Affective gaming using adaptive speed controlled by biofeedback

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ABSTRACT

This work is part of a larger project exploring how affective computing can support the design of player-adaptive video games. We investigate how controlling some of the game mechanics using biofeedback affects physiological reactions, performance, and the experience of the player. More specifically, we assess how different game speeds affect player physiological responses and game performance. We developed a game prototype with Unity[1] which includes a biofeedback loop system based on the level of physiological activation through skin resistance (SKR) measured with a smart wristband. In two conditions, the player moving speed was driven by SKR, to increase (respectively decrease) speed when the player is less activated (SKR decreases). A control condition was also used where player speed is not affected by SKR. We collected and synchronized biosignals (heart rate [HR], skin temperature [SKT] and SKR), and game information, such as the total time to complete a level, the number of ennemy collisions, and their timestamps. Additionally, emotional profiling (TIPI, I-Panas-SF), measured using a Likert scale in a post-task questionnaire, and semi-open questions about the game experience were used. The results show that SKR was significantly higher in the speed down condition, and game performance improved in the speed up condition. Study collected data involved 13 participants (10 males, 3 females) aged from 18 to 50 (M = 24.30, SD = 9.00). Most of the participants felt engaged with the game (M = 6.46, SD = 0.96) and their level of immersion was not affected by wearing the prototype smartband. Thematic analysis (TA) revealed that the game speed impacted the participants stress levels such as high speed was more stressful than hypothesized; many participants described game level-specific effects in which they felt that their speed of movement reflected their level of stress or relaxation. Slowing down the participants indeed increased the participant stress levels, but counter intuitively, more stress was detected in high speed situations.

CCS CONCEPTS

• **Computer systems organization → Sensors and actuators**; • **Human-centered computing → Activity centered design**; **Interface design prototyping**; **User centered design**; **User interface design**; **User studies**; **User centered design**; **Laboratory experiments**.

KEYWORDS

Affective computing, Biosignals, Human-Computer Interaction, Video game design, Video game, Physiological signals, Affective gaming, Player experience, Biofeedback, Emotions

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1 INTRODUCTION

In recent years, research on the use of physiological signals in video game design has increased in popularity. The use of biofeedback loops in game design, where players use physiological input about their emotional state while playing, is a growing field of research [19]. This work is part of a larger project investigating how biofeedback loops can be used in video game design and how they impact the player experience (see figure 1).

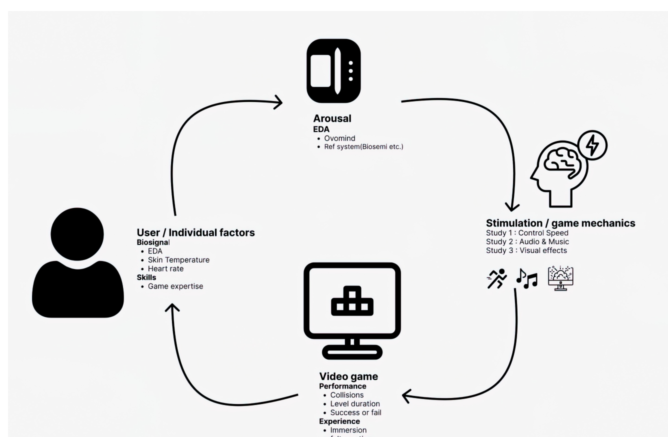

Figure 1: Diagram for the biofeedback loop

Emotions impact the physiology, electrodermal activity (EDA) can be used as indicator for activation [15]. The primary research questions in this study were about how varied game speeds using

[1]https://unity.com/

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an EDA feedback loop influenced players' physiological reactions, affected players' performance, user experience (UX), taking into account player gaming skills. To study these questions, we developed a time-restricted labyrinth game, a type of game known to affect the activation of players [24]. The study also sought to discover how game design and, in particular, biofeedback loops can be leveraged to generate a range of emotional responses and new experiences in players. The quality of the overall gaming experience can be improved by customizing the game to the player's present emotional state.

2 RELATED WORK

2.1 Emotion assessment with biosignals

A well-established finding is that emotions affect human physiology and, consequently, related biosignals. For example, stress detection is possible using biosignals. Wearable systems such as Shimmer3[2] or Empatica[3] are now effective and can accurately measure stress (81.82%)[21]. Furthermore, the nature of emotions generates different physiological reactions. Multimodal emotional classification using biosignals has been demonstrated to be effective with various emotions producing various physiological effects [7].

EDA, which monitors variations in sweat gland activity that reflect the level of activation [20], is one of the biosignals most commonly used for emotional forecasting. The tonic EDA component, which is more constant and acts as a baseline indicator of a person's level of vigilance or general arousal, is different from the phasic EDA component, which causes rapid and fleeting variations in skin conductance in response to specific stimuli.

Another important biosignal for emotional evaluation is photoplethysmography (PPG), which is often available on smart bands or smartwatch devices. PPG is an optically obtained plethysmogram that can be used to detect changes in blood volume in the microvascular bed of the tissue. Gil et al. (2010) analyzed HRV using PPG and pulse rate variability (PRV) and obtained in rest conditions a 99% correlation between heart rate variability (HRV) estimated with electrocardiogram (ECG) which is the gold standard, and PRV estimated with PPG [11]. Results were confirmed by Schafer (2013) and his review of studies [22].

Body temperature and skin temperature (SKT) are also important features for emotional assessment [18]. Nummenmaa et al. (2014) stated that emotions trigger topographic changes in human body temperature.

Other biosignals such as electrocardiogram (ECG), electromyography (EMG), and respiration (RSP) have been used for emotional evaluation with varying degrees of success. For example, Scherer (2005) used these biosignals which yielded a recognition accuracy of 92% for joy, anger, sadness, and pleasure (music stimulation) [23].

Furthermore, multimodal classification and regression using biosignals [7] is a promising method to assess emotions, with signal processing and characteristic estimation used to extract meaningful characteristics from raw data. Self-assessment is generally used to obtain ground truth in multimodal classification studies [13]. Multimodal deep learning classification [25] is also commonly used to further enhance the accuracy of emotional assessment using biosignals.

2.2 Affective games

Current studies on human-computer interaction (HCI) in video games frequently ignore the impact of player emotions. According to Bontchev (2016), playing video games is more emotional than cognitive, and research on interface design issues may not take this into account because video games are software and games with specific goals and rules at the same time [5]. Video games, according to Barr et al. (2007), integrate player-adopted value systems that influence how the game is played. They observed that in order to win a game, players must accept certain morals, such as "shooting alien attackers" in Space Invaders (Taito, 1978) [2]. Video games also have the ability to generate emotions and emotions are involved the learning process [6] by motivating players to accomplish tasks or goals. A technique to identify the feelings that players feel while playing is missing from the current generation of HCI in video games. Kim and Doh (2017) examined emotional transitions from different emotional states (fear, anger etc.) in popular games and discovered that they occur 3.3 times more frequently in the commercially successful games [14]. In a study on emotionally-charged video games, Nogueira et al. (2016) created a horror game with adaption rules [12] that alter the player's experience based on physiological responses. The study found that attributes characterizing the player experience including immersion, tension induced by the music (see [3] for a review of music and emotions studies) and soundscape, and valence, were significantly affected by biofeedback functionality, several versions of the game were proposed and they integrated varying biofeedback mechanisms [17].

Several methods can be used in order to collect biosignals with different devices such as wired electrodes, finger clips, or wearable devices. Ferreira et al. (2023) used a sock form factor for measuring PPG and EDA and the results support the feasibility of sock form factor for unobtrusive EDA and PPG monitoring [10]. Cantento et al. (2011) obtained recognition rates for emotions of 81% to distinguish between positive and negative emotion with multimodal biosignal sensor data only [7].

In light of this, this research suggests that integrating emotion recognition in HCI systems for video games and using player emotions as part of the game design may improve player experience. Games that offer a more immersive and engaging experience for players might be designed by examining emotional reactions and identifying the emotions that drive players [8]. This study expands on previous research and sets the foundations for future studies on the function of emotions in HCI for video games.

3 METHODOLOGY

For the purpose of identifying players' emotional states, we collected and analyzed data from player biosignals from research and mass market devices. In this study, an Ovomind-developed smart wristband that includes real-time(RT) biosignal analysis technology[4] is used to predict the player's arousal. We also used Biosemi Active-Two for the reference EDA signal[5].

[2]https://shimmersensing.com/
[3]https://www.empatica.com/
[4]www.ovomind.com
[5]https://www.biosemi.com/products.htm

3.1 Hypotheses

This study aims to examine how the game character speed affects the performance of the player and affects their physiological levels (heart rate, skin temperature, and SKR). In this study, two main conditions were proposed: speed up (to facilitate the game) and speed down (to make it more difficult); to control the effects, we also have a control condition without a biofeedback loop. We formulated research hypotheses on the impact of game character speed on SKR and player game performance. the impact of game speed on SKR and game performance in players. The following hypotheses are advanced in relation to the control condition:

(1) H1: The first hypothesis suggests that player SKR would decrease in the speed down condition. This theory is based on the premise that slowing down the game character makes it more difficult for the player to advance and complete the level in the allotted time. This increased difficulty is predicted to increase the levels of arousal, since the player is likely to feel dissatisfied and agitated as a result of the challenge. This notion is supported by earlier studies on arousal, which indicate that higher arousal levels are associated with difficult activities and high levels of stress [1].
(2) H2: The second hypothesis suggests that player SKR would increase in the speed up scenario. This theory is based on the premise that increasing the speed of the game makes it easier for the player to manoeuvre and complete the level in the allotted time. This reduced difficulty is predicted to result in lower levels of arousal, as the player is likely to feel more confident and calm. This notion is also supported by earlier studies on arousal, which indicate that lower levels of arousal are related to simple activities and low levels of stress.
(3) H3: The third hypothesis implies that player game performance would be reduced under the speed down condition. This theory is based on the premise that slowing down the game makes it more difficult for the player to manoeuvre, avoid adversaries, and complete the level in the allotted time. This increased difficulty expected to result in poorer game performance, since the player is more likely to make mistakes and take longer to complete the level. Previous research on performance supports this concept [16], indicating that increased work demands and stress levels are related to worse performance.
(4) H4: The fourth hypothesis suggests that player game performance would be improved under the speed up condition. This theory is based on the premise that increasing the pace of the game character makes it easier for the player to manoeuvre, escape adversaries, and complete the level in the allotted time. This improved ease of use is predicted to result in higher game performance, since the player will make fewer mistakes and complete the level faster. Morgeson & Humphrey (2006) stated that lower task demands and stress levels are related to better performance.

3.2 Physiological measures

In order to integrate physiological reactions in the video game mechanics we used the Ovomind smart band. To analyze the impact of biofeedback interactivity, we used a reference EDA signal measured with the Biosemi system[6]. The biosensor specifications and sampling rates for the Ovomind prototype are:

- PPG signal with a 50 Hz sampling rate
- SKR signal with a 8 Hz sampling rate (refreshing at 1 Hz)
- Accelerometer 3-axis with a 8 Hz sampling rate
- SKT signal with a 0.5 Hz sampling rate
- Heart rate (HR) data with a 0.5 Hz sampling rate (buffer of 4 seconds).

The current prototype uses a Nordic single board development kit supporting Bluetooth Low Energy[7]. Smart band data is received on the gaming computer using an emulated serial port.

The Biosemi reference biosensor system has the following specifications:

- PPG signal with a 2048 Hz sampling rate,
- SKR signal with a 2048 Hz sampling rate,
- SKT signal with a 2048 Hz sampling rate,

The skin conductance (SKC) was obtained by taking the inverse of the skin resistance multiplied by a factor of 1M to obtain micro Siemens (μ_S).

The library used is Neurokit2[8] was used to extract the EDA tonic component (trend) and the phasic components (number of peaks and amplitude of peaks). A peak represents a sudden change in participant physiological activation. The number of peaks and their amplitude indicate the short-term activity and the tonic (trend) component represents a longer activity.

The tonic component is the mean value of the tonic component (signal trend) without the phasic component (peaks) of all participants.

We used EDA as dependent variables in our statistical analyzes:

- SKR finger position (Biosemi)
- SKC finger position phasic number of peaks (Biosemi)
- SKC finger position phasic peaks amplitude (Biosemi)
- SKC finger position tonic (Biosemi)

The current version of the Ovomind software algorithm yields a arousal component out of the Ovomind smart band SKR raw data as a float between 0 (most activated) and 1 (less activated) that can be used as an arousal coefficient game variable (ACGV) directly in Unity.

3.3 Adaptive game prototype

3.3.1 Conditions. The goal was to make the game reactive to the EDA signal in a synchronous way. We chose to impact the game speed in different ways across three conditions:

(1) **speed up**: In this condition, we expect an increase in player performance due to a higher game character speed; this affects their ability to increase the player's performance by increasing the speed of the player's movement and their ability to dodge enemies (fewer collisions) and to finish the level in time (success or failure). To achieve this, we implemented a speed modifier variable which was added to the default speed. The speed modifier was empirically set to 5

[6]https://www.biosemi.com
[7]https://www.nordicsemi.com/Products/Development-hardware/nrf52-dk
[8]https://neurokit2.readthedocs.io/

times the ACGV. After pilot tests, the default game character speed value was set to 10 (float) and the maximum increase in speed value allowed by the loop was 5 while ACGV was reaching 1. The increase in movement speed should make it easier to find the key and exit door.

(2) **speed down**: In this condition, we expect a decrease in player performance due to the slower game character speed; this affects the ability to decrease the player's performance by decreasing the speed of their movement and ability to dodge enemies (more collisions) and to finish levels on time. In this condition the speed modifier is subtracted to the default speed. The speed modifier was empirically set to 5 times the ACGV. The maximum reduction possible in the moving speed was 5 points to stay within realistic gameplay controls. The decrease in speed should make the goal of finding the key and exit door more difficult.

(3) **Control**: Under this condition which acts as control, we maintained a constant moving speed value of 10 speed units.

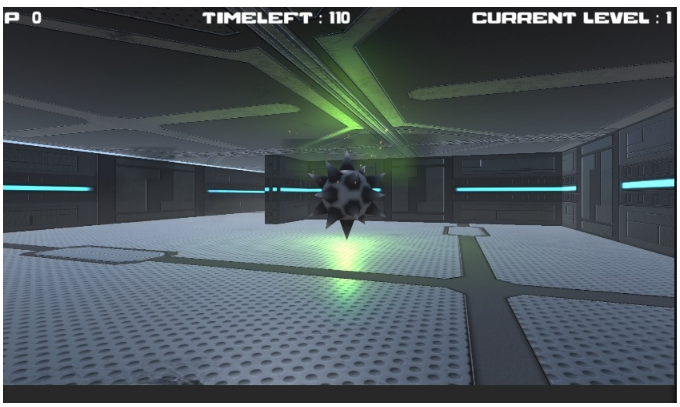

Figure 2: Game user interface and enemy

3.3.2 Game Design. Our adaptive game prototype takes into account the emotional condition of the player and adjusts the mechanics of the game and the difficulty level accordingly. This strategy uses biofeedback technology to collect objective measures about players' physiological reactions, which may then be used to modify the game's mechanics, music, or even visual effects. An adaptive game design should also take the player skills into account. To avoid feelings of irritation or boredom that may result from a game that is either too easy or too challenging, an adaptive game could modify its mechanics in accordance with the player's competence. This may represent a more individualized and entertaining experience that meets each player's unique emotional responses and cognitive demands. Participants had 120 seconds to complete each level using only an analog stick to navigate the levels. The 120 seconds time limit was chosen after the pilot tests sessions. To complete and succeed in a level, each participant needs to find a key and exit door while avoiding moving enemies (see figure 2). The collisions with the enemies are not lethal, but a sound evoking that the game character has been hurt is played each time to act on the player arousal. The order of passage of the conditions (game levels) across participants were defined using the Latin square method. This approach ensures a balanced order of the conditions to minimize any bias due to order effects. The level number is displayed in the main user interface (UI) (see figure 1), for the participant to link the condition with a level and to be able to fill the post-task questionnaires. In the game prototype, level 2 was the speed up condition, level 3 the speed down and level 4 was the control condition.

3.3.3 Game learning and controls. First, it was crucial that players could understand the game's rules quickly. There was a tutorial level available to help with this. Second, especially under the circumstance of the speed down condition, we had the challenge to establish attainable goals. Finally, because Biosemi equipment rendered players' non-playing hand immobile, the game had to be playable with the left hand due to the position of the analog stick on the game controller used.

3.3.4 Affective adaptation mechanism. SKR was used as a RT input for game settings (movement speed) through dynamic game mechanics that responded to the player's EDA levels. Each participant's gaming experience was customized using their SKR data. The parameter to be controlled in this particular research was the player's movement speed which is a key parameter in time limited tasks and in video games.

3.4 Experimental protocol

3.4.1 Participants. All participants were recruited for the study through an invitation letter distributed through a mailing list at the University of Geneva (UNIGE) and through posters. Participants were offered a reward of CHF 10 in the form of a game coupon for their participation in the 1-hour experiment. 16 participants (12 males and 4 females), of 18 to 50 years of age ($M = 23.93$, $SD = 8.25$), completed the study. We were only able to use data from 13 of the 16 participants due to defective collected data. We evaluated the video game expertise of the participants, in order to understand the habits and motivations of the panel, as proposed in [4]. Most of the participants (15) were students and there was one researcher in the group. Regarding video game expertise, 10 of the participants were classified as experts, 4 as casual players, and 2 as beginners.

3.4.2 Ethical approval / consent forms. This study was approved by the QMUL Electronic Engineering and Computer Science Devolved School Research Ethics Committee (EECS DSREC) with the following reference: QMERC20.565.DSEECS22.073. Participants gave their informed written consent to participate in this study.

3.4.3 Structure of the experiment. Four primary components made up the experiment: introduction, training, tasks, and post-task questionnaires. Participants were seated and data collection tools were set during the introduction. Participants signed consent forms, received detailed instructions and guidelines during the training phase, and followed a tutorial level to become familiar with the game. Three game levels (one for each condition) each lasting maximum 120 seconds each had to be finished during the tasks phase. Participants were then asked to submit a post-task questionnaire using the Google Forms platform once all the sensors and equipment had been removed. The whole experiment took between 50 and 60 minutes for each participant.

3.4.4 Questionnaires. We used several questionnaires to collect information about individual factors, including the Ten-Item Personality Inventory (TIPI), the short form of the Positive and Negative Affect Schedule (I-PANAS-SF), a custom-designed User Experience (UX) 7-item Likert scale, and open-ended questions about the controls and feedback of the game. TIPI was used to gain an understanding of the personality traits present within the participants.
To analyze the collected data, the responses were coded accordingly with numbers from "Strongly disagree": 1 to "Strongly agree": 7, 4 representing a neutral statement. The TIPI measures the five major dimensions of personality as outlined by the Big Five personality theory, namely: extraversion, agreeableness, conscientiousness, emotional stability, and openness to experience. It is a widely used assessment tool with demonstrated reliability and validity. I-PANAS-SF was used to measure both positive and negative affect, providing a picture of the affective states of the participants at the beginning of the experiment. The UX 7-item Likert scale allowed the collection of subjective experiences. Open-ended questions were also used to collect qualitative data to obtain insights into the emotional and cognitive processes behind the game experience. In general, the collected data was analyzed to gain a comprehensive understanding of the participant's physiological and psychological responses to the experimental task, as well as their subjective experience of the task.

3.4.5 Thematic analysis. We conducted a thematic analysis (TA) [9] to examine the responses of the participants obtained in post-task questionnaires (open-ended questions). As outlined by Braun & Clarke (2014), TA is a systematic approach to identify, organize, and interpret patterns of meaning (themes). As a qualitative research method, TA aims to extract meaning from data rather than uncover phenomenological insights about individual participants. The goal is to identify patterns or recurring phenomena within the data. TA is well suited for this type of research, as it allows the identification of shared sentiments among participants.

3.5 Statistical analyses

For our analysis, we chose to use a linear mixed-effects model (LMEM) to analyze the fixed effects induced by each condition (speed up, speed down and control) and taking into account the random effect generated by the participants (13) for each dependent variable. LMEM is an effective method to study the dynamics of physiological responses related to task demands. It can account for individual variations in SKR patterns, as well as variability associated with an experimental treatment, by adding fixed and random factors. In the context of a biofeedback game study in which participants experience different game character speed conditions, LMEM can help identify the effects of game speed on physiological responses and game performance while controlling for confounders such as game expertise.

We treated participants as random effects, considering different intercepts for each participant, which means that the intercepts may differ between individuals. Furthermore, LMEM provided for the estimate of fixed effects (effects of the independent variable) and random effects (effects of participant-specific intercepts). This study, which attempts to assess the link between character speed in the game, player performance, and physiological reactions (heart rate, skin temperature, and SKR), is based on hypothesis testing. The study offers three separate conditions: a control condition without biofeedback, a speed-up condition, and a speed-down condition. The main focus of the study is to understand how differences in game character speed affect both SKR/SKC and player game performance. To better understand how game design affects player experiences, this study uses hypothesis testing to explore the complex interactions between game mechanics, physiological reactions, and player performance. Hypothesis H1 suggests that slowing the character of the game will result in a decrease in SKR or an increase in SKC, which will represent an increased arousal caused by greater difficulty. On the contrary, H2 claims that speeding up the game would result in higher SKR (lower SKC), which corresponds to a decreased arousal given that the game becomes less challenging. H3 suggests that slowing down the game will impede player performance, creating errors and delays. H4 suggests that increasing game speed would improve player performance by reducing errors and completion time.

We used a Python library[9] from Statsmodels to fit the LMEMs with fixed and random effects specified as variables in the data frame. MixedLM is a Python library to fit linear mixed effects models. It is used to analyze data subject to fixed and random effects. The library works using maximum likelihood estimation (MLE) (more complex than for models only based on fixed effects because it includes both fixed and random effects) to fit the models. The model was fitted using the well-established Restricted Maximum Likelihood (REML), REML technique, which allows the estimation of both fixed and random effects in the model. As a comparative study within subjects, we assessed the effects of game character speed on the following dependent variables:

Biosignals

- SKR finger position (Biosemi)
- SKC finger position phasic number of peaks (Biosemi)
- SKC finger position phasic peaks amplitude (Biosemi)
- SKC finger position tonic (Biosemi)

Game performance

- Number of enemy collisions (Unity)
- Completion of the level (Unity)
- Duration of the level/condition (Unity)

The sample size (number of observations) for the Biosemi SKR LMEM model was 7,858,570 (game level completion times for the 13 participants ranged between about 90s to 120s across the three conditions and the Biosemi SKR signal was sampled at 2048 Hz). The sample size for the all the other LMEM models was 39 as there was one observation per participant (13 in total) for each of the three conditions.

4 RESULTS

4.1 Effect of speed on EDA

[9]https://www.statsmodels.org/stable/index.html

Name	Coef.	Std.Err.	z	P>|z|	0.025	0.975
Intercept(Control)	1976.536	256.808	7.697	0.000	1473.202	2479.870
C(Condition)[speed up]	-72.582	0.420	-172.962	0.000	-73.404	-71.759
C(Condition)[speed down]	248.545	0.394	630.176	0.000	247.772	249.318
Group Var	857352.025	151.247				

Table 1: LMEM raw SKR in ohms

Name	Coef.	Std.Err.	z	P>|z|	0.025	0.975
Intercept(Control)	8.846	0.972	9.099	0.000	6.941	10.752
C(Condition)[speed up]	-0.077	1.260	-0.061	0.951	-2.547	2.393
C(Condition)[speed down]	-0.615	1.260	-0.488	0.625	-3.085	1.855
Group Var	1.964	0.841				

Table 2: LMEM SKC number of peaks

4.1.1 Impact on SKR. The data set has 7,858,570 observations, with a minimum group size of 455,873 and a maximum group size of 693,837, serving as the basis for the study. With a standard error of 0.420, the coefficient for the condition speed up is 1903.95 Ω, while one with a standard error of 0.394 is for the condition speed down (positive coefficient of 2225.08 Ω) compared to the intercept. The fact that both coefficients are highly significant ($p < 0.001$) shows that the various situations differ significantly. The intercept represents the control condition without speed modification (intercept) and has a coefficient of 1976.53 Ω.

Our main hypothesis (H1) suggested higher stress and arousal in the speed down condition (this would mean a lower SKR). However, the speed down condition yielded a significantly higher SKR compared to the control condition. Similarly, in the speed up condition, the SKR is lower (higher stress) than in the control condition and what we hypothesized (H2). This is partially explained by the possibility that the moving speed value was sometimes inappropriate to properly navigate the map (M = 12.29, SD = 1.22) and probably made the game controls even more stressful than in the control condition. The variance component analysis shows group-level variability, with a group variance estimated to be 857,352.025 with a standard error of 151.247. This suggests that the differences between the groups are rather large. According to the model output, the intercept coefficient is 1976.536 with a 256.808 standard deviation. The intercept is considerably different from zero, as shown by the matching z-value of 7.697 ($p < 0.001$). The intercept's 95% confidence interval is between 1473.202 and 2479.870.

We evaluated the goodness-of-fit of the model using a number of measures. The R-squared value, which gauges the amount of variation described by the model, is 0.9791, showing that the model provides a significant amount of the variability of the dependent variable. In general, the findings point to a substantial correlation between the condition variable and the dependent variable Biosemi SKR. Substantial impacts on intercept and condition levels suggest that the various conditions have an impact on the dependent variable. The study also shows significant group-level variation. The data is well matched by the model, which accounts for a large percentage of the variability. It seems that this result is disapproving our hypothesis (H1) with a higher SKR in the speed down condition. The significant decrease of SKR in the speed up condition indicates that increasing game character speed following their player EDA variations overall increased the arousal of the participants compared to a fixed game character speed (control condition).

4.1.2 Impact on number of EDA peaks. We extracted the number of skin conductance peaks to estimate the phasic activity of the participants. Peaks were extracted from the converted SKR to SKC signal and we used the *neurokit2* python library and the *eda process* function to find peaks and their respective amplitudes. 39 observations (3 conditions for each 13 participants) were analyzed.

The model scale was 10.3227 and represents the variance of the random effects in the model. The results of the LMEM regression findings are reported in Table 2.

The predicted number of EDA peaks in the control condition is represented by the intercept coefficient. The intercept's predicted value is 8.846, with a 0.972 standard deviation. The baseline level of the EDA peaks is significantly higher than 0.

There are no statistical differences in the number of EDA peaks between the control and the speed up or speed down conditions.

The model's goodness-of-fit metrics are also presented. The model explains around 26.64% of the variance in the number of peaks in the EDA, according to the R-squared value of 0.266. These results indicate that the number of SKC peaks has a limited association with the game speed variations.

4.1.3 Impact on the amplitude of the EDA peaks. We used the *eda process* method to estimate a second component of the phasic EDA activity of the participants, which is the amplitude of the peaks. 39 observations of the mean peak amplitude value were analyzed (3 conditions for each of the 13 participants).

Name	Coef.	Std.Err.	z	P>|z|	0.025	0.975
Intercept(Control)	29.860	47.360	0.630	0.528	-62.964	122.683
C(Condition)[speed up]	67.377	49.092	1.372	0.170	-28.842	163.597
C(Condition)[speed down]	71.683	49.092	1.460	0.144	-24.536	167.902
Group Var	13492.793	74.763				

Table 3: LMEM SKC peaks amplitude mean in µS

The intercept coefficient provides the estimated mean value of the amplitude of the EDA peaks in the control condition. The intercept estimate is 29.860 µS with a standard error of 47.360 µS. The mean EDA peak amplitude does not differ statistically from zero at the reference level, neither speed up nor speed down significantly deviate from the reference level in terms of the mean value of the amplitude of EDA peaks. According to the R-squared value of 0.607, the model accounts for around 60.76% of the variation in the mean amplitude of EDA peaks. The MSE, RMSE, and MAE are 10985.1863, 104.8102, and 54.8075, respectively. These results indicate that the amplitude of the EDA peaks is relatively associated with the game speed variations.

4.1.4 Impact on tonic EDA. We extracted the number of skin conductance tonic components to estimate the overall skin conductance activity of the participants. 39 observations of the mean of the tonic EDA value were analyzed (3 conditions for each of the 13 participants).

The tonic EDA in the control condition is given by the intercept. With a standard error of 58.833, the intercept's predicted value is 367.962. The baseline of the level of EDA tonic is substantially greater than zero, and there are no statistically significant differences in the mean value of EDA tonic between the control and

Name	Coef.	Std.Err.	z	P>|z|	0.025	0.975
Intercept(Control)	367.962	58.833	6.254	0.000	252.652	483.271
C(Condition)[speed up]	60.358	43.228	1.396	0.163	-24.368	145.084
C(Condition)[speed down]	42.561	43.228	0.985	0.325	-42.164	127.287
Group Var	32850.044	167.401				

Table 4: LMEM SKC tonic mean in μS

the speed up condition. The model accounts for around 81.31% of the variation in the mean value of the EDA tonic, according to the R-squared value of 0.813. The MSE, RMSE, and MAE are 7884.8155, 88.7965, and 47.0531, respectively.

4.1.5 Impact on game performance: collisions with enemies. In the current study, in which participants navigated the game levels, it was hypothesized that increasing the speed of movement would lead to an increase in the success rate, reduce the duration of levels, and potentially reduce the number of collisions, particularly in cases where a time constraint limited the participant. Several lines of reasoning support this hypothesis. Increasing the speed of movement allows the participant to cover more ground in a shorter period of time, increasing the probability of successfully completing the labyrinth before time runs out. Furthermore, faster movement can also lead to a more efficient use of cognitive resources, as the participant can process more information and make decisions more quickly. There is also evidence that individuals tend to perform better on tasks that are self-paced than those that are externally paced. This suggests that increasing the speed of movement can potentially increase or decrease the performance of the task. Table 5 reports the LMEM analysis of the number of collisions per condition.

Name	Coef.	Std.Err.	z	P>|z|	0.025	0.975
Intercept(Control)	3.000	0.501	5.986	0.000	2.018	3.982
C(Condition)[speed up]	-0.538	0.609	-0.883	0.377	-1.733	0.656
C(Condition)[speed down]	-0.769	0.609	-1.262	0.207	-1.964	0.425
Group Var	0.850	0.533				

Table 5: LMEM number of collisions with enemies

The results revealed that the intercept (that is, the predicted value of collisions in the control condition) is 3.000. The model accounts for around 40.7% of the variation in the number of collisions with the game enemies, according to the R-squared value of 0.407. A small reduction in enemy collision was found for the speed up condition (0.2031) and a stronger reduction for the speed down condition (-0.769) compared to the control condition.

4.1.6 Impact on game performance: time to complete the level. Participants had a maximum of 120 seconds to complete a level. If the time limit is passed, the next level is automatically loaded. Table 6 reports the LMEM analysis of the level duration per condition.

Name	Coef.	Std.Err.	z	P>|z|	0.025	0.975
Intercept(Control)	94.439	5.876	16.073	0.000	82.923	105.955
C(Condition)[speed up]	-6.356	7.817	-0.813	0.416	-21.677	8.965
C(Condition)[speed down]	18.227	7.817	2.332	0.020	2.906	33.548
Group Var	51.607	4.616				

Table 6: LMEM level duration in seconds

Participants spent on average 94.44 seconds to complete the levels under the control conditions. Taking into account the speed variation conditions, participants spent 6.35 seconds less per level in the speed up condition and 18.22 seconds more per level in the speed down condition. The model accounts for around 36.4% of the variation in the duration in seconds by condition, according to the R-squared value of 0.364.

4.1.7 Impact on game performance: level success. To assess success which is recorded as Boolean output (true or false), Success implied the participant finds the key and the exit door before the end of the time limit. The coefficient for the variable game speed over the conditions was found to be statistically significant, with a negative effect (more successes) for the speed down compared to the control condition. This result goes against our hypothesis (H3). In terms of percentage of success rate per condition, in the control condition with fixed speed, the participants successfully completed the level, 38.45% of the time. This percentage reaches 46.15% in the speed up condition and 61.54% for the speed down condition.

4.2 Thematic analysis

4.2.1 Game controls: Open-ended questions. TA was based on the responses of 13 participants to open-ended questions about their game play experiences (UX). Participants described precise levels at which they believed that their speed of movement represented their level of tension or relaxation, which dealt with level-specific experiences. Personal levels of stress that influenced speed were also discovered and 7 individuals noted that their own degree of tension or worry affected how quickly they moved. There was a relationship between difficulty and speed, with 2 individuals discovering that a level's difficulty affected how quickly they moved. Last but not least, 2 participants stated that they did not believe that their movement speed really indicated their degree of tension or relaxation. The participants said that variations in speed had an impact on their feelings of stress, and also whether they traveled at a faster or slower pace. 8 participants saw that speed causes stress, while others observed that speed causes tension when it decreases. Some could pinpoint the exact points at which speed variations increased or decreased their stress levels. 3 participants said that altering the pace of the movement had no effect on how relaxed or stressed they felt. Most of the participants (9 out of 13) indicated that changes in movement speed had an impact on their degrees of relaxation when asked about this. Due to the decrease in speed and the requirement to reach the goal in a certain period of time, participants reported feeling pressured. At high speeds, some participants also reported feeling more at ease, but as speed reached a certain level, they had more difficulty unwinding, this statement can explain the SKR LMEM counter intuitive result. In general, the findings imply a complicated and multifaceted link between movement speed and tension or relaxation.

4.2.2 Feedback: Open-ended questions. The participants were asked their opinions on their experiences using the smart wristband and participating in the game. They were also asked about the game's positives and negatives, any recommendations for enhancements, and if they were interested in playing games that react to their emotions. The first question in this section asked about the comfort of using the smart wristband for the task. The wristband was deemed to be comfortable to wear for 8 participants, and 2 participants even forgot that they had it on. The comfort of the electrodes and other sensors affixed to the hands and fingers was the subject of the second question. The sensors did not cause any problems for most of the participants and had no impact on how they played. The first theme that emerged was immersive audio, with 4 participants noticing the ability of the game to create an immersive experience through its sound design. The participants enjoyed the atmospheric aspects to evoke fear and suspense, as well as level design and movement, strategic components, creative direction, and immersive soundtrack. The use of jump scares and loud sounds, the monotony of the game's locales and stages, its complexity and challenge, its aesthetic and design features, its restrictive controls and mechanics, and its sound design were all highlighted as dislikes. For example, 2 participants noting that jump scare noise and screamers were disruptive and added unnecessary stress to the game experience. One theme was the desire to add more context and storytelling to the game. It could also be made more dynamic and difficult by adding more stages with more varied features. Some participants also call for a greater focus on calm states as a progressive condition because excitement often outweighs calming emotions during play. Overall, participants reported an interest in playing games that respond to their emotions.

5 DISCUSSION

Thematic analysis of open-ended questions revealed several key themes related to game controls and the impact on players' levels of stress and relaxation. Regarding the impact of game controls, participants described level-specific experiences in which they felt that their movement speed accurately reflected their level of stress or relaxation at certain levels and personal factors that influenced their speed. Few participants did not connect the speed adjustment to their own stress. However, when we asked about the effects of changing their speed of movement, participants reported that speed changes affected their stress levels, with levels 2 (speed up) and 3 (speed down) being the most frequently cited. In terms of the desire for games that respond to emotions, participants were interested in playing such games, but some found the technology to be useful for certain types of game, such as story-telling games but not on a broader scale. Participants also suggested improvements to such games, such as adding more context, storylines, interactive elements, and a more dynamic and challenging game experience. Furthermore, only one LMEM analysis showed that emotional conditioning significantly affected SKR, with speed down and speed up conditions having a positive influence on SKR. SKR changes in each condition show that participants were more likely to be stressed in the speed up condition with 46% of success rate and less stressed in the speed down condition with a 61% of success rate, which is in opposition to our main hypothesis, but the LMEM and TA results converged to illustrate this statement.The SKR biofeedback loop driving the game character speed adaptation used for this study has shown some limitations and more adaptation rules need to be tested, such as a smoothing of the speed augmentation following a logarithmic growth instead of linear transitions to avoid the game becoming uncontrollable and stressful.

6 CONCLUSION

We examined the effects of emotion-driven game character speed on biosignals and the impact of the game controls and experience on player stress and relaxation levels using linear mixed-effects model analysis and thematic analysis. Linear mixed-effects model analysis showed that emotion-driven game speed had a significant effect on SKR, with speed up decreasing SKR (higher arousal) and speed down increasing SKR (lower arousal). Thematic analysis revealed several themes on how game controls and experience affect stress and relaxation levels, including level-specific experiences and changing moving speed. Participants expressed interest in playing games that respond to emotions and provided constructive feedback for improvement. In conclusion, this work supports the use of SKR/SKC in the biofeedback loop for video games. The results offer new insights that can guide the creation of games that respond to emotions or biosignals. The analyses did not confirm the H1 and H2 hypotheses as contrary to what we expected, increasing the game character speed led to an increase of arousal and decreasing the speed led to a decrease of arousal. This corroborates the fact that the majority of participants felt more stressed when character speed increased. The H3 hypothesis was only partially confirmed as reducing speed led to an increase in level completion time (reduced performance), but also led to a slight decrease in number of collisions with enemies (improved performance), although the latter was not significant. The analyses tend to support H4 since increasing speed reduces both the number of collisions and completion time, hence improving player game performance (however, the effects were not found to be significant). To be in a position of using EDA in a biofeedback loop, the following limitations need to be addressed: Individual differences in SKR reactions caused by factors such as skin type and moisture levels could lead to uneven emotional readings and possibly unwanted game responses. To maintain player satisfaction and prevent undesired frustrations, it is important to carefully design the integration of SKR-based game mechanisms, especially when game controls are involved. The present study was conducted with a fairly small number of participants (13) which means that some significant effects may have been missed. Larger sample size studies should be conducted to reduce error in the determination of effects, taking into account individual factors such as culture and gender. Our future work will focus on affective gaming using biosensor-driven music. Future studies will use musical cues for the biofeedback loop, such as variations in the tension of the music with the assumption that music can effectively alter the emotional state of the player during gameplay.

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