as the interplay between cognition and physiological responses to threats [11] [12], insights from this research effort may also have implications for refining clinical methods used in desensitization and exposure-based therapies for treating phobias and anxiety disorders [13] [14].

## 2. Related work

### 2.1 Factors affecting fear responses

Fear reactions are influenced by multiple factors ranging from cognitive to contextual elements, as well as the mode of stimulus presentation. For instance, Castaneda and Segerstrom [15] demonstrated that

physiological activation is dependent on the cognitive anticipation of negative events (worries) and the type of stimulus used. They noted that high worry may dampen physiological responses to fearful imagery but not to actual feared stimuli. Cognitive elements can be even less relevant yet effective, as Terkildsen et al. [16] found that physiological arousal from jump scares increased as mental workload levels rose. Other researchers have explored the influence of actual [17] and perceived control over the stimulus [18], the role of the environment [19], and conscious awareness of the fearful stimulus [20].

The mode of presentation also plays a crucial role, with visually evoked threats leading to significant fear responses as evidenced by cerebral activity [21]. Media such as images [22] and video clips [23] have been found effective, and more recently, immersive technologies like virtual reality (VR) have been employed to study physiological responses to scary stimuli [24]. Madsen [25] observed heightened physiological activation when participants played a horror-themed video game compared to watching similar content, highlighting the impact of agency on fear induction. The importance of the auditory element and the additive effects of multimodal stimulation have also been demonstrated [26] [27]. These factors not only affect physiological responses but also influence perceived fear, although these aspects are not always correlated [28].

## 2.2 The role of multiple exposures to fear stimuli

The fear response is primarily an adaptive process and is based on "contingency awareness" [29]. This means that effective responses depend on the interplay between lower-level processes of stimulus conditioning and higher cognitive aspects to assess impending threats. On one hand, stimulus generalization refers to the organism's ability to behave in a new situation—and respond to novel stimuli—in a manner learned in other similar situations [30]. Viewing the same phenomenon from a cognitive perspective, responses to novel fearful stimuli depend on previously stored evaluations [31]. Therefore, the distinction between these processes may be less significant at the physiological level, as cognitive evaluations ultimately influence physiological arousal levels. Both cognitive appraisals and physiological activations ultimately determine the observed behavior [32].

The above theoretical framework helps explain findings like those of Evans et al. [26], who noted that participants' physiological responses to a scary scene presented for the first time differed markedly from their responses to the same scene presented a second time. However, the nature of this difference is not always clear. It is beneficial to consider whether physiological responses to repeated or similar, novel fearful stimuli decrease due to habituation or increase due to heightened alertness. While animal studies may require multiple trials to achieve habituation to a frightening stimulus [33], in humans, this may occur much more rapidly depending on the context, stimulus characteristics and order, or individual traits [34] [35] [36]. Dampened arousal responses are particularly observed in heart rate and skin conductance levels [37]. Conversely, alertness, which is typically associated with high levels of arousal, has the opposite effect on subsequent responses as it tends to delay habituation and increase prestimulus activation levels of autonomic response elements. This highlights how mental processes such as attention and expectancy can influence the habituation process [38]. Additionally, arousal may transfer between semantically related, temporally adjacent events, underscoring the significance of stimulus timing [39].

Given the complexity of these mechanisms, studying similar high-arousal, scary stimuli presented to the same participants, and examining both their temporal distance and the arousal content between them, can provide important insights.

## 2.3 Present study

The aim of the present study is to contribute to the understanding of the factors affecting physiological responses to fear stimuli, by focusing on temporal and contextual factors. By examining how the temporal distance of two fear-inducing stimuli and the arousal content between them affects the change in the physiological responses to the second stimulus, this study carries significance for applications in the

entertainment industry but also potential clinical applications. Adding to this body of knowledge has direct implications for creators and advertisers of horror media and developers and publishers of horror games. Understanding the optimal pacing and intensity of horror content enables the design of more engaging and balanced experiences, increasing viewer and gamer satisfaction and enjoyment, without causing excessive discomfort.

Insights gained from this study have significant implications for clinical psychology, particularly in the treatment of anxiety and phobia disorders. By understanding how different patterns of fear exposure influence physiological responses, therapists can refine exposure-based therapies. This could lead to better outcomes in such therapeutic approaches, improving patients' quality of life.

Considering the most appropriate measure to use to assess physiological reaction to fear stimuli, Electrocardiograph (ECG) and Galvanic Skin Response signals seem the most appropriate. Although EEG and facial expressions data have been used for emotion analysis [40] it seems that these metrics may be better suited for analysing valence. In our case the focus is on ECG and GSR data as reliable indicators of Autonomic Nervous System (ANS) activation [41] which indicates arousal and is uniquely suited for studying the fear response [42] [43].

For that we formulated a research question based on the Continuously Annotated Signals of Emotion (CASE) dataset, developed by Sharma et al. [44] which combines emotional real-time annotation with physiological measures. Video excerpts are used of different intended arousal and valence. Videos vary in order and presentation sequence. Among other types of videos participants always watch two scary videos. We formulated our RQ as follows: *How do the interlude duration and the proportion of low-arousal content between two scary videos affect the differences in physiological responses (ECG and GSR metrics) from the first video to the second in the Continuously Annotated Signals of Emotion (CASE) dataset?*

To the best of our knowledge, the CASE dataset has been exclusively used for evaluating machine learning algorithms for emotion detection (e.g. [45] [46] [47]), with only small variation in research questions and exceptions such as Gargano et al. [48], who compared different emotion models. In this area, our study demonstrates a novel application by focusing on the temporal dynamics and contextual influence of interleaving content on physiological responses. This can encourage other researchers to explore creative ways of leveraging this or similar high quality and comprehensive datasets.

# 3. Methodology

## 3.1 Data

The Continuously Annotated Signals of Emotion (CASE) dataset [44], offers an important resource for analyzing emotional responses through physiological measures and simultaneous emotion annotations. It includes high-quality recordings of physiological signals such as electrocardiogram (ECG), blood volume pulse (BVP), electromyography (EMG) on three channels, galvanic skin response (GSR), respiration, and skin temperature, all captured at 1000 Hz and 16-bit resolution. The unique aspect of the CASE dataset is its use of a joystick-based interface for continuous and real-time annotation of valence and arousal by the participants. This method overcomes limitations inherent in traditional annotation tools, which typically record these dimensions separately and may fail to fully capture the dynamic nature of emotional experiences.

In total, thirty (N=30) participants (M=15, F=15), aged between 22 to 37 years, were exposed to a series of validated video excerpts designed to elicit specific emotional states such as amusement, boredom, relaxation, and fear. The videos (8 in total, 2 for each type) had different durations and were shown in a pseudo-random order to mitigate sequence effects, with each session interleaved by blue screens to allow rest and minimize carry over effects from previous stimuli (Fig. 1). For further exploration and detailed information regarding the methodology and data characteristics, readers are encouraged to consult the original publication.

| Source | Video-Label | Video-ID | Intended Attributes | | Dur. [s] |
|---|---|---|---|---|---|
| | | | Valence | Arousal | |
| Hangover | amusing-1 | 1 | med/high | med/high | 185 |
| When Harry Met Sally | amusing-2 | 2 | med/high | med/high | 173 |
| European Travel Skills | boring-1 | 3 | low | low | 119 |
| Matcha: The way of Tea | boring-2 | 4 | low | low | 160 |
| Relaxing Music with Beach | relaxing-1 | 5 | med/high | low | 145 |
| Natural World: Zambezi | relaxing-2 | 6 | med/high | low | 147 |
| Shutter | scary-1 | 7 | low | high | 197 |
| Mama | scary-2 | 8 | low | high | 144 |
| Great Barrier Reef | startVid | 10 | — | — | 101 |
| Blue screen with end credits | endVid | 12 | — | — | 120 |
| Blue screen | bluVid | 11 | — | — | 120 |

Figure 1: Table showing the videos, labels, intended valence-arousal attributes, and durations. Note: Reprinted from [44], p. 4

This dataset is particularly relevant to our study as it contains precise, high-quality ECG and GSR data, which can be used for feature extraction and analysis of arousal levels. This is key to understanding fear-induced physiological changes. Furthermore, the continuous annotation attribute allows for detailed segmentation of emotional states tied to specific moments within the video, which allows for more refined analysis. The variation in video sequence order across participants allows for analysis of the effects of temporal and contextual factors on physiological responses to videos with similar emotional content.

## 3.2 Preprocessing and feature extraction

Preprocessing and feature extraction are critical steps in preparing physiological data for analysis. They ensure that the data is clean, relevant, and structured in a way that facilitates meaningful comparisons and insights. These steps involve segmenting raw signals, removing noise, and extracting essential features that reflect the physiological responses of participants during the experiment.

### 3.2.1 Dependent Variables Extraction

Raw ECG and GSR signals were segmented based on the two scary videos. Signals were cleaned and physiological features were extracted using the Python package `NeuroKit2`. The following features were extracted per segment:

1. **Mean Heart Rate:** Calculated over the entire segment to provide an average measure of the participant's heart rate during the stimulus exposure.
2. **HRV SDNN (Standard Deviation of NN Intervals):** This time-domain measure of heart rate variability provides insights into autonomic nervous system activity.
3. **Mean RR Interval:** The average time interval between successive heartbeats, which is inversely related to heart rate.

For GSR signals, the features extracted were:

1. **Skin Conductance Level (SCL):** The mean tonic level of skin conductance, indicating baseline sympathetic arousal.
2. **Skin Conductance Response (SCR):** The mean phasic level of skin conductance, reflecting transient changes in arousal in response to stimuli.

3. **Peak Amplitude:** The maximum amplitude of the SCR peaks, which is indicative of the intensity of the participant's physiological response.

More features than necessarily needed were extracted in case they would be later used as dependent variables in the multivariate model we used. To enable the statistical comparison by extracting one value from each participant representing the difference in physiological reactions to the two videos, we calculated the differences between the above values (value from the 2nd scary - value from the 1st scary).

Both Heart Rate and GSR Peak Amplitude are reliable measures of sympathetic nervous system activity and are suitable to use in this context to study responses to stress or fear. So the dependent variables used in the statistical analysis are:

- *ECGHeartRate*: Heart Rate mean (2nd) - Heart Rate mean (1st)

- *GSRPeakAmplitude*: GSR Peak Amplitude (2nd) - GSR Peak Amplitude (1st)

In general, physiological measures used in the analysis always represent differences between the same feature extracted from the physiological data of each scary video.

### 3.2.2 Independent Variables Extraction

The metadata provided with the dataset included details about the videos shown to the participants, such as the intended emotional type and their duration, along with the order in which each participant watched them. It was used to identify which scary video was seen first for each participant, what type of videos were presented between the two scary, and the total time these other videos lasted. The start and end timestamps of each video were important to be able to link precisely with the physiological and annotation data. The neutral intermissions (bluVid) presented between each video were not countes as low arousal content, because they were always the same they did not vary in a meaningful way. However, they had to be included in the total duration between the two videos.

Interlude duration was computed by subtracting the end time of the first scary video from the start time of the second scary video. The ratio of low arousal videos in the interlude period was computed by counting the number of videos presented and identifying how many of these videos were low-arousal (boring, relaxing) and dividing by the total count of the interlude videos. A log transformation was applied to this metric to avoid numerical problems if the two videos are presented consecutively.
The independent variables used in the analysis were:

1. *InterludeDuration*: total time between the two scary videos

2. *LowArousalRatioLog*: the logarithmic ratio of the count of low-arousal interlude videos to the total number of interlude videos, adjusted by adding 1 to both the numerator and the denominator to prevent division by zero. (*see eq* 1)

$$\text{LowArousalRatioLog} = \log\left(\frac{\text{low-arousal interlude videos} + 1}{\text{total interlude videos} + 1}\right) \tag{1}$$

### 3.2.3 Change Point Analysis (CPA)

In a supplementary analysis, to further leverage the attributes of the dataset, we segmented the physiological data based on Change Point Analysis (CPA) on the annotation data. CPA was applied to the valence and arousal signals, pinpointing moments of substantial shifts in emotional intensity. This allowed us to isolate the segment of the video that was the most emotionally important within each scary video following a similar procedure [44]

**Algorithm 1** Perform CPA on Annotations

```
function PERFORM_CPA_ON_ANNOTATIONS(files)
    Initialize all_start_points and all_end_points as empty lists
    for each file in files do
        data ← load_csv_data(annotations_file_path)
        valence, arousal ← data['valence'], data['arousal']
        combined_intensity ← combine_valence_arousal(valence, arousal)
        pen ← 15, threshold ← 8
        while True do
            change_points ← detect_change_points(combined_intensity.to_frame(), pen)
            if length of change_points ≤ change_points_threshold then
                break
            end if
            pen ← pen + 5
        end while
        start, end ← get_segments_excluding_first_last(change_points, len(combined_intensity))
        Append start to all_start_points
        Append end to all_end_points
    end for
    if all_start_points and all_end_points are not empty then
        avg_start_point, avg_end_point ← mean(all_start_points), mean(all_end_points)
    else
        avg_start_point, avg_end_point ← 0, len(combined_intensity)
    end if
    return avg_start_point, avg_end_point
end function
```

**Combine Valence and Arousal** To derive a single measure of emotional intensity, we calculated the absolute distance of each valence and arousal value from a neutral point (set at 5) and summed these distances. The combined intensity score reflected the overall emotional arousal, providing a comprehensive view of the participant's emotional state.

**Detect Change Points** We utilized the PELT (Pruned Exact Linear Time) algorithm for CPA, which detects distributional shifts in time series data. To ensure significant changes were identified without over-segmentation, we iteratively adjusted the penalty parameter (pen) until the number of detected change points reached a predetermined threshold, ensuring that we captured significant emotional changes without over-segmentation.

**Identify Significant Segments** Post-CPA, we segmented the data and excluded the first and last segments, typically representing neutral states at the beginning and end of videos. We then computed the average start and end points across all participants for each scary video standardizing the segments for further analysis. This method ensured that the emotional segments analyzed were consistent, enabling more meaningful comparisons and analyses.

**Apply Standardized Segments** Finally, we applied the averaged start and end points to each participant's data, so the emotional segments analyzed were consistent across participants. By repeating the feature extraction for these segments and not the entirety of the video could shift the focus to the most emotionally impacting part of the video and thus increase the validity of the analysis (Fig. 2). The complete method used to perform CPA on annotations is described in Algorithm 1.

## 3.3 Statistical analysis

To explore the relationship between the two predictors, *InterludeDuration* and LowArousalRatioLog, and the dependent variables, ECG Heart Rate and GSR Peak Amplitude, a Multivariate Multiple Regression

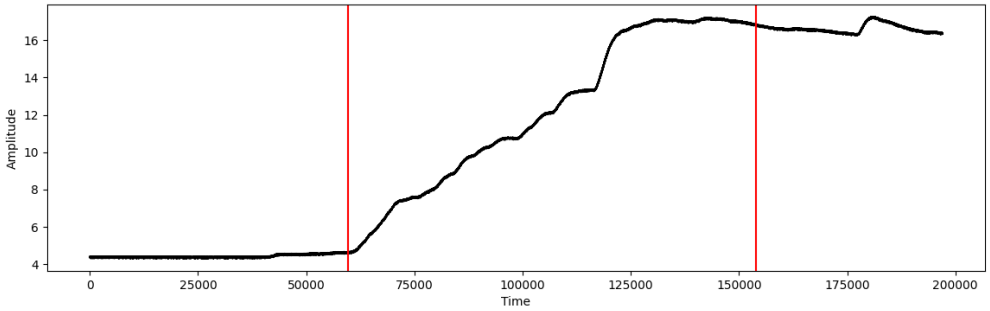


Figure 2: The final segment obtained after applying the averaged CPA results of all the participants to a GSR signal.

(MMR) model was used. This approach is particularly suited to our study as it allows for the simultaneous evaluation of multiple independent variables and their collective impact on more than one dependent variables. Prior to conducting the MMR, as suggested by and potentially post-hoc multiple and simple regression analyses, it was assessed whether univariate and multivariate assumptions were met.

**Assumptions Checking** We ensured that all independent variables exhibited non-zero variances and assessed multicollinearity using the Variance Inflation Factor (VIF). Extreme values were examined with box plots and the Interquartile Range (IQR) method and outliers were identified from the standardized residual values. A threshold of 2.5 was used as per the convention, as for this exploratory analysis a threshold of 2 was deemed too strict.

For both ECG Heart Rate and GSR Peak Amplitude, the same diagnostic process was followed to check for regression and multivariate analysis assumptions. Linearity was checked through scatter plots and partial regression plots to confirm a linear relationship between the predictors and each dependent variable. We assessed the independence of residuals using the Durbin-Watson statistic to exclude autocorrelation. The normality of residuals was verified through Q-Q plots, Shapiro-Wilk, and Jarque-Bera tests. Homoscedasticity was assessed with the use of Breusch-Pagan test along with visual inspection of the residuals vs fitted values plots.

For proceeding with multivariate models, multivariate normality is an important assumption that needs to be satisfied. The Henze-Zirkler test was used, along with the detection of potential multivariate outliers through the Mahalanobis distance. A very very conservative probability estimate for the x2 test was used (p=0.01) as recommended by USING-MULTI P.74

**Post-hoc Regression Analysis** Following the primary multivariate analysis, we conducted separate multiple linear regressions for each dependent variable. This provides more insight into how each predictor differentially influences the dependent variable. If necessary, simple regression models were also considered to focus more closely on the relationship between one predictor and one outcome.

**Post-hoc Correlation Analysis** The Pearson's product-moment correlation was performed to examine the strength and direction of relationships between each pair of variables. This allowed for further examination of the bivariate relationships between the predictors and the dependent variables and provided further information on multicollinearity of the predictors and significant correlations between the dependent variables.

**Multivariate GLM** We identified a moment when a multivariate Generalized Linear Model (GLM) would be warranted to inspect the effect of a single predictor to two correlated variables (that is two GSR features). However, we avoided introducing more predictors beyond our hypothesis. All separate

models were fitted as post-hoc steps in order to clarify the characteristics of the relationships examined and following the observed combined and individual contributions of the larger model.

**Supplementary Analysis on CPA-segmented data** Finally the complete analysis was repeated on the CPA-segmented physiological data, with some room for different decisions, such as including an interaction term, based on new results.

**Power Analysis** Using G*Power software, an a priori power analysis was conducted to determine the necessary sample sizes for all the statistical models considered. All analyses targeted used a desired power level of 0.8, a medium effect size of $f^2 = 0.15$, and an alpha level at $a = 0.05$. The analysis for a simple linear regression required a sample size of 55 participants while for multiple linear regression with two predictors, the analysis suggested a need for 68 participants. Required sample size for the multivariate models was calculated using an effect size of $f(V) = 0.0625$. A multivariate multiple regression with two response variables and two predictors would need 99 participants. Lastly, a multivariate model with one predictor with two response variables was calculated to require 158 participants to achieve the defined power. Although the current sample size is not sufficient, this analysis can be used as a guidance for follow up studies and future work.

# 4. Results

## 4.1 Multivariate Multiple Regression (MMR)

A multivariate multiple regression (MMR) model was fitted to examine the effects of the predictors $InterludeDuration$ and $LowArousalRatioLog$ on the dependent variables, ($ECGHeartRate$ and $GSRPeakAmplitude$).

### 4.1.1 Assumptions Checking

**Assumptions for Independent Variables** The data met the assumption of non-zero variances ($InterludeDuration = 325.840, LowArousalRatioLog = 0.180$). Both variables had a Variance Inflation Factor (VIF) of 4.040, indicating an absence of significant multicollinearity. An extreme value was identified in $LowArousalRatioLog$ (participant 27), which fell outside of 1.5 times the interquartile range (IQR). Excluding this participant's data did not affect the model outcomes, as detailed in the Appendix.

**ECG - Heart Rate** Inspection of scatter plots and partial regression plots suggested an approximately linear relationship between predictors and the $ECGHeartRate$ difference, with a slight negative trend observed for both predictors. Independence of residuals was confirmed by a Durbin-Watson statistic of 2.059, indicating no autocorrelation. Normality of residuals was assessed both by Q-Q plots and using Shapiro-Wilk and Jarque-Bera tests ($W = 0.971, p = 0.578; JB = 0.786, p = 0.675$), with results suggesting no significant deviation from normality. The homoscedasticity assumption was met as evaluated with a Breusch-Pagan test ($\chi^2 = 0.150, p = 0.928$). No significant outliers were detected, with all standardized residuals falling within $\pm 2.5$. Leverage points marginally exceeded a threshold of 0.2 but were not influential as Cook's distance values were well below 1.

**GSR - Peak Amplitude** Visual inspection revealed a uniform distribution of data points with minimal skewness. Scatter plots and partial regression plots indicated a generally linear relationship between predictors and the $GSRPeakAmplitude$ difference, with a notable positive trend associated with Interlude Duration. The independence of residuals, confirmed by a Durbin-Watson statistic of 2.796, demonstrated an absence of autocorrelation. Residuals were approximately normally distributed as verified through Q-Q plots, Shapiro-Wilk test ($W = 0.981, p = 0.867$), and Jarque-Bera test ($JB = 0.256, p = 0.880$).

Homoscedasticity was confirmed via a Breusch-Pagan test ($\chi^2 = 2.480, p = 0.289$). Although one potential outlier was identified in participant 5 using the IQR method on the original data, no outliers were observed in the residual analysis, with all standardized residuals remaining within ±2.5. While leverage values slightly exceeded a threshold of 0.200, none were deemed influential as indicated by Cook's distance values below 1.

**Multivariate Assumptions** The combined distribution of the dependent variables did not significantly deviate from multivariate normality, as assessed by the Henze-Zirkler test ($HZ = 0.617, p = 0.166$). Additionally, the Mahalanobis distance measure detected no multivariate outliers, supporting the suitability of proceeding with the multivariate analysis.

#### 4.1.2 Model Fitting

Results of the multivariate analysis indicated that, when examining the effects of *InterludeDuration*, the test approached significance at an alpha level of $a = 0.100$, indicating a possible influence on the physiological measures (Wilks' Lambda $= 0.831, F(2, 26) = 2.643, p = 0.090$). In contrast, the effects of Low Arousal Ratio on the dependent measures were not significant (Wilks' Lambda $= 0.993, F(2, 26) = 0.088, p = 0.916$).

These observations suggest there may be some effect of the predictors on one or both dependent variables. Post-hoc analyses with individual multiple regressions were conducted for each dependent variable to further clarify whether there is such an effect and the specific contributions of each predictor to the observed changes in physiological measures.

#### 4.1.3 Post-hoc: Multiple Linear Regression

The regression model predicting differences in *ECGHeartRate* from *InterludeDuration* and *LowArousalRatioLog* was not statistically significant ($F(2, 27) = 0.124, p = 0.884$). Neither predictor, *InterludeDuration* ($\beta = -0.001, p = 0.662$) nor *LowArousalRatioLog* ($\beta = -1.834, p = 0.720$), was significantly associated with changes in heart rate between the two videos. On the contrary, the regression model to predict changes in *GSRPeakAmplitude* achieved statistical significance at an alpha level of $a = 0.100$ ($F(2, 27) = 3.035, p = 0.065$) accounting for approximately 18.4% of the variance in the dependent variable. As hinted by the multivariate model, *InterludeDuration* was the sole significant predictor for *GSRPeakAmplitude* differences between the two scary videos ($\beta = 0.001, p = 0.035$). *LowArousalRatioLog* did not significantly predict changes in *GSRPeakAmplitude* ($\beta = -0.180, p = 0.787$).

#### 4.1.4 Adjusting the Model

The results primarily indicate that the observed trend in the multivariate model was driven by *InterludeDuration*'s significant association with *GSRPeakAmplitude*. Given these findings, further exploration of *InterludeDuration* within a multivariate framework is warranted. Incorporating Skin Conductance Level (SCL) as an additional dependent variable may elucidate whether *InterludeDuration* consistently influences relevant and correlated physiological response measures.

### 4.2 Multivariate Generalized Linear Model for GSR Data

A multivariate general linear model was used to assess the predictive value of *InterludeDuration* on differences in *GSRSCL* and *GSRPeakAmplitude* between the two scary videos.

#### 4.2.1 Assumptions checking

Both univariate and multivariate assumptions were checked.

**GSR - Peak Amplitude** For *GSRPeakAmplitude* difference, there was independence of residuals as assessed by a Durbin-Watson statistic of 2.773. Both Q-Q plots and statistical tests showed normality of residuals ($W = 0.975, p = 0.693$; $JB = 0.419, p = 0.811$) and homoscedasticity was confirmed via a Breusch-Pagan test ($\chi^2 = 0.965, p = 0.326$). As mentioned above, an outlier (participant 5) was identified with the IQR method but was not found significant in residual analysis (standardized residuals within $\pm 2.5$). One leverage value marginally exceeded a threshold of 0.2, but was not influential (Cook's distance $< 0.5$).

**GSR - Skin Conductance Level** For GSR Skin Conductance Level (*GSRSCL*) difference, there was independence of residuals as assessed by a Durbin-Watson statistic of 2.778. Residuals were approximately normally distributed ($W = 0.974, p = 0.667$; $JB = 0.236, p = 0.888$) and there was no violation of homoscedasticity ($\chi^2 = 0.965, p = 0.326$). A potential outlier (participant 17) was identified with the IQR method, but all residuals were within $\pm 2.5$. A single leverage value slightly exceeded a threshold of 0.2, but was not problematic (Cook's distance $< 0.5$). Multivariate normality was met as verified by the Henze-Zirkler test ($HZ = 0.536, p = 0.271$) and no multivariate outliers were detected via Mahalanobis distance.

#### 4.2.2 Model Fitting

The analysis revealed a significant multivariate effect of *InterludeDuration* (Wilks' Lambda $\Lambda = 0.673, F(2, 27) = 6.448, p = 0.005$), indicating that variations in *InterludeDuration* are significantly associated with changes in both GSR features. Repeating the analysis excluding an identified IQR outlier (participant 5) demonstrated similar, or even marginally better, model significance ($\Lambda = 0.650, F(2, 26) = 7.007, p = 0.004$). The exclusion of the outlier did not affect the significance of the model, supporting the finding that *InterludeDuration* is a significant multivariate predictor of physiological response changes using both GSR metrics.

#### 4.2.3 Post-hoc: Separate Simple Regression Models

Separate Ordinary Least Squares (OLS) regression models were fitted for each dependent variable to further investigate the individual contributions of *InterludeDuration*. The OLS regression for *GSRSCL* demonstrated no significant predictive value of *InterludeDuration*, $F(1, 28) = 0.143, p = 0.708$, with the model explaining approximately 0.5% of the variance in Skin Conductance Level. Conversely, the OLS regression for *GSRPeakAmplitude* was statistically significant at an alpha level of $a = 0.05$, $F(1, 28) = 6.200, p = 0.019$, accounting for approximately 18.1% of the variance in *GSRPeakAmplitude* differences between the physiological responses to the two videos (Fig. 3). This analysis clarifies that there is a strong positive relationship between *InterludeDuration* and changes in *GSRPeakAmplitude* from the first scary video to the second ($\beta = 0.001, p = 0.019$). This relationship significantly contributes to the main effect observed in both multivariate models assessed so far.

### 4.3 Post-hoc Correlation Analysis

A Pearson's product-moment correlation was run as a post-hoc measure to assess the relationship between all pairs of variables examined so far (see Fig. 4 for an overview of the ones achieving significance). The Pearson correlation matrix (Fig. 5) provides insights into the bivariate relationships among various the extracted independent variables and the physiological measures.

**Independent and Dependent Variables** Notably, the matrix revealed a positive correlation between *InterludeDuration* and *GSRPeakAmplitude* difference ($r = 0.430, p = 0.019$), suggesting that as the duration between scary video clips increases, there is an increase in *GSRPeakAmplitude*. This correlation aligns with the trends observed in the regression analyses where *InterludeDuration* significantly predicted changes in *GSRPeakAmplitude*. In contrast, no significant correlation was found between

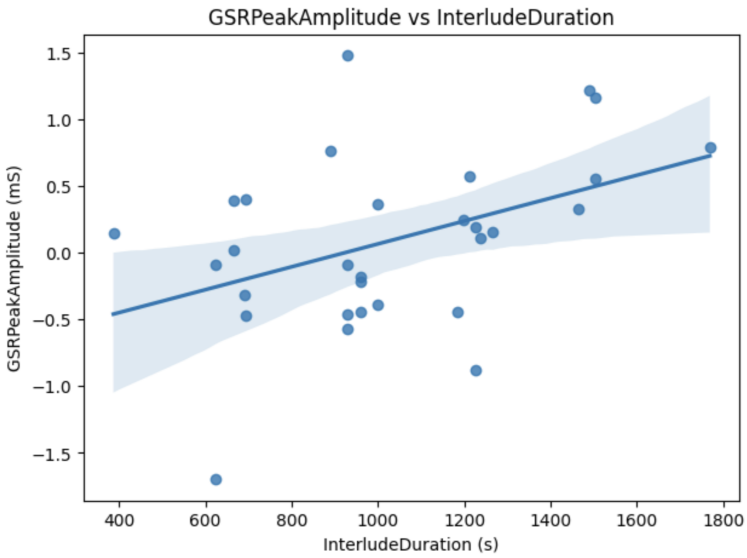


Figure 3: Scatterplot with fitted regression line of GSR Peak Amplitude differences between the two videos vs Interlude Duration.

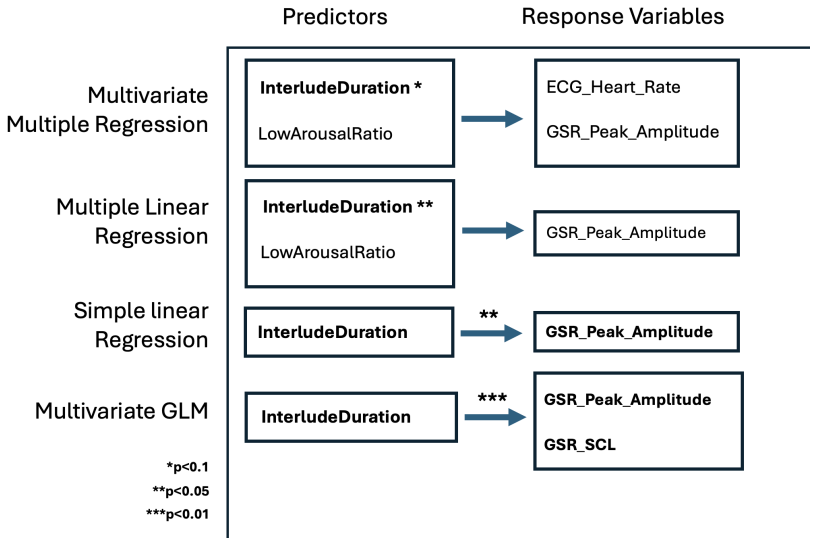


Figure 4: Overview of models that achieved significance

*InterludeDuration* and differences in *ECGHeartRate* ($r = -0.070, p = 0.731$). This finding is consistent with the regression results, which showed no significant effect of *InterludeDuration* on *ECGHeartRate* differences. The correlation between *InterludeDuration* and differences in *GSRSCL* was also non-significant ($r = -0.070, p = 0.708$). This observation implies that there might be other factors or types of relationships affecting SCL changes in the multivariate analysis reported above.

**Dependent Variables** The physiological measures themselves showed expected correlations; differences in *ECGHeartRate* were moderately correlated with differences in *GSRSCL* ($r = 0.520, p = 0.003$), and differences in *GSRPeakAmplitude* were moderately correlated with differences in *GSRSCL* ($r = 0.560, p = 0.001$).

**Predictors** Regarding the predictors, the correlation analysis highlighted that the independent variables did not exhibit strong correlations with each other (*InterludeDuration* and *LowArousalRatioLog* : $r = -0.330, p = 0.073$), supporting the absence of multicollinearity concerns in the regression models, which is also consistent with the Variance Inflation Factor (VIF) values reported for both predictors.

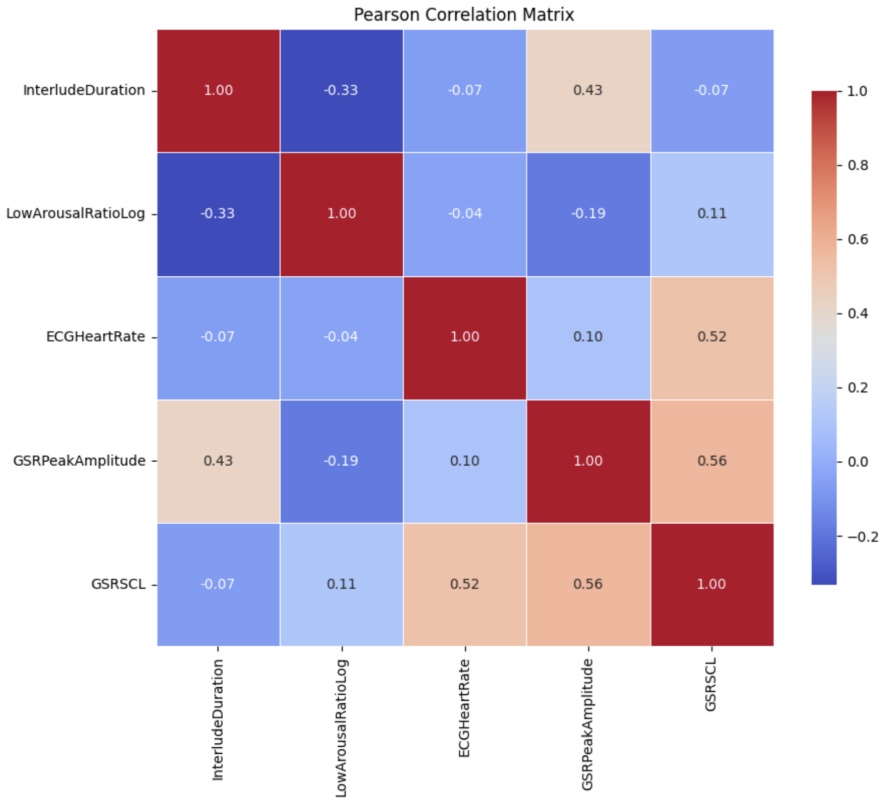


Figure 5: Post-hoc correlation matrix of all examined variables.

## 4.4 Post-CPA Analysis

The analysis was repeated on the segmented physiological data after the Change Point Analysis (CPA) had been applied. From the general results, it seems that the segmentation did not add or remove much explanatory power from the individual models, but resulted in a slightly different data distribution. Now, the extreme value of the *GSRPeakAmplitude* differences data (participant 5) was deemed as a true outlier based on standardized residuals below -2.5 (Fig. 6).

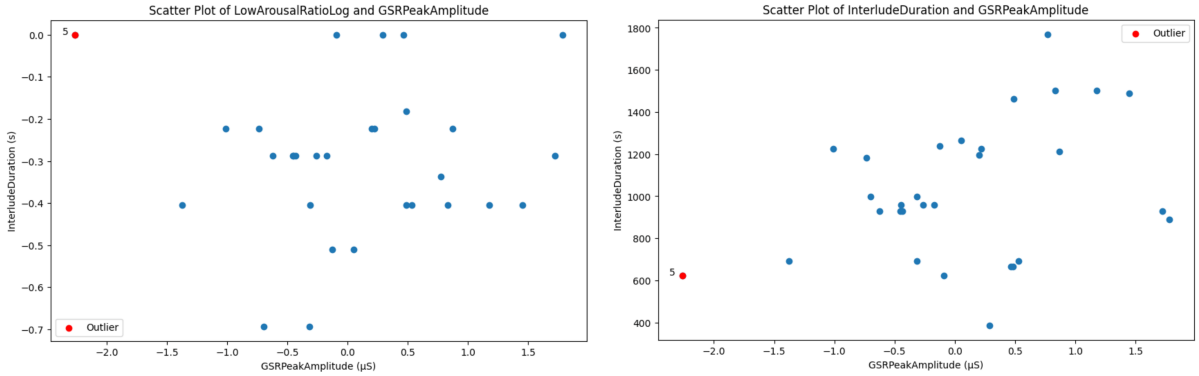


Figure 6: Scatterplot showing GSR Peak Amplitude difference values plotted against both independent variables post-CPA. The extreme value is visibly different.

**Model Fitting without the Outlier** Fitting the multiple regression model for *GSRPeakAmplitude* while removing the outlier revealed influences of both *InterludeDuration* and *LowArousalRatioLog* (at an alpha level of $a = 0.1$). The regression model achieved statistical significance at $a = 0.1$ ($F(2, 26) = 2.758, p = 0.082$) and explained approximately 11.2% of the variance in *GSRPeakAmplitude* (adj $R^2 = 0.112$). In this model, both *InterludeDuration* ($\beta = 0.001, p = 0.057$) and *LowArousalRatioLog*

($\beta = 1.448, p = 0.091$) were significant predictors of the change in $GSRPeakAmplitude$.

**Interaction Term** Exploring this finding further, an interaction term was included ($InterludeDuration \times LowArousalRatioLog$). However, the interaction term did not significantly enhance the explanatory power of the model. It still accounted for approximately 12.6% of the variance (adj $R^2 = 0.127$), and was marginally statistically significant at $a = 0.100$, $F(3, 25) = 2.341, p = 0.098$. None of the predictors were individually significant in the model, including the interaction term ($\beta = -0.004, p = 0.245$).

# 5. Discussion and conclusion

The main finding from our investigation is that the temporal interval between scary videos significantly predicts changes in the galvanic skin response (GSR) peak amplitude. It has been effectively demonstrated that the physiological GSR reaction to a subsequent scary video is a function of their temporal distance. Furthermore, by examining the exact results, we notice that the values of the differences between the two physiological reactions can be positive after a certain time interval. This essentially means that the response to the second exposure can be even higher than that of the first, with clear implications for creators and publishers of horror media.

Our study also explored the relationship of interlude duration with other GSR metrics through a multivariate analysis. The findings were inconclusive for variables like skin conductance level (SCL), indicating that while the simple regression model did not predict these outcomes, the complex relationship captured by the multivariate GLM suggests that other unexamined dynamics may influence these responses. However, conclusions about that are tentative mostly because of statistical power issues as discusses later. On the other hand, changes in the physiological responses as captured by mean heart rate did not seem to be related predicted by neither the temporal distance nor the proportion of low arousal content between the two videos.

Interestingly, it was shown that differences in GSR Peak Amplitude can be predicted by both the time between the two presentations and the amount of low arousal content in between. However this result required to focus only on the emotionally relevant excerpt of each video and only after the exclusion of an outlier. Even though the extreme value was indeed significant, it skewed the distribution, and it was not masking others, problems with statistical power remain.

All things considered, the most robust finding, since it is also the simplest model, is the positive linear relationship identified by the regression model and corroborated by the correlation analysis, between interlude duration and GSR activation (as measured by GSR peak amplitude).

This observation aligns with the findings of Andersen et al. [4], who explored how the pacing of horror content affects physiological arousal. This connection underscores the theory that appropriate spacing between stimuli can enhance the fear experience without overwhelming the viewer, a concept also supported by research attempts on the effects of stimulus timing on arousal transfer [39].

Of course it is not easy to explain an effect like this and the inconclusive results from the multivariate model are not encouraging. At the same time, this may precisely reflect the complexities highlighted in the literature, for example by Castaneda and Segerstrom [15], who discuss how various factors, including cognitive anticipation and stimulus type, can impact physiological responses.

**Limitations** A primary limitation of our study is the insufficient sample size. Power analysis indicated that to achieve reliable statistical power with the complexity of our models, we would require significantly larger sample sizes—55 participants for simple linear regression and up to 158 for more complex multivariate analyses. Our study involved only 30 participants, which poses a risk of Type II errors, where true effects might fail to reach statistical significance. This limitation is particularly critical in the context of exploring subtle and complex physiological interactions, as observed between the timing and content of scary video exposure.

Another important issue is the scale of our data. The variables analyzed in our study exhibited considerable disparity in their scale of measurement. Such discrepancies in scale can introduce issues related to the sensitivity of statistical tests, potentially skewing the outcomes and impacting the regression models' stability and interpretability. The significant range differences could also affect the normalization process and the efficacy of multivariate techniques, making it difficult to compare and interpret the effects across different scales effectively. Additionally, the fact that we are comparing already computed differences, creates the need for some sort of standardization.

**Future work** There are two main directions for future research. On the one hand, discretization will allow the use of Analysis of Variance techniques. For example, categorizing the time intervals between scary videos into short, medium, and long allows to perform an ANCOVA and control for the low arousal ratio, or explore completely novel hypotheses, leveraging the flexibility of these statistical tools.

The other directions is a continuation from the observation of the current study. What determines when the physiological difference to the second stimulus is higher or lower? A logistic regression model, for example, to predict the sign of the difference could be a first step. Insights from this can pave the way for other types of classification and machine learning techniques.

Finally, using the same framework for other high-low arousal pairs such as amusing and boring videos in the CASE dataset can move the research forward in other ways.

**Conclusion** This study, despite its considerable shortcomings, offers insights that could scale to practical guidelines for enhancing horror media through content pacing, and for refining therapeutic practices based on exposure to feared stimuli. It also demonstrates how comprehensive physiological datasets can be utilized for exploring emotion-related research questions across various fields, encouraging broader and more innovative research efforts and applications.

# References


[1] *The Numbers - Box Office Performance History for Horror Movies*, https://www.the-numbers.com/market/genre/Horror. (visited on 14/05/2024).

[2] *Halloween horror: Feeding audiences' appetites for cheap and bloody thrills*, https://www2.deloitte.com/uk/en/insights/industry/technology/horror-movie-audience-statistics.html. (visited on 14/05/2024).

[3] G. N. Martin, '(Why) Do You Like Scary Movies? A Review of the Empirical Research on Psychological Responses to Horror Films,' *Frontiers in Psychology*, vol. 10, p. 2298, Oct. 2019, ISSN: 1664-1078. DOI: 10.3389/fpsyg.2019.02298. (visited on 08/05/2024).

[4] M. M. Andersen, U. Schjoedt, H. Price, F. E. Rosas, C. Scrivner and M. Clasen, 'Playing With Fear: A Field Study in Recreational Horror,' *Psychological Science*, vol. 31, no. 12, pp. 1497–1510, Dec. 2020, ISSN: 0956-7976. DOI: 10.1177/0956797620972116. (visited on 09/05/2024).

[5] C. A. Hoffner and K. J. Levine, 'Enjoyment of Mediated Fright and Violence: A Meta-Analysis,' *Media Psychology*, vol. 7, no. 2, pp. 207–237, May 2005, ISSN: 1521-3269. DOI: 10.1207/S1532785XMEP0702_5. (visited on 09/05/2024).

[6] A. Tudor, 'Why Horror? The Peculiar Pleasures of a Popular Genre,' *Cultural Studies*, vol. 11, no. 3, pp. 443–463, Oct. 1997, ISSN: 0950-2386. DOI: 10.1080/095023897335691. (visited on 09/05/2024).

[7] K. Harrison and J. Cantor, 'Tales from the Screen: Enduring Fright Reactions to Scary Media,' *Media Psychology*, vol. 1, no. 2, pp. 97–116, Jun. 1999, ISSN: 1521-3269. DOI: 10.1207/s1532785xmep0102_1. (visited on 09/05/2024).

[8] M. Hudson, K. Seppälä, V. Putkinen *et al.*, 'Dissociable neural systems for unconditioned acute and sustained fear,' *NeuroImage*, vol. 216, p. 116 522, Aug. 2020, ISSN: 1053-8119. DOI: 10.1016/j.neuroimage.2020.116522. (visited on 09/05/2024).

[9] J. Bruckbauer, A. Entwistle, B. Malas and S. Patin, 'Physiological Responses in the Anticipation of an Auditory and Visual Stimulus,' 2018.

[10] S. Poli, M. Sarlo, M. Bortoletto, G. Buodo and D. Palomba, 'Stimulus-Preceding Negativity and heart rate changes in anticipation of affective pictures,' *International Journal of Psychophysiology*, vol. 65, no. 1, pp. 32–39, Jul. 2007, ISSN: 0167-8760. DOI: 10.1016/j.ijpsycho.2007.02.008. (visited on 09/05/2024).

[11] J. E. LeDoux and D. S. Pine, 'Using Neuroscience to Help Understand Fear and Anxiety: A Two-System Framework,' *American Journal of Psychiatry*, vol. 173, no. 11, pp. 1083–1093, Nov. 2016, ISSN: 0002-953X, 1535-7228. DOI: 10.1176/appi.ajp.2016.16030353. (visited on 09/05/2024).

[12] M. Fredrikson, H. Fischer and G. Wik, 'Cerebral blood flow during anxiety provocation,' *The Journal of Clinical Psychiatry*, vol. 58 Suppl 16, pp. 16–21, 1997, ISSN: 0160-6689.

[13] K. G. Benito, J. Machan, J. B. Freeman *et al.*, 'Measuring fear change within exposures: Functionally-defined habituation predicts outcome in three randomized controlled trials for pediatric OCD,' *Journal of Consulting and Clinical Psychology*, vol. 86, no. 7, pp. 615–630, 2018, ISSN: 1939-2117. DOI: 10.1037/ccp0000315.

[14] M. H. Lader and A. M. Mathews, 'A physiological model of phobic anxiety and desensitization,' *Behaviour Research and Therapy*, vol. 6, no. 4, pp. 411–421, Nov. 1968, ISSN: 0005-7967. DOI: 10.1016/0005-7967(68)90021-1. (visited on 10/05/2024).

[15] J. O. Castaneda and S. C. Segerstrom, 'Effect of stimulus type and worry on physiological response to fear,' *Journal of Anxiety Disorders*, vol. 18, no. 6, pp. 809–823, Jan. 2004, ISSN: 0887-6185. DOI: 10.1016/j.janxdis.2003.10.003. (visited on 11/05/2024).

[16] T. Terkildsen, L. Engelst and M. Clasen, 'Work Hard, Scare Hard? An Investigation of How Mental Workload Impacts Jump Scare Intensity,' *Proceedings of the ACM on Human-Computer Interaction*, vol. 7, no. CHI PLAY, 375:27–375:44, Oct. 2023. DOI: 10.1145/3611021. (visited on 09/05/2024).

[17] A. Healey, W. Mansell and S. Tai, 'An experimental test of the role of control in spider fear,' *Journal of Anxiety Disorders*, vol. 49, pp. 12–20, Jun. 2017, ISSN: 0887-6185. DOI: 10.1016/j.janxdis.2017.03.005. (visited on 11/05/2024).

[18] J. M. Armfield, 'Manipulating perceptions of spider characteristics and predicted spider fear: Evidence for the cognitive vulnerability model of the etiology of fear,' *Journal of Anxiety Disorders*, vol. 21, no. 5, pp. 691–703, Jan. 2007, ISSN: 0887-6185. DOI: 10.1016/j.janxdis.2006.10.005. (visited on 11/05/2024).

[19] B. Adkins, E. Brennan, H. Hoffmann, K. Patel and C. Schmit, 'Physiological Startle Response to Frightening Stimuli in Light and Dark Environment,' 2019. (visited on 09/05/2024).

[20] K. Carlsson, K. M. Petersson, D. Lundqvist, A. Karlsson, M. Ingvar and A. Ohman, 'Fear and the amygdala: Manipulation of awareness generates differential cerebral responses to phobic and fear-relevant (but nonfeared) stimuli,' *Emotion (Washington, D.C.)*, vol. 4, no. 4, pp. 340–353, Dec. 2004, ISSN: 1528-3542. DOI: 10.1037/1528-3542.4.4.340.

[21] G. Wik, M. Fredrikson, K. Ericson, L. Eriksson, S. Stone-Elander and T. Greitz, 'A functional cerebral response to frightening visual stimulation,' *Psychiatry Research: Neuroimaging*, vol. 50, no. 1, pp. 15–24, Apr. 1993, ISSN: 0925-4927. DOI: 10.1016/0925-4927(93)90020-I. (visited on 08/05/2024).

[22] N. Gunaratne, C. Viejo, T. Gunaratne *et al.*, 'Effects of Imagery as Visual Stimuli on the Physiological and Emotional Responses,' *J*, vol. 2, no. 2, pp. 206–225, Jun. 2019, ISSN: 2571-8800. DOI: 10.3390/j2020015. (visited on 08/05/2024).

[23] J. J. Gross and R. W. Levenson, 'Emotion elicitation using films,' *Cognition and Emotion*, vol. 9, no. 1, pp. 87–108, Jan. 1995, ISSN: 0269-9931. DOI: 10.1080/02699939508408966. (visited on 08/05/2024).

[24] M. Yilmaz Balban, E. Cafaro, L. Saue-Fletcher *et al.*, 'Human Responses to Visually Evoked Threat,' *Current Biology*, vol. 31, no. 3, 601–612.e3, Feb. 2021, ISSN: 0960-9822. DOI: 10.1016/j.cub.2020.11.035. (visited on 09/05/2024).

[25] K. E. Madsen, 'The differential effects of agency on fear induction using a horror-themed video game,' *Computers in Human Behavior*, vol. 56, pp. 142–146, Mar. 2016, ISSN: 0747-5632. DOI: 10.1016/j.chb.2015.11.041. (visited on 09/05/2024).

[26] T. Evans, J. Hatab, E. Linsmeier, T. Olson, J. Rabichev and A. Reisner, 'Differences in Physiological Responses to Exposure of Disturbing Auditory Versus Audiovisual Stimuli,' 2016. (visited on 09/05/2024).

[27] I. Tara, S. Okamoto, Y. Akiyama and Y. Yamada, 'Heightening fear response to horror video scenes by applying vibratory stimuli to upper bodies of viewers,' in *2022 IEEE 4th Global Conference on Life Sciences and Technologies (LifeTech)*, Mar. 2022, pp. 250–252. DOI: 10.1109/LifeTech53646.2022.9754946. (visited on 08/05/2024).

[28] C. S. Inman, K. R. Bijanki, D. I. Bass, R. E. Gross, S. Hamann and J. T. Willie, 'Human amygdala stimulation effects on emotion physiology and emotional experience,' *Neuropsychologia*, The Neural Basis of Emotion, vol. 145, p. 106 722, Aug. 2020, ISSN: 0028-3932. DOI: 10.1016/j.neuropsychologia.2018.03.019. (visited on 09/05/2024).

[29] A. O. Hamm and A. I. Weike, 'The neuropsychology of fear learning and fear regulation,' *International Journal of Psychophysiology*, Neurobiology of Fear and Disgust, vol. 57, no. 1, pp. 5–14, Jul. 2005, ISSN: 0167-8760. DOI: 10.1016/j.ijpsycho.2005.01.006. (visited on 13/05/2024).

[30] *Grdenfors*, 'CONCEPT LEARNING AND NONMONOTONIC REASONING1,' in *Handbook of Categorization in Cognitive Science*, H. Cohen and C. Lefebvre, Eds., Oxford: Elsevier Science Ltd, Jan. 2005, pp. 823–843, ISBN: 978-0-08-044612-7. DOI: 10.1016/B978-008044612-7/50092-5. (visited on 13/05/2024).

[31] K. L. Duckworth, J. A. Bargh, M. Garcia and S. Chaiken, 'The Automatic Evaluation of Novel Stimuli,' *Psychological Science*, Nov. 2002, ISSN: 1467-9280. (visited on 09/05/2024).

[32] S. J. Llera and M. G. Newman, 'Effects of worry on physiological and subjective reactivity to emotional stimuli in generalized anxiety disorder and nonanxious control participants.,' *Emotion*, vol. 10, no. 5, pp. 640–650, 2010, ISSN: 1931-1516, 1528-3542. DOI: 10.1037/a0019351. (visited on 09/05/2024).

[33] J. W. Christensen, M. Rundgren and K. Olsson, 'Training methods for horses: Habituation to a frightening stimulus,' *Equine Veterinary Journal*, vol. 38, no. 5, pp. 439–443, 2006, ISSN: 2042-3306. DOI: 10.2746/042516406778400574. (visited on 11/05/2024).

[34] W. Hulstijn, 'Habituation of the orienting response as a function of arousal induced by three different tasks,' *Biological Psychology*, vol. 7, no. 1, pp. 109–124, Sep. 1978, ISSN: 0301-0511. DOI: 10.1016/0301-0511(78)90044-3. (visited on 11/05/2024).

[35] R. Klorman, 'Habituation of fear: Effects of intensity and stimulus order,' *Psychophysiology*, vol. 11, no. 1, pp. 15–26, Jan. 1974, ISSN: 0048-5772. DOI: 10.1111/j.1469-8986.1974.tb00817.x.

[36] J. S. Marzillier, D. Carroll and J. R. Newland, 'Self-report and physiological changes accompanying repeated imagining of a phobic scene,' *Behaviour Research and Therapy*, vol. 17, no. 1, pp. 71–77, Jan. 1979, ISSN: 0005-7967. DOI: 10.1016/0005-7967(79)90052-4. (visited on 11/05/2024).

[37] J. P. Watson, R. Gaind and I. M. Marks, 'Physiological habituation to continuous phobic stimulation,' *Behaviour Research and Therapy*, vol. 10, no. 3, pp. 269–278, Aug. 1972, ISSN: 0005-7967. DOI: 10.1016/0005-7967(72)90043-5. (visited on 11/05/2024).

[38] T. Scholander, 'Habituation of Autonomic Response Elements under two Conditions of Alertness,' *Acta Physiologica Scandinavica*, vol. 50, no. 3-4, pp. 259–268, 1960, ISSN: 1365-201X. DOI: 10.1111/j.1748-1716.1960.tb00180.x. (visited on 10/05/2024).

[39] R. G. Cummins, W. T. Wise and B. H. Nutting, 'Excitation Transfer Effects Between Semantically Related and Temporally Adjacent Stimuli,' *Media Psychology*, vol. 15, no. 4, pp. 420–442, Oct. 2012, ISSN: 1521-3269. DOI: 10.1080/15213269.2012.723120. (visited on 09/05/2024).

[40] M. Soleymani, S. Asghari-Esfeden, M. Pantic and Y. Fu, 'Continuous emotion detection using EEG signals and facial expressions,' in *2014 IEEE International Conference on Multimedia and Expo (ICME)*, Jul. 2014, pp. 1–6. DOI: 10.1109/ICME.2014.6890301. (visited on 08/05/2024).

[41] P. Das, A. Khasnobish and D. Tibarewala, 'Emotion recognition employing ECG and GSR signals as markers of ANS,' in *2016 Conference on Advances in Signal Processing (CASP)*, Jun. 2016, pp. 37–42. DOI: 10.1109/CASP.2016.7746134. (visited on 07/05/2024).

[42] F. Agrafioti, D. Hatzinakos and A. K. Anderson, 'ECG Pattern Analysis for Emotion Detection,' *IEEE Transactions on Affective Computing*, vol. 3, no. 1, pp. 102–115, Jan. 2012, ISSN: 1949-3045. DOI: 10.1109/T-AFFC.2011.28. (visited on 07/05/2024).

[43] D. Nikolova, P. Petkova, A. Manolova and P. Georgieva, 'ECG-based Emotion Recognition: Overview of Methods and Applications,' Sep. 2018.

[44] K. Sharma, C. Castellini, E. L. van den Broek, A. Albu-Schaeffer and F. Schwenker, 'A dataset of continuous affect annotations and physiological signals for emotion analysis,' *Scientific Data*, vol. 6, no. 1, p. 196, Oct. 2019, ISSN: 2052-4463. DOI: 10.1038/s41597-019-0209-0. (visited on 25/04/2024).

[45] P. Sriram Kumar, P. K. Govarthan, N. Ganapathy and J. F. A. Ronickom, 'Electrodermal activity-based analysis of emotion recognition using temporal-morphological features and machine learning algorithms,' *Journal of Mechanics in Medicine and Biology*, vol. 23, no. 06, p. 2 340 044, Aug. 2023, ISSN: 0219-5194. DOI: 10.1142/S0219519423400444. (visited on 09/05/2024).

[46] P. J. Swarubini, S. K. P, P. K. Govarthan *et al.*, 'ECG based Categorical emotion classification using time-domain features and Machine Learning,' *Current Directions in Biomedical Engineering*, vol. 9, no. 1, pp. 694–697, Sep. 2023, ISSN: 2364-5504. DOI: 10.1515/cdbme-2023-1174. (visited on 09/05/2024).

[47] N. T. Vu, V. T. Huynh, H.-J. Yang and S.-H. Kim, 'Multiscale Transformer-Based for Multimodal Affective States Estimation from Physiological Signals,' in *Pattern Recognition*, H. Lu, M. Blumenstein, S.-B. Cho, C.-L. Liu, Y. Yagi and T. Kamiya, Eds., Cham: Springer Nature Switzerland, 2023, pp. 113–122, ISBN: 978-3-031-47665-5. DOI: 10.1007/978-3-031-47665-5_10.

[48] A. Gargano, E. P. Scilingo and M. Nardelli, 'Comparing Valence-Arousal and Positive-Negative Affect Models of Affect: A Nonlinear Analysis of Continuously Annotated Emotion Ratings,' in *MEDICON'23 and CMBEBIH'23*, A. Badnjević and L. Gurbeta Pokvić, Eds., Cham: Springer Nature Switzerland, 2024, pp. 86–95, ISBN: 978-3-031-49062-0. DOI: 10.1007/978-3-031-49062-0_10.