Exploring EEG signals during the different phases of game-player interaction

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***Abstract*—Games are nowadays used to enhance different learning and teaching practices in institutions, companies and other venues. Factors that increase the adoption and integration of learning games have been widely studied in the past. However, the effect of different backgrounds and designs on learners'/players' electroencephalographic (EEG) signals during game-play remains under-explored. These insights may enable us to design and utilize games in a way that adapts to users' cognitive abilities and facilitates learning. In this paper, we describe a controlled study consisted of 251 game sessions and 17 players that focused on skill development (i.e., user's ability to master complex tasks), while collecting EEG and game-play data. Our results unveiled factors that relate to the game-phases and learners'/players' expertise and affect their mental effort when playing a learning game. In particular, our analysis showed an effect of players background (experience and performance) and games design (number of attempts/lives and difficulty) on players mental effort during the game-play. Finally, we discussed how such effects could benefit the design and application of games for learning as well as, directions for future research.**

***Index Terms*—mental effort, EEG, game-play**

I. Introduction

The growth of games for learning in the last years has heavily impacted the contemporary learning practices [1]. There is a vast amount of research indicating that game-play provides learners with a "mental workout", while the activities associated with a game enhance learners' motivation and boost a number of important skills [2]. During the game-play learners face a stream of decisions, and typically employ problem solving strategies, which involve the engagement in a series of complex tasks and nested sub-tasks [3]. An exemplification of this is the four-part cycle [4], that highlights the periods where learners engage/probe, hypothesize, re-probe, and rethink during the play time of a game. In the same vein, Garris et al., [5] depict that games engage learners in repeated judgment-behavior feedback loops. Moreover, McFarlane et al., [6] linked game-playing with the development of skills in decision making, design, strategy, cooperation, and problem solving.

The emergence of games for learning has further facilitated the wide adoption of certain design elements in game-design (e.g., game mechanics, increased difficulty, etc.) that have proved their value in the learning arena [7]. In addition, games for learning have drawn significant attention from learning institutes and business organizations. However, the introduction of games to teaching and learning is often complex, it is unclear how the different design elements of games contribute to, or how students are benefited from, games for learning [8], [9]. In theory, an explicit engagement in learning materials (including learning games) increases learners mental effort and provokes deeper learning strategies [10]. However, the effect of different designs and end-users' expertise on learners' mental effort during game-play is still an open question. Therefore, in this study we investigate "How mental effort differs in the phases of the game (associated with the design) and in relation to users' expertise?".

In this paper, we present a controlled study, in which we captured data generated during the interaction with a game that focuses on simple skill development (i.e., intuitive learning/mastery through play [11]). We collected data associated with learners' mental effort (via electroencephalography – EEG) and game-play. Next, we tested the effect of difficulty (i.e., different stages of difficulty of the game), expertise (i.e., beginners VS the ones with experience), number of remaining attempts (i.e., number of lives left) and performance (i.e., low vs. high performers) in learners' mental effort.

The paper is structured as follows: The next section outlines the related work and hypotheses for this study. The third section describes the employed methodology. The forth section presents the results of the study. The fifth section of the paper, discusses the results, the limitations, and the implications of the study, and the last section provides the conclusions and the future work.

II. Related work

Digital games for learning has been extensively studied in the past, with several studies focusing on game mechanisms and others in practices that can be better help teaching and learning. It is common knowledge that digital games help learners to develop a disposition toward collaboration, problem-solving, communication, and experimentation, all attributes that promote success in a rapidly-changing, information-based society [12]. Skills attained through gaming are more likely to transfer than when practiced on a single kind of problem; this leads to the knowledge and skills becoming automatized and consolidated in memory, so that the learner can begin to focus consciously on comprehending and applying new information [13]. Digital games for learning put the user in the role of decision-maker, pushing him through ever harder challenges, accomplishing learning through trial and error procedures [2].

Digital games were initially designed for entertainment and proved beneficial for cognitive, behavioural, and social skills development [14]. In particular, for digital games for cognitive development, there is a growing body of research about their potential benefits (e.g. accelerating information processing, [15]); however, there is limited research on how the phases of game-play and expertise affects mental effort. Currently, we can find principles that support the use of digital games into formal and informal learning settings [12], as well as in game-design and games ability to change perspectives and behaviours [2]. Previous research on mental effort utilizes electroencephalography (EEG) for monitoring subjects during the game-play activity by observing changes in their brain activity [16], [17] in favour of improved neural efficiency when performing certain tasks [18], [19]. The electrical activation in the brain has a topographical classification where we can observe changes that originate from external perception [17]. These variants in activity of different brain zones / bands allow us to infer cognitive processes such as attention, and concentration, aspects that are critical during the engagement with the digital games for learning [17], [20].

Advances in neuropsychology provide the necessary background for this work. Particularly, it is known that changes in EEG brain waves are connected with the response to external stimulus [17]. Monitoring the different brain areas and their wave frequency bands enable us to infer users' cognitive states, such as by distinguishing different brain waves (i.e., alpha, beta, gamma or theta waves are the most relevant for our work, since the delta band is associated with deep sleep) in the four different brain areas (i.e., parietal, frontal, temporal and occipital). Based on prior literature [21], the main EEG brain waves for humans are categorized into four frequency patterns: Theta (4 - 8 Hz), Alpha (8 - 13 Hz), Beta (13 - 30 Hz) and Gamma (above 30 Hz). Research has shown that these patterns are strongly correlated to human emotions and cognitive states [22], [23], and are widely used to accurately estimate task engagement and effort based on the amplitudes of Alpha, Beta and Theta waves.

Specifically, the alpha band frequency range has been associated with creativity and attention, and these waves are more intense on the rear regions of the head, in the occipital areas [24]. Beta activity is more intense in the frontal lobe and is connected to decision making, problem solving, concentration and intense mental activity [25]. Gamma activity is associated with higher mental activity, motor function and cognition [26], [27]. Finally, theta waves are located mainly in the temporal lobe and are associated with emotional stress, frustration and memory recall [17]. Thus, brain-wave activity as captured by EEG holds a significant amount of information about players' interaction with the game and the associated cognitive processes exhibited during the game-play experience.

III. Hypotheses

In the current study, we address four main hypotheses. The first investigates whether users exhibiting high performance with the game have higher levels of EEG band power modulation. If increased performance serves to increase processing and activity, we predict that it will lead to higher game-activity and EEG band power modulation. The second hypothesis investigates whether users who have experience with the game have higher levels of mental effort. If increased experience also increases engagement and game-activity, we predict that it will lead to higher mental effort as measured by EEG. The other two hypotheses center in how two very common game-play design elements, namely number of attempts/lives and level of difficulty, relate with mental effort.

1) **Players' performance with the game displays a positive relation with their mental effort.** Previous work utilized standarized assessment tests and game scores, and showed that higher scores in a learning game does not necessarily mean higher learning outcome and effort, especially when we talk about high performers [28]. Hence, investigating this relationship utilizing brain activity can help us to better understand the relationship of learning-game performance cognitive abilities.
2) **Players' experience with the game has a positive relation with their mental effort.** As players' attain experience their skills and competences do change [29], we hypothesize that those skills are core determinants of their mental effort, and thus would result in increased mental effort.
3) **Players' "number of lives left" has a positive relation with players' mental effort (the fewer the lives, the higher the mental effort).** The number of attempts/lives left is a core design element in learning games [30]. Low number of lives (or having left with just one life) is a peculiar situation [31], and previous game designs (e.g., power ups) have been utilized for improving the learning experience [32]. However, further work is need utilizing objective measurements (e.g., EEG) for explaining the association between the number of attempts left and the mental effort of the user.
4) **The difficulty of the game has a positive relation with players' mental effort (a more difficult game results in higher degree of mental effort).** Research has shown that difficulty plays an important role in users' mental effort [33], [34], however, investigating and even quantifying this effect will help us to derive further design insights.

IV. Methodology

A. The Game

In this study, we designed a controlled experiment focusing on skill acquisition. Skill acquisition (commonly termed also as movement-motor learning [35]) is a loosely defined term that encompasses motor adaptation and decision-making [36], [37]. In our study, we used "Pac-Man", a time-testing game that has been employed to measure specific skills (motor skills) in the past [38]. In particular, we used Pac-Man following all the game play elements and providing 3 lives for each session (see Figure 1). The game was controlled by the 4 arrow buttons of the keyboard. The difficulty of the game increased progressively from one session to the other.

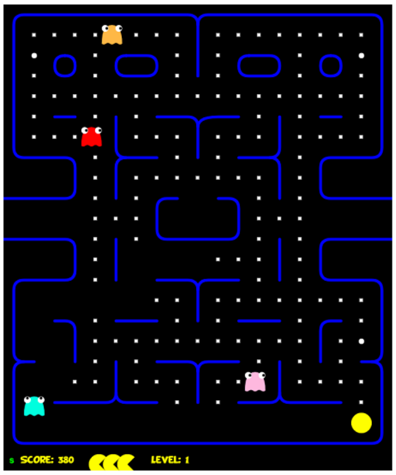

Fig. 1. Screenshot of the Pac-Man game used in the study.

B. Participants

We recruited a total of 17 participants (7 females) aged between 17 and 49 years (mean = 32.05, SD = 8.84). Participants were recruited from the participant pool of the Norwegian University of Science and Technology in Trondheim. Participants were familiar with the game, but none of them had played the game in the previous 2 years. Prior to completing the tasks, participants were informed about the purpose and procedure of the experiment and of the harmlessness of the equipment. Participants were given a movie theater ticket upon completion of the study, as a compensation for their time.

C. Procedure and experimental design

Upon obtaining consent, the researcher escorted the participant to the room, which contained a chair facing a large computer monitor (see Figure 2). The participant wore the EEG cap, and then connected and calibrated the data collection devices. The researcher explained the mechanisms of the game and the respective keystrokes, double checked the data collection device, and exited the room. The participant had approximately 40 minutes to master the game and achieve a score that was as high as possible. The research design of our study is a single-group time series design [39] with continuous (repeated) measurement of a group with the experimental treatment induced. Each participant played on average 16 game-sessions (SD=7), until their allocated time ran out. Each game-session started with 3 lives and ended when the participant lost all the three lives. For each level in a game-session, the speed of the ghosts increased.

Fig. 2. Setup of the experiment.

D. Measurements and Data Analyses

During the study, we captured participants' achieved score for each game session, while collecting EEG data for each participant and for all sessions. In particular, we recorded 20-channel EEG data organized following the international 10-20 system, as shown in figure 3. We built upon previous studies that utilize EEG headsets in detecting cognitive engagement in the learning domain [22], [23], [40]. The raw EEG data was recorded at 500 Hz using a portable EEG cap by ENOBIO (ENOBIO 20 EEG device), Fz was used as reference electrode, 2 channels were used for EOG correction, 1 channel for reference and 3-Channel accelerometer with a sampling rate at 100 Hz. We also applied an Electro-OculoGraphy (EOG) filter for removing noise from eye blinks.

EEG signals were processed in MATLAB (MathWorks Inc., Massachusetts, US) with EEGLAB toolbox [42] for extracting the Power Spectral Density (PSD). PSD was extracted for the following frequency bands (table I) for each of the four lobes (i.e., parietal, frontal, temporal, occipital).

TABLE I
CONNECTION BETWEEN BANDS, FREQUENCY RANGE AND BRAIN STATE

Wave / Band	**Frequency range**	**Major functions (based on [17], [27])**
Theta	4Hz - 8Hz	Idling, inefficiency, related to ADHD
Alpha	8Hz - 13Hz	Relax, eyes closing
Beta	13Hz - 30Hz	Focus, anxious thinking
Gamma	above 30Hz	Cognition / Higher mental activity

To test the four hypotheses, we sliced the data-set:

1) by performing median split on game-time and forming novice game-time (first half) and experienced game-time (the second-half) - **Experience**;

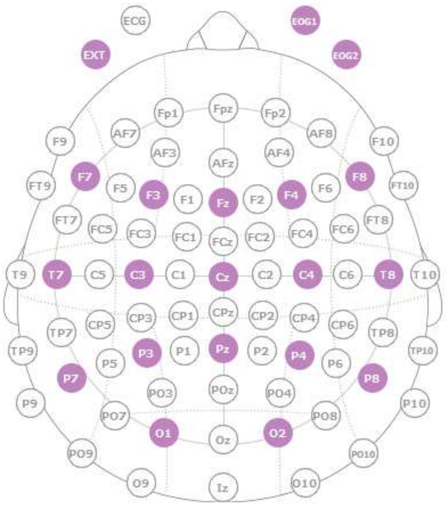

Fig. 3. Electrode layout of 20 channels (17 channels were used for EEG) for the experiment. The coloured ones are the electrodes being used . The white ones are those that the ENOBIO cap provides option for. This is the Standard electrode layout provided by the EEG capturing software. This is also considered as Good all-around montage [41].

2) by performing median split on the average game-score and forming low- (first half) and high- (the second-half) performers - **Performance**;
3) by separating the play-time of the first, the second and higher level of difficulty - **Difficulty**; and
4) by separating the play-time when the learner has 1 life, 2 lives and above - **Number of Lives left**.

Next, an independent samples Analysis of Variance (ANOVA) was conducted in order to examine the effect of Experience, Performance, Difficulty, and the number of lives on each of the four wave bands (i.e., Alpha, Beta, Gamma, Theta) and four lobes (i.e., Parietal, Frontal, Temporal, Occipital). Thus, four dependent variables (i.e., Experience, Performance, Difficulty and the number of lives) and sixteen independent variables (i.e., every possible combination of the four lobes and four wave bands) were included to our analyses. All statistical analyses reported were conducted with a significant level of less than .05 (i.e., $p < .05$).

V. RESULTS

A. *Difference between novices and experienced*

To examine the research hypotheses regarding the effect of experience on users' mental effort we performed ANOVA including users' EEG-band modulation as a dependent variables and their Experience as independent variables.

From the outcome data in Table II, Experience has indicated an impact on Parietal Alpha, Frontal Alpha, Frontal Beta, Frontal Gamma, Occipital Theta and Occipital Gamma. In figure 4, we can observe that experience has a negative effect only on Occipital Gamma, whereas the significant effect on all the other cases is positive (i.e., high experience results higher power in the respective band).

TABLE II
THE EFFECT OF EXPERIENCE IN MENTAL EFFORT. SIGNIFICANCE LEVELS AT $p < .05$ (*), $p < .01$ (**), AND $p < .001$ (***).

	High Exp.		**Low Exp.**		
Band	**mean**	**sd**	**mean**	**sd**	**F**
ParietalAlpha	.038	.012	.03	.01	**4.45***
ParietalBeta	.036	.011	.031	.01	1.92
ParietalTheta	.039	.012	.035	.013	.86
ParietalGamma	.036	.009	.039	.01	.84
FrontalAlpha	.013	.006	.009	.004	**5.23***
FrontalBeta	.013	.006	.009	.004	**5.23***
FrontalTheta	.007	.004	.006	.004	.53
FrontalGamma	.019	.008	.014	.006	**4.25***
TemporalAlpha	.022	.007	.021	.006	.2
TemporalBeta	.023	.007	.022	.007	.17
TemporalTheta	.065	.016	.057	.014	2.4
TemporalGamma	.036	.008	.035	.008	.13
OccipitalAlpha	.083	.023	.076	.022	.82
OccipitalBeta	.022	.007	.036	.011	**19.6*** **
OccipitalTheta	.116	.034	.099	.031	2.32
OccipitalGamma	.034	.01	.049	.013	**14.22*** **

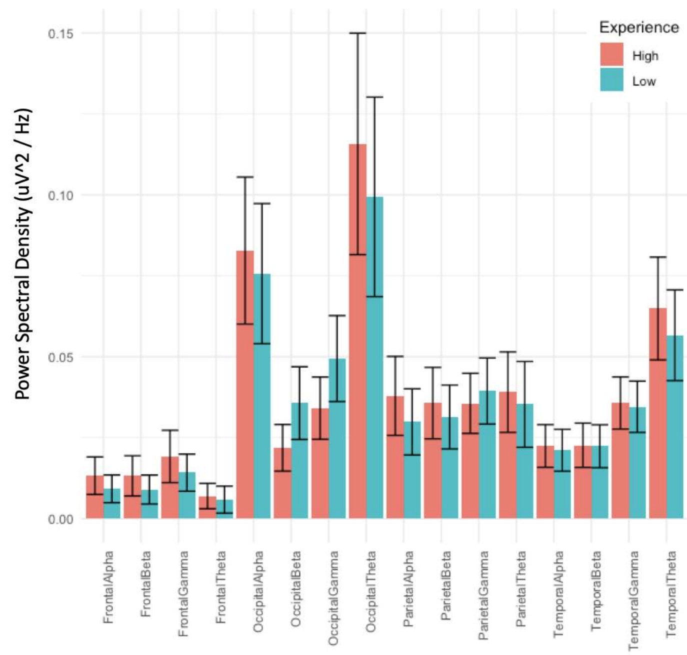

Fig. 4. The influence of Experience.

B. *Difference between high and low performers*

To examine the research hypothesis about the effect of performance on participants' mental effort, we performed ANOVA including users' EEG-band modulation as dependent variables and their Performance as independent variables.

As we can see from the outcome data in Table III, Performance has indicated an impact on all the bands except the Temporal Theta. In figure 5, we can observe that performance has negative effect only on Occipital Alpha and Occipital Theta, while the significant effect on all the other cases is positive (i.e., high performers have significantly higher power in the respective band).

TABLE III
THE EFFECT OF PERFORMANCE IN MENTAL EFFORT. SIGNIFICANCE LEVELS AT $p < .05$ (*), $p < .01$ (**), AND $p < .001$ (***).

	High Performance		Low Performance		
Band	**meanH**	**sdH**	**meanL**	**sdL**	**F**
ParietalAlpha	.051	.015	.017	.006	**75.3*****
ParietalBeta	.052	.013	.016	.006	**107.5*****
ParietalTheta	.057	.017	.018	.006	**79.56*****
ParietalGamma	.057	.012	.019	.006	**136.4*****
FrontalAlpha	.018	.006	.005	.004	**55.25*****
FrontalBeta	.016	.006	.007	.005	**22.57*****
FrontalTheta	.008	.004	.005	.004	**4.18***
FrontalGamma	.026	.008	.008	.005	**61.89*****
TemporalAlpha	.033	.008	.011	.005	**92.45*****
TemporalBeta	.035	.008	.011	.004	**122.4*****
TemporalTheta	.059	.015	.062	.015	.34
TemporalGamma	.047	.01	.023	.005	**78.34*****
OccipitalAlpha	.034	.009	.124	.029	**149.3*****
OccipitalBeta	.033	.007	.025	.011	**6.4***
OccipitalTheta	.03	.01	.183	.043	**204.2*****
OccipitalGamma	.055	.011	.029	.012	**43.37*****

TABLE IV
THE EFFECT OF THE NUMBER OF LIVES IN MENTAL EFFORT. SIGNIFICANCE LEVELS AT $p < .05$ (*), $p < .01$ (**), AND $p < .001$ (***).

	1 life		2 lives		3 lives		
Band	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**F**
ParietalAlpha	.025	.008	.039	.013	.048	.014	**15.97*****
ParietalBeta	.023	.008	.04	.012	.049	.013	**23.58*****
ParietalTheta	.022	.008	.05	.016	.056	.017	**27.58*****
ParietalGamma	.028	.007	.045	.012	.05	.012	**2.13*****
FrontalAlpha	.007	.004	.014	.005	.018	.006	**2.53*****
FrontalBeta	.007	.005	.014	.006	.018	.006	**16.3*****
FrontalTheta	.005	.004	.008	.005	.009	.004	**3.87***
FrontalGamma	.01	.006	.018	.007	.029	.009	**27.96*****
TemporalAlpha	.016	.005	.03	.008	.026	.007	**19.22*****
TemporalBeta	.018	.005	.029	.008	.026	.007	**11.95*****
TemporalTheta	.057	.014	.074	.017	.059	.015	**6.20****
TemporalGamma	.034	.007	.039	.01	.036	.008	1.51
OccipitalAlpha	.089	.024	.065	.019	.07	.019	**6.3****
OccipitalBeta	.021	.008	.034	.009	.04	.011	**18.09*****
OccipitalTheta	.129	.036	.079	.027	.088	.027	**13.15*****
OccipitalGamma	.029	.01	.052	.012	.058	.014	**27.16*****

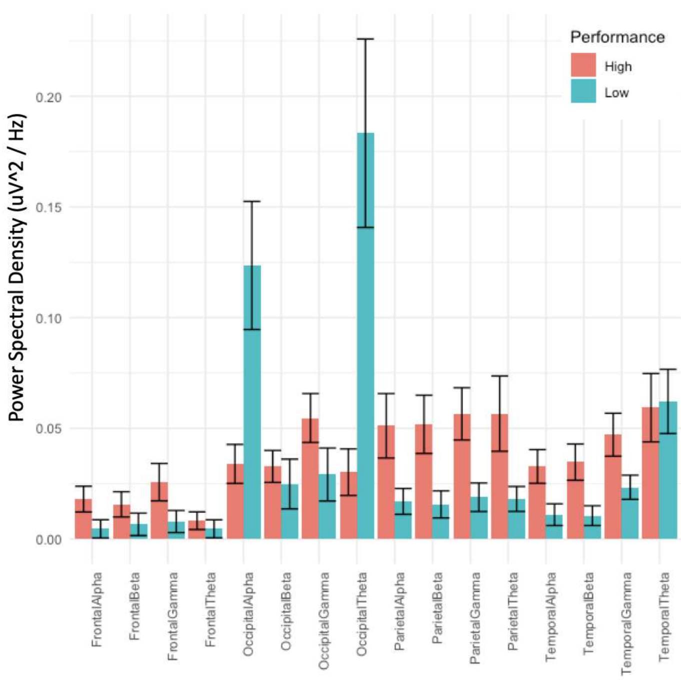

Fig. 5. The influence of Performance.

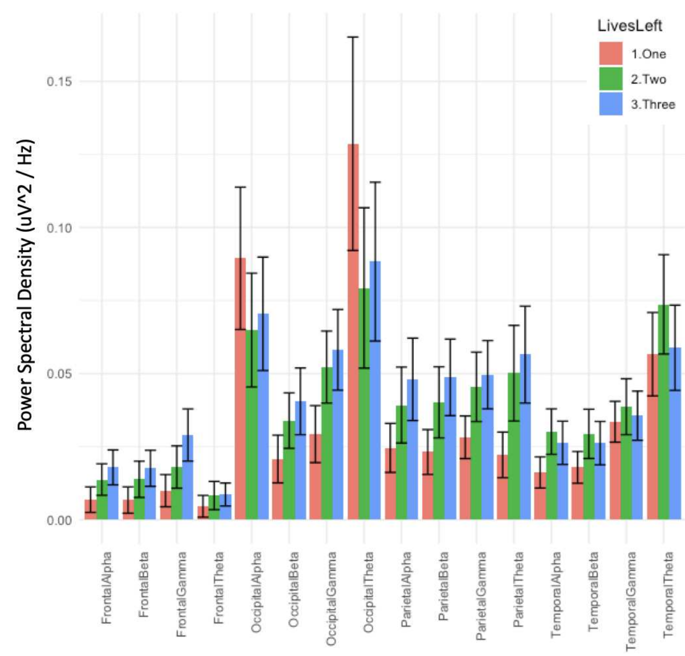

Fig. 6. The influence of the number of lives.

C. The Effect of the Number of Lives

To examine the research hypothesis regarding the effect of the number of lives left on users' mental effort we performed ANOVA including users' EEG-band modulation as a dependent variables and their lives left as an independent variable. In the outcome data in Table IV, the number of lives has indicated an impact on all the bands except for the Temporal Gamma. In figure 6, we can observe that the number of lives has a negative effect only on Occipital Alpha and Occipital Theta, whereas the significant effect on all the other cases is positive (i.e., high number of lives left results significantly higher power in the respective band).

D. The Effect of the Level of Difficulty

To examine the research hypothesis about the effect of game difficulty on users' mental effort, we performed an ANOVA including users' EEG-band modulation as dependent variables and the game level (i.e., difficulty) as an independent variable.

As we can see from the outcome data in Table V, difficulty has indicated an impact on all the bands. In figure 7, we can observe that difficulty has a negative effect on Occipital Alpha and Occipital Theta, while the significant effect on all the other cases is positive (i.e., high difficulty of the game results significantly higher power in the respective band).

TABLE V
THE EFFECT OF THE DIFFICULTY IN MENTAL EFFORT. SIGNIFICANCE LEVELS AT $p < .05$ (*), $p < .01$ (**), AND $p < .001$ (***).

	Level 1		**Level 2**		**Higher levels**		
Wave	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**F**
ParietalAlpha	.018	.006	.032	.012	.056	.014	**5.1*****
ParietalBeta	.014	.005	.033	.011	.058	.013	**76.85*****
ParietalTheta	.011	.003	.042	.013	.061	.018	**64.72*****
ParietalGamma	.018	.005	.032	.009	.069	.013	**128.8*****
FrontalAlpha	.002	.004	.015	.006	.017	.005	**43.94*****
FrontalBeta	.002	.004	.017	.007	.013	.005	**34.19*****
FrontalTheta	.002	.003	.008	.005	.009	.004	**14.62*****
FrontalGamma	.004	.004	.026	.009	.019	.007	**44.13*****
TemporalAlpha	.007	.004	.019	.007	.043	.008	**132.8*****
TemporalBeta	.01	.004	.017	.007	.046	.009	**127.3*****
TemporalTheta	.047	.013	.06	.015	.079	.017	**19.34*****
TemporalGamma	.028	.005	.023	.007	.062	.011	**117.8*****
OccipitalAlpha	.095	.026	.091	.024	.042	.008	**33.76*****
OccipitalBeta	.01	.007	.034	.012	.044	.007	**64.35*****
OccipitalTheta	.145	.04	.131	.035	.028	.006	**72.17*****
OccipitalGamma	.011	.006	.044	.014	.076	.012	**143.3*****

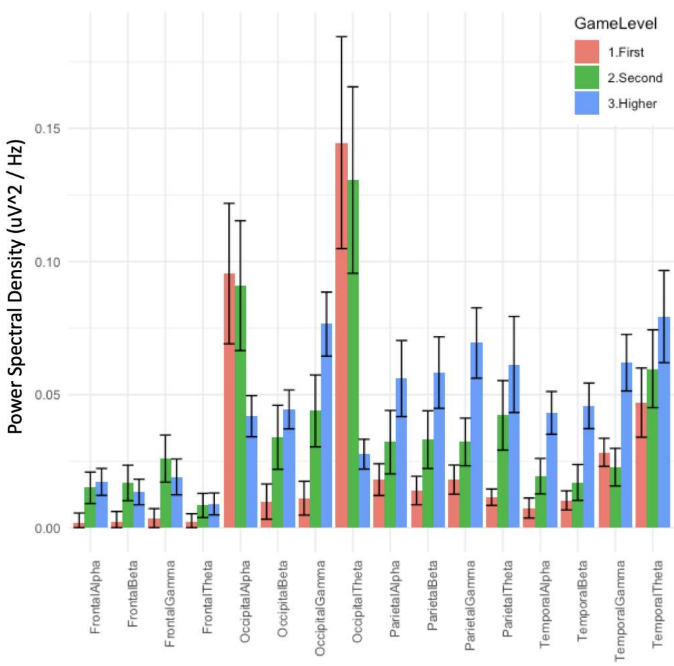

Fig. 7. The influence of the level of the difficulty.

VI. DISCUSSION

This work reports findings useful for the design and application of video games for learning. The results identify the effect of two important elements of player's background (i.e., experience, performance) and two important elements of game's design (i.e., number of attempts/lives, difficulty) on players' mental effort during the game-play.

Regarding the experience of the player, we found that as experience increases it results in higher levels of attention (Alpha), enables players to make decisions easier (Beta), and bears some connection with memory recall and stress (Theta). This is inline with the literature that proposes to maintain the player/user in a ”flow experience” [43], allowing them to engage in more challenging tasks over-time, that require higher attention and effort. Thus, while several game-elements might hinder a quick and smooth start early on, it is possible to gradually introduce them in a latter phase, when the player will be in a state of higher attention, faster decision making, and more precise memory recall.

Regarding the players' performance, we found that as performance increases, it results in higher level of mental effort (and all the respective cognitive abilities: attention, concentration, problem-solving etc.), with two exceptions (i.e. Occipital Alpha and Occipital Theta). The results are not surprising, since performance is closely related to experience and the literature of ”flow experience” [43], justifies that. It is interesting to observe different results in some of the measurements (e.g., Occipital Theta), however in the data we can see that there are several discrepancies between the evolution of experience and performance, thus resulting in some differences in the EEG measurements. This can be explained by the fact that experience and performance did not co-evolve. For example, some players needed more time to build up more experience and increase their performance, whereas some people did not manage to increase their performance while their experience increased.

Regarding the number of attempts/lives of the game, we found, with only few exceptions, that the more attempts the player has, the higher level of his/her mental effort (and all the respective cognitive abilities). This means that the attention and concentration is reduced when the player loses a life. As we can see in figure 6, this is especially evident when the player stays with only one attempt left. Thus, it's critical for the progression of the game that the developers will pay particular emphasis on the phase of the game, enabling the player to concentrate and nurturing his cognitive abilities (instead of simply losing his last life, as we can say from the qualitative data in our case).

We also found that difficulty affects the level of players' mental effort. This is an expected result, since during a very easy game, the player does not challenge his/her cognitive abilities and may result in boredom. This has been studied extensively in the area of digital games (e.g., [44]), and our study proves that this pattern is followed in games for learning. The results of this work can assist researchers working in the area of serious games for developing video games that adapt adequately, avoiding consuming players' cognitive abilities (e.g., attention, concentration, and short-term memory) during the critical phases of the game-play (e.g., beginning of the game, last life of the game). This could be achieved with the development of the necessary mechanics that can better nurture and activate players' abilities.

Finally, our study comes with certain limitations. Our participants are undergraduate students and the study was conducted in a controlled environment, thus, such conditions may have induced a certain bias on the ecological validity of the study (e.g., certain performance and behavior). Nonetheless, the population represents the end-users we are normally focusing on (i.e., university students), in a typical in-lab setup employed in similar user studies. In our study, we used a game that has very shallow learning curve and has been used to measure basic skills development in the past. This type of learning is using the procedural component of long-term memory, where new skills are stored unconsciously. The semantic memory where knowledge is consciously stored is an entirely different component of the long-term memory. Thus, the generalizability of our findings is constrained by that. Nevertheless, Grissmer et al. [45] conducted a meta-analysis of several studies and shown that skill development is a strong predictor of cognitive learning performance (by analyzing data from six different data-sets), and thus, skill development has central role in studies focusing on learning.

VII. Conclusion

Overall, our work shows that players' background and games' design affect EEG band power modulation during the game-play. Thus, increasing game difficulty for more experienced players, or adjusting the game as experience and performance increases, could help players to better utilize their cognitive abilities. A more detailed investigation of the connection between game-design and users' characteristics with their effort (EEG band power modulation) during the game-play will enable us to understand how to design and utilize games in more holistic and tailored ways.

In our future work, we will include the analyses of specific electrode locations, and even try to triangulate our results with data coming from different modalities (e.g., camera) and from different games. In addition, as also proposed by the relevant literature [46], we intend to investigate other associations between different user-groups (e.g., age, skills, gender) or stimulus used, and the produced mental effort. In addition, other quantitative methods, such as surveys, and qualitative methods, such as interviews and video recordings, could be used to supplement the collection of data.

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