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Using EEG data as Dynamic Difficulty Adjustment in a serious game about the plastic pollution in the oceans

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ABSTRACT

In this work, it is explored whether real-time EEG (Electroencephalography) can adjust the difficulty in a serious game focused on engagement, attention, and learning about plastic pollution in our oceans. Using EEG to balance the game around the players' affective state by measuring brain activity in real time, it is aimed to better fit the player's skill level, enabling a stable flow state. The experimental study included 34 participants with an experimental group (n=17), and a control group (n=17). The experimental group played the game about the plastic pollution in our oceans with an adaptive difficulty adjustment (DDA) based on changes in their levels of attention and calm measured by EEG. The evaluation is based on a user engagement questionnaire, structured interviews, the EEG data, and a knowledge test. The results revealed high engagement in the game from both the experimental group and the control group. However, the participants in the control group were more attentive while playing the game and scored higher on all questions in the knowledge test compared to the experimental group. In conclusion, our study cannot provide evidence for using EEG-DDA to increase the engagement, attention, and learnings about pollution in the oceans in a serious game. However, there are still advantages for including EEG in game related research, and much future research is needed in how to provide optimal learning in serious games.

CCS CONCEPTS

• Human-centered computing; **• Empirical studies in HCI**; **• Applied computing**; **• Computer games**; **• Software and its engineering**; **• Interactive games.**;

KEYWORDS

Serious games, Eco-games, EEG, Dynamic Difficulty Adjustment, Engagement, Attention, Calm, Game-based Learning

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1 INTRODUCTION

The ability to retain a player's engagement and attention is an important aspect of video game development [1]. Similarly, the ability of serious games to maintain engagement and concentration is essential to meet the intended educational and behavioral goals [1]. Due to these goals, game developers and researchers have attempted various balancing methods, such as linear, stepwise, and dynamic difficulty adjustments [2, 3]. Dynamic Difficulty Adjustment (DDA) techniques attempt to produce an experience customized to each player, intending to keep the player engaged throughout [3]. There are different approaches for using DDA, included e.g., precision (shots, hits), object collection (number of won or lost pieces), life points, evolution/ progression, and time. Traditional linear methods risk creating predetermined difficulties that may not match the players' abilities, which can lead to perceived anxiety or boredom [4, 5]. Or in other words, DDA can reduce the difficulty for the weaker player, or increase the difficulty for the stronger player, and by that keep the player's engagement. This match of abilities is commonly used in game research by employing Csikszentmihalyi's flow theory, which focuses on balancing challenge and skill for specific tasks [4, 5]. Undoubtedly, it is essential to understand the impact of challenges on the player experience and to determine when a player of serious games is appropriately challenged based on their skills [6–8]. However, a key question is when and how to activate the difficulty adjustment for matching the individual player's appropriate level. Various methods are used to evaluate the appropriate level of challenge in serious games, including especially self-reports [6, 9, 10] and in-game metrics (log data) [6, 11]. In this paper, it is explored whether real-time EEG (Electroencephalography) can adjust the difficulty level in a serious game focused on learning about plastic pollution in our oceans. By using EEG, it is aimed to better fit the player's skill level in real time, enabling a stable flow state, and thus avoiding negative experiences (like boredom or anxiety). The research questions are as follows:

RQ1: Can real-time EEG data be used as Dynamic Difficulty Adjustment (DDA) in a serious game? RQ2: Can DDA increase the engagement, attention, and learnings about pollution in the oceans? The reason for using EEG linked to DDA is inspired by previous studies [26, 47], showing that DDA based on EEG can increase the players excitement and improve the gaming experience [47]. EEG record the electrical activity of a human brain through electrodes attached to the scalp. Unlike self-reporting, EEG can be measured without drawing the gamer's awareness away from the primary task or asking them to remember or predict their past or future states of engagement. The main advantage of using EEG measurements is that the method potentially can delineate unconscious emotional responses to the game experience (including balancing challenges and skills) with no delay between the game stimulus and the EEG reaction. Via the EEG data, it is possible to identify the areas of interest, such as the attention and calm, and by that adjust the difficulty level. In the literature it is already emphasized that optimal learning content is characterized by an intermediate level of cognitive load [20–22]. There is a general agreement that there is no one-size-fits-all when it comes to learning through gaming [30, 31, 50, 54]. However, there is still a need to address how to match individual differences in game-based education to provide optimal learning. The novelty within this study derives from the applied research of using an EEG-DDA method in an eco-game context. This paper share experiences and incorporate methodological advantages and limitations when using real-time EEG as a DDA in a serious game about protection of the oceans.

2 PREVIOUS RESEARCH

Despite the much interest in DDA [12], previous reporting is inconsistent in their findings of balancing learning-based game's difficulty with the player's skill level and positive motivational outcomes. Koskinen et al. [6] outlined this inconsistency with included findings with no (or not always) positive effects [13–15] and others with positive outcomes [16, 17]. The inconsistency can be explained by having different approaches, contexts, game genres, and target groups. There is a fast-growing amount of research on in-game difficulty balancing [23–27] and how psycho- physiological measures can be used as an alternative or supplement to self-reporting during video game play [25–29]. This includes monitoring near-infrared spectroscopy, heart rate, pupil diameter, skin conductance, blood volume pulse, and electroencephalography [25, 26, 28, 29, 32–34, 50]. The main reason for using psychophysiological in game research is often to provide emotional responses during gameplay (in a here-and-now) and using other methods than verbal and written stimuli as the gateway to emotions [18, 19, 35]. However, despite interest in DDA and serious games, there is limited research that used psychophysiological methods in ecological games to provide awareness of the wide variety of ecological issues. Video games with ecological themes, or simply ecological games, have developed quickly during the last decade [36, 37, 45, 51]. Current ecological games propose enhancing comprehensive knowledge of the climate crisis by providing new learning and awareness opportunities. Ecological games are often categorized as games for change [37] because they contribute to ecological thought and encourage people to become more environmentally active [51]. Ecological games exhibit huge variations, both as serious games for specific learning purposes and as games for entertainment. As many scholars have already outlined, there is no consensus on the definition of serious games. The definitions are applied differently, sometimes focusing on various perspectives depending on their purpose, player goals, and content. Previous definitions have emphasized that serious games are applications designed to serve more than as a purpose for entertainment [38]. However, some unsolved categorical challenges remain as to what a serious game is and what it means for them to strive for more than entertainment. Furthermore, some categorical problems often exist within the terminology associated with serious games, gamification, and their connection to ecological games.

The United Nations "17 Sustainable Development Goals" are a universal call to action to end poverty, protect the planet, and improve the lives and prospects of everyone everywhere [39]. The goals consist partly of addressing environmental dangers, establishing health and well-being, reducing inequalities, promoting climate action and peace, and life on land and below water. One of the most pressing environmental issues is plastic pollution in the ocean [40]. UNESCO reported about 50 to 75 trillion pieces of plastic and microplastics in the ocean [40]. Plastic generally takes 500 and 1,000 years to degrade, most becoming microplastics without completely degrading. Plastic pollution in the ocean devastates marine life, ecosystems, and human beings [40]. The plastic in the ocean is in our food chain and affects the body's endocrine system, causing developmental, neurological, reproductive, and immune disorders [40].

3 METHODS

3.1 Participants

Participants were recruited from Aalborg University. The study included 34 participants, with 17 participants in the experimental group (EG) and 17 in the control group (CG). The experimental group had 13 males and 4 females (age M = 22.6; SD = 1.7. Average play time per week: 15.5 hours). The control group included 13 males and 4 females (age. M = 25.4; SD = 4.5. Average play time per week: 11.5 hours). The participants were all students from various programs (bachelor- and master's degrees) within natural sciences. All participants gave informed consent and were told they could withdraw from the study at any time. In addition, all participants were provided with anonymized ID numbers, and all data were labeled with these IDs. We applied special considerations when recruiting participants for an EEG study in accordance with Danish law, and the international code of conduct.

3.2 Procedure

The test was designed as an experimental group (EG)/Control Group (CG) experiment, where the EG played the game about the plastic pollution in our oceans with an adaptive difficulty based on changes in their levels of attention and calm measured by the Neurora headset (Figure 1). The Neurora headset recorded the EEG band power values for delta, theta, alpha, beta, and gamma [41]. To do this, it used a ThinkGear AM (TGAM) module [41] to process the cognitive signals. The output data of this device were the attention and calmness metrics of the brain via its built-in patented eSense biometric algorithms [41]. The metrics for attention and calm were displayed in the range of 1 to 100. This scale made it possible to analyze whether the subject was focused or calm in relation to the task at that time. The gaming EEG-system uses gold- plated contact sensors fixed to a wireless headset (Figure 1).

The CG played the same game but with linearly increasing difficulty. Both groups wore the EEG headset and had their brainwaves logged for later analysis. The headset was thoroughly cleaned between sessions. The game experience consisted of playing the game for 7 minutes. During the game (in-game), the participants were provided information about plastic pollution in our oceans. The information was provided every time the participant died in the game. The game was designed so that no matter of the participant's

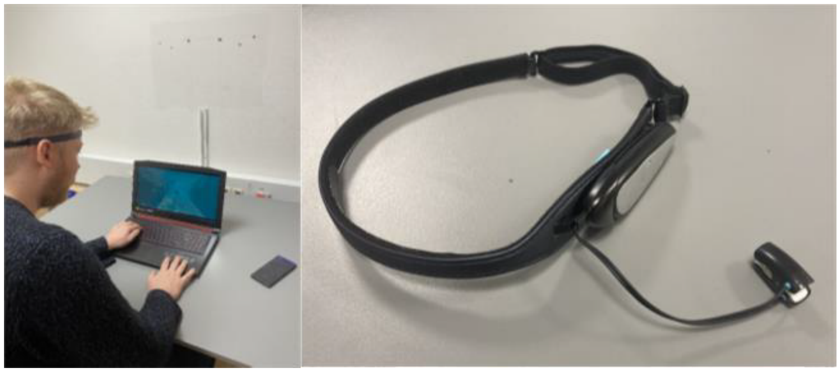

Figure 1: The used EEG headset (Neurora).

skill level, there was an inevitable death in the third level. This was included to affect all players, regardless of ability, and check if the knowledge for the death in the third level was recalled better than other information's death. After the game, there was a questionnaire, with items inspired by the validated GUESS18 (The Game User Experience Satisfaction Scale)[42] and the UES-SF (User Engagement Scale -Short form) [43], followed by a knowledge test to identify the number of correct recalls, based on the given in-game information about the plastic pollution. Finally, they were subjected to a short, structured interview where they were asked to provide their impressions of the game, difficulty of the game, and experience wearing the EEG headset.

3.3 Analysis

The questionnaire was analyzed using cumulative frequency. Following the guidelines of GUESS18 [42], a composite mean was calculated for each category. A Mann-Whitney U test was performed on the questionnaire data within a nonparametric test. The EEG data were analyzed in SPSS. The experimental and control groups' data were aggregated and composited into a single dataset. This allowed for calculating the mean and graphs of the two aggregated signal data, 'attention' and 'calm', over time. Spearman's rank correlation coefficient was used as within a nonparametric measure of rank correlations. The interviews were analyzed following the four steps of traditional coding [52]: organizing, recognizing, coding, and interpretation. The recordings were transcribed verbatim. Following the procedure for qualitative intercoder reliability [44], two researchers separately analyzed the data to find concepts and themes and coded and labeled the data.

4 DESIGN AND IMPLEMENTATION

The game was developed in Unity using C#. The game was situated in an ocean environment (Figure 2), and a fish was used as the user-controlled character, which linearly increased its speed the longer it played, making it more difficult for the players to complete a level. The dynamic difficulty adjustment (DDA) was included with different speed and obstacle spawn rate levels. For the experimental group, EEG adjusted the DDA, and the calmer a player was, the more difficult it became, and vice versa. In the control group, the speed of the fish and the number of obstacles spawned increased linearly for each frame.

The players were presented with the controls (WASD and the arrow keys) at the beginning of the play session. Both control options were included as non-gamers tend to find WASD more challenging. The players had to avoid being hit by floating plastic or rock formations (Figure 2). If the player hits any plastic object, the level will finish. When a level was finished, either by completion or death, the players were presented with information about plastic pollution (Figure 3). The information was provided after the participants died, as within a high arousal stimulus. Arousal is an indication of emotional activation, and it is well described in the literature that high arousal is in general remembered better than stimuli with low arousal [46].

The players were presented with a total of five information's about the pollution in our ocean. The information was based on the UN's environment program [30] and the European Commission's Zero Pollution Action Plan [31]. The 3D models used in the game (like plastic bottles, barrels, cups, baskets) were imported, adjusted, or created in Blender and Adobe Photoshop, and were used as scenery of the tile sets and as trash objects floating in the oceans. Two sound clips were implemented in the game including background music (an upbeat song) and a hit/death sound. A low pass filter was used to attenuate high frequencies and create a muffled sound, as the game environment is underwater. Additionally, the sound clips were looped seamlessly. As part of the gameplay process, a huge container was implemented (Figure 4) that could not be avoided and, by that, an inevitable death occurs.

An inevitable death was implemented (Figure 4) to observe any difference in the EEG signals and to evaluate if there were better recalls from this third-level death information.

We developed a dynamic difficulty adjustment using EEG signals in real time. The EEG software development kit included available code at both Android and iOS mobile applications. The Neurora headset uses Bluetooth LTE (version 3.0 and 4.0) to send the signal to the mobile application. After some improved UI in the mobile application, it was possible to display the incoming brain signal values in the application. A session name was applied, allowing to separate and identify the various scanning sessions.

Figure 2: A fish was used as the user-controlled character.

Figure 3: Information about the plastic pollution provided after level completion or death.

5 RESULTS

5.1 Engagement in the game

As revealed in Table 1, based on the 15 items from the user-engagement (Q1.1 – Q5.5), there is a general equal high engagement for both the control group (Mean average: 4.04) and the experimental group (Mean average: 4.07). The game's controls worked very well, and 94% of the players in both CG and the experimental group EG agreed or strongly agreed that the game's controls were straightforward (Q1.1).

Despite the inevitable death in the third level, more than 80% of the CG and EG agreed or strongly agreed that they felt in control while playing the game (Q1.2). 94% of the participants in the CG agreed that the game was fun, while in EG, 82% agreed or strongly agreed on this item (Q2.1). The audio items (Q3.1 – Q3.3) were rated similar positively with an average mean score of accordingly 4.1 (CG) and 4.04 (EG). The visuals (Q4.1 – Q4.3) were also rated very similar between the CG (average mean score: 4.3) and EG (average mean score: 4.35). It is interesting that the lowest score (EG: M: 3.12) is in the Q5.1 item "The game's content made me curious to learn more". However, this can be explained by not having enough focus on the potential to provide an active and engaging learning content, but too much focus on the game design and methodological EEG advancement. Many participants in both the CG (90%) and EG 94%) agreed or strongly agreed with a desire to do as well as possible during the game (Q5.3). More than half of the participants found the game rewarding (CG: M: 3.59 EG: M: 3.41). However, the lowest mean score was found in the item "the content of the game made me curious to learn more" (CG: M: 3.35. EG: M: 3.12). The only significant difference (p=0.030) between the CG and EG was found in the Q5.5 item "I was so involved in the game that I lost track of time" (CG: M: 3.29. EG: M: 4.00).

The interviews confirmed the questionnaire results and revealed that most participants perceived a high engagement in the game. Most participants mentioned being engaged, or described their experience in related terms such as captivating, fun, enjoyable, or feeling immersed:

> "The game was nice and rather captivating. It was fun. It was one of those very simple games, but it keeps you wanting to do better each time (CG, ID10, Male, aged 25)."

> "There was a question about 'losing track of time,' which was the emotion I felt (EG, ID31, Male, aged 24)."

From the interviews, 8 participants from the CG mentioned the speed reset that occurred when the participants died and restarted the game. Only one participant from the EG mentioned this. The interviews also revealed more negative comments regarding engagement in the CG (without the EEG-controlled DDA) than in the EG. Some negative elements included perceived boredom (ID3, ID16), demoralization (ID8), annoyance (ID32), and frustration (ID30). The responses suggest a period of disengagement when the difficulty is decreased far below the players' skill level and a desire to return to

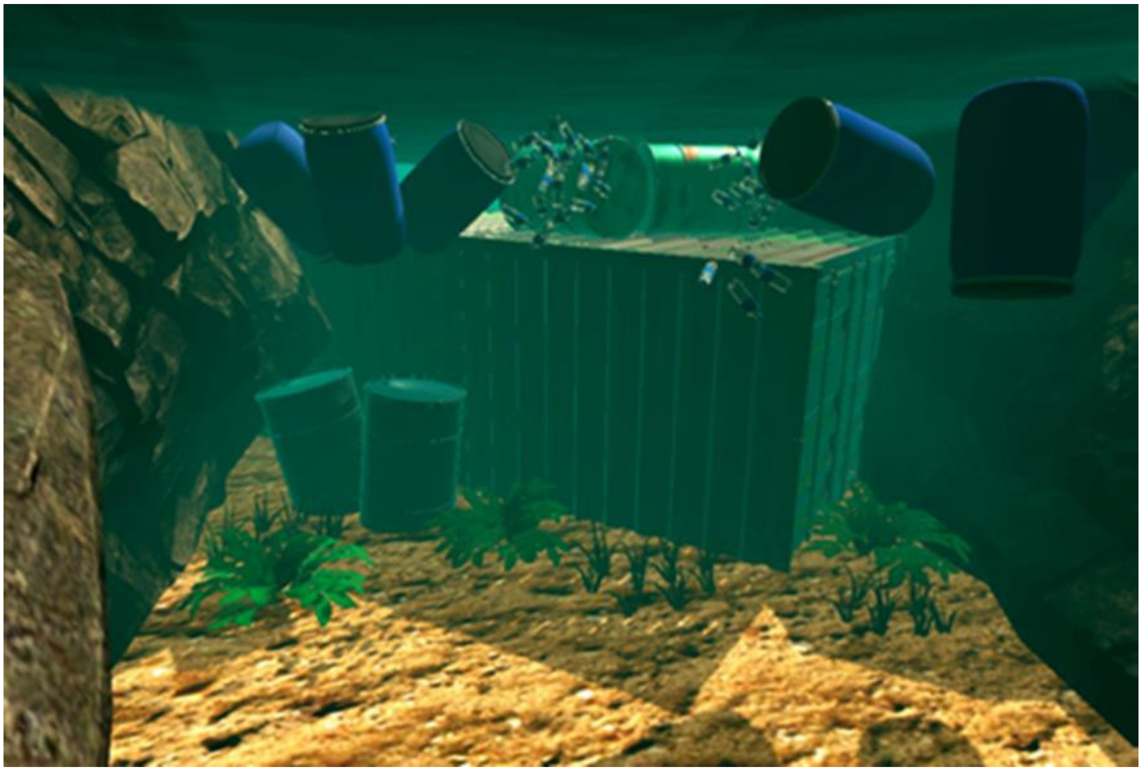

Figure 4: A container for an inevitable death in the third level

the higher difficulty experienced at higher speeds. Another aspect that most participants recalled and mentioned was the container event (Figure 2, right) and the inevitable death, despite not being directly asked about it. Interestingly, most participants mention the container event in neutral wording (neither positive nor negative statements), simply acknowledging that there was a container that was unavoidable. Only one participant commented negatively on the container by stating, "it was frustrating there was no way out (CG, ID6, Male, aged 23)."

When asked about the participants first impressions of the game, most positively mentioned the visuals (ID13, ID16, ID21, ID30), music (ID10, ID13, ID23, ID28), and animations (ID19, ID30). Most participants responded positively when asked about wearing the EEG headset, and many participants (ID6, ID20, ID29), mentioned forgetting about it or not noticing it while playing.

5.2 Attention and calm

Our results revealed that the participants in the control group were more attentive while playing the game than the experimental group (Table 2).

The results seem logical as the control group played the game with a linear difficulty curve, while the experimental group played with a dynamic adaptive curve. The version of the game that uses a linear difficulty curve is considerably more complex than the adaptive version, as speed and trash spawn only increase over time, requiring the player to be more attentive. The line plot below (Figure 5) reveals the change in attention over time. The x-axis is time in seconds, and each testing session lasted about 420 seconds. The y-axis is the change in the attention signals throughout a testing session.

The attention value in both the EG and CG increases linearly over time as the game progresses. When comparing the EG and CG, it can be observed that the attention for the CG is slightly higher than the experimental group, although the trend is somewhat similar. The attention signals have a strong correlation coefficient (Rho=0.864) corresponding to an increasing monotonic trend between time in seconds and attention. On the contrary, the correlation coefficient of calm is almost zero (Rho=0.88) with a non-monotonic trend (Figure 6).

In Figure 6, the changes in calm are revealed. The x-axis is time in seconds, and each testing session lasted about 420 seconds. The y-axis is the change in the calm signals throughout the testing session with aggregated data from 34 participants. Our results showed that calm is more stable and distributed randomly than attention, so there is no clear indication of an increase or decline over time. Unlike attention, calm does not increase over time. The calm value for the experimental and control groups is similar, although the experimental group sometimes reaches a higher peak of calm than the control group.

5.3 Learnings about the pollution in the oceans

The result from the knowledge test is very interesting and corresponds with the results from the EEG data. As revealed from the EEG data, the participants in the control group were more attentive

Table 1: Styles available in the Word template

1 = Strongly Disagree. 2 = Disagree. 3 = Neither or disagree. 4 = Agree. 5 = Strongly agree	**CG / EG**	**1**	**2**	**3**	**4**	**5**	**Total**	**Mean**	**SD**	**MWP-value**
1. Control										
Q1.1 The controls were straightforward	CG	1	0	0	3	13	17	4.59	1.00	
	EG	0	0	1	1	15	17	4.82	0.53	0.406
Q1.2 I felt in control while playing the game	CG	0	0	2	9	6	17	4.24	0.66	
	EG	0	0	3	6	8	17	4.29	0.77	0.735
2. Enjoyment										
Q2.1 The game was fun	CG	0	0	1	16	0	17	3.94	0.24	
	EG	0	0	3	8	6	17	4.18	0.73	0.326
Q2.2 If given the chance, I would like to play this game again	CG	0	1	8	6	2	17	3.53	0.80	
	EG	0	1	3	9	4	17	3.94	0.83	0.117
3. Audio										
Q3.1 I enjoyed the sound effects in the game	CG	0	0	4	10	3	17	3.94	0.66	
	EG	0	0	3	12	2	17	3.94	0.56	1.000
Q3.2 The audio enhanced my gaming experience	CG	0	0	2	8	7	17	4.29	0.69	
	EG	0	0	4	10	3	17	3.94	0.66	0.133
Q3.3 I enjoyed the music in the game	CG	0	0	2	10	5	17	4.18	0.64	
	EG	0	0	3	7	7	17	4.24	0.75	0.747
4. Visuals										
Q4.1 I liked the game's graphics	CG	0	0	1	9	7	17	4.35	0.61	
	EG	0	0	1	10	6	17	4.29	0.59	0.768
Q4.2 The game was visually appealing	CG	0	0	3	8	6	17	4.18	0.73	
	EG	0	0	1	10	6	17	4.29	0.59	0.687
Q4.3 The graphics fit the mood or style of the game	CG	0	0	1	6	10	17	4.53	0.62	
	EG	0	0	1	7	9	17	4.47	0.62	0.768
5. Gratification										
Q5.1. The game's content made me curious to learn more	CG	0	2	8	6	1	17	3.35	0.79	
	EG	1	5	4	5	2	17	3.12	1.17	0.540
Q5.2 My curiosity was stimulated because of playing the game	CG	0	1	6	5	5	17	3.82	0.95	
	EG	1	1	7	7	1	17	3.35	0.93	0.209
Q5.3 I wanted to do as well as possible during the game	CG	0	0	0	5	12	17	4.71	0.47	
	EG	0	0	1	3	13	17	4.71	0.59	0.805
Q5.4 My experience with the game was rewarding	CG	0	2	5	8	2	17	3.59	0.87	
	EG	1	0	7	9	0	17	3.41	0.80	0.610
Q5.5 I was so involved in the game that I lost track of time	CG	1	1	8	6	1	17	3.29	0.92	
	EG	0	2	2	7	6	17	4.00	1.00	0.030*

Table 2: Attention and Calm values (aggregated for each timestamp) for the experimental and control group.

	Attention Mean	Calm Mean
Experimental group (n=17)	32.49	52.33
Control group (n=17)	36.80	51.28

while playing the game than the experimental group, and probably by that also answered correct in the knowledge test to a much higher degree than the experimental group. The results from the knowledge test are revealed in Table 3. The first question received 7 correct answers (21 %), with only 2 correct answers from the experimental group (EG). There were 5 correct answers (30%) from the control group (CG) for the first question.

The second question received a total of 13 correct answers (38 %). A total of 6 correct answers were from the EG and 7 from the CG. The third question received 12 correct answers (35 %). However, only 3 of the correct answers were from the EG. The fourth question had 77 % correct answers, and by that the question with the highest number of correct answers. 71 % correct answers from the EG and 82 % from the CG. The fifth question received almost equally number of correct answers from the EG and CG with just below half of the

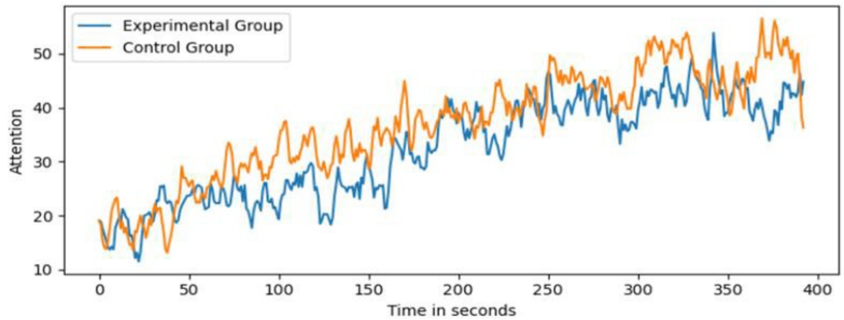

Figure 5: Experimental group vs. control group in attention.

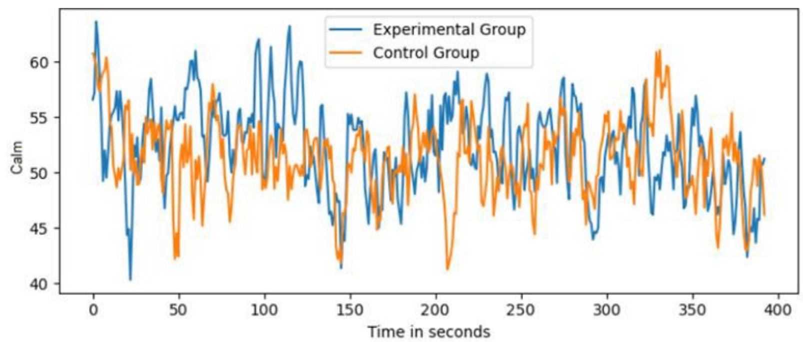

Figure 6: Experimental group vs. control group in calm.

Table 3: Results from the knowledge test (n=34, with 17 participants in both the EG and CG)

	The correct answer	%Correct answers EG	%Correct answers CG	Difference EG/ CG
Q1: How much plastic is currently in the oceans	75-200 million tons	12 %	30 %	18 %
Q2: How much of the ocean waste is plastic	85 %	35 %	41%	6 %
Q3: How much plastic has been discarded in the environment since 1950	5000 million tons	18%	53%	35 %
Q4: How much plastic gets recycled	10 %	71 %	82%	11 %
Q5: How much does the Zero Pollution Plan aim to reduce plastic litter at sea	50 %	44 %	46 %	2 %

participants. It is worth to emphasize, that the questions were not equally easy to recall; it might be easier to recall 10% than 75-200 million tons. Despite the very specific and difficult read information, we had expected higher number of correct answers. However, the interesting part is the difference in favor of the CG, answering correct with higher percentage than the EG for all questions.

6 ADVANTAGES AND LIMITATIONS

The main advantage of using EEG in game research, also for dynamic difficult adjustments and flow optimization, is to supplement the traditional self-reporting methods. With self-reports as the only source of data, researchers get a limited picture of the gaming experience – including balancing challenges and skills for specific tasks in the game. The problem is that gaming experiences and self-reports are, in many ways, a mismatch. There are three main reasons for this: First, the sole use of self-reports to state players' gaming experiences is rather problematic, as it can be extremely difficult getting players to register, evaluate, or simply talk about their gaming experiences based on the challenges and their skills, as they are not always readily accessible from their consciousness [48]. Second, understandings of gamers' minds and attitudes are most often based on verbal stimuli as the gateway to emotions. Third, gamers usually provide self-reports after their exposure to stimuli, and the self-report thus represent a summary of the whole game experience, not the here-and now experience. One of the advantages to EEG is the ability to see brain activity as it unfolds in real time, at the level of milliseconds[53].

Because of this mismatch between gaming experiences and self-reports, there is an emerging area of gaming research using a mixed methods approach, combining self-reports and neuroscientific methods. New technological advancements in EEG might supplement the common use of self-reporting to better understanding of flow and learning practices. Evaluation of flow consisting only of self-reports will continue to be a popular and necessary method in game studies because they are easy to access financially and minimally time consuming. It would be wrong to discredit the method as such. An EEG-approach towards flow evaluation of game-based learning is not necessarily more valid than the use of only one method; the validity of the approach depends on the research question. However, when presented with an evaluation of flow based solely on self-reports, it is important to remember the problems that this method faces, and that these problems affect the conclusions that are drawn. In addition, it is very important not to allow the psychophysiological data to be too appealing and not be influenced by current interest and hype around psychophysiological measurements in various game studies.

However, there are also several limitations that needs to address when using real-time EEG as a DDA in a serious game context. Despite the many design guidelines and frameworks on EEG and DDA, there is still a limited understanding of combining learning theories with an approach or process that would guide the design path for including specific learning goals. The aim of providing information about plastic pollution in our ocean by a serious game involves many variables, including e.g., motivation, emotional engagement, expectations, involvement, preferences, skills, and competences. It is challenging to account for all these variables in an evaluation. Another limitation is the number of channels used in this stud. EEG systems can have as few as a single channel to as many as 256 channels. However, an increase in the number of channels also follows an increased amount of data input to be analyzed, and 256 channels would probably be way too much within game research purposes. There is also needed major ethical considerations regarding intrusiveness and discussions of how far we should go in measuring game flow, attention, and engagement. Physiological processes are not related to psychological phenomena with a one-to-one relationship, which makes interpreting the EEG signals challenging. Digital games are difficult stimuli, as there are many sensory outputs in various dynamic modalities with complex cognitive processing on different levels [49]. Therefore, it also worth asking within the use of EEG methods in game research - do we really measure what we think we are measuring.

7 CONCLUSION AND FUTURE WORKS

The answer to RQ1 (Can real-time EEG data be used as Dynamic Difficulty Adjustment in a serious game?) comes with some complexity in the conclusion. Our study included findings with no (or not always) positive effects for using real-time EEG data as dynamic difficulty adjustments. Setting up the perfect research design when including EEG and DDA is exceedingly difficult. Firstly, it is difficult to have many participants and an equal distribution of for example gender. Secondly, as many other scholars have mentioned [6, 26], we also had difficulties keeping the EEG equipment work stable, with included uncertainties in the consistency and accuracy. Throughout testing, there were several issues that required intervention and termination of the experiment. Thirdly, it is time consuming and work extensive, and it demands further preparation to use EEG as part of the game study. This includes e.g., finding a suited test-location (with limited disturbance, quiet space by sound-proof walls, and limited electrical noise), cleaning the equipment (after and before new participants), include time to make a baseline, having the participants feeling comfortable wearing the headset, and to account for additional procedures within ethical guidelines.

The answer to RQ2 (Can DDA increase the engagement, attention, and learnings about pollution in the oceans?) comes with a clearer conclusion, though with some unexpected outcome. The control group with a linear difficult curve were more attentive and scored higher in all five knowledge test questions about the pollution in our oceans. The control group and experimental group were equally high engaged in game. However, the participants in the control group perceived more fun in the game and had a higher curiosity to learn more than the experimental group. The conclusion is interesting, as the version of the game that uses a linear difficulty curve is considerably more complex than the adaptive version, as speed and trash spawn only increase over time, requiring the player to be more attentive. The only significant difference in favor for the experimental group (with used EEG-DDA) was found in a perceived lost track of time. The experimental group was also more likely to play the game again. From the interviews the results reveled very positive feedback toward the game from both the control group and the experimental group. However, more than half of the participants from the control group mentioned becoming disengaged when faced with a speed reset. Despite the inevitable death in the third level, the participants in both groups felt in control while playing the game.

For future work it is suggested taking greater advantage of EEG and DDA approaches, and to include clear learning goals in the objectives. Learning is a multidimensional construct including behavioral, affective, and cognitive dimensions. In future studies, it would be interesting to explore psychophysiological measurements conducted in a natural learning environment. Future studies should also provide much further insights and include best practice for how to interpret the EEG signals. Further work is also needed to improve the EEG and DDA approach into more specific learning potentials and learning styles. The results in this study could be biased by the genre of game. The participants were not neccesary interesed in neither the topic nor the game genre. Future studies could repeat this experiment but with other game genres, matching the users' preferences, e.g., with a puzzle game or adventure game.

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