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3 authors:

Athanasios Vourvopoulos
Universidade da Madeira

Sergi Bermúdez i Badia
Universidade da Madeira

Fotis Liarokapis
Masaryk University

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ORIGINAL ARTICLE

EEG correlates of video game experience and user profile in motor-imagery-based brain–computer interaction

Athanasios Vourvopoulos[1,2] · **Sergi Bermudez i Badia**[1,2] · **Fotis Liarokapis**[3]

Abstract Through the use of brain–computer interfaces (BCIs), neurogames have become increasingly more advanced by incorporating immersive virtual environments and 3D worlds. However, training both the user and the system requires long and repetitive trials resulting in fatigue and low performance. Moreover, many users are unable to voluntarily modulate the amplitude of their brain activity to control the neurofeedback loop. In this study, we are focusing on the effect that gaming experience has in brain activity modulation as an attempt to systematically identify the elements that contribute to high BCI control and to be utilized in neurogame design. Based on the current literature, we argue that experienced gamers could have better performance in BCI training due to enhanced sensorimotor learning derived from gaming. To investigate this, two experimental studies were conducted with 20 participants overall, undergoing 3 BCI sessions, resulting in 88 EEG datasets. Results indicate (a) an effect from both demographic and gaming experience data to the activity patterns of EEG rhythms, and (b) increased gaming experience might not increase significantly performance, but it could provide faster learning for 'Hardcore' gamers.

Keywords Brain–computer interfaces · Motor-imagery · EEG · Gaming experience

✉ Athanasios Vourvopoulos
athanasios.vourvopoulos@m-iti.org

Sergi Bermudez i Badia
sergi.bermudez@m-iti.org

Fotis Liarokapis
liarokap@fi.muni.cz

[1] Faculdade das Ciências Exatas e da Engenharia, Universidade da Madeira, Campus Universitário da Penteada, 9020-105 Funchal, Portugal

[2] Madeira Interactive Technologies Institute, Polo Científico e Tecnológico da Madeira, Caminho da Penteada, 9020-105 Funchal, Portugal

[3] Human-Computer Interaction Laboratory, Masaryk University, Brno, Czech Republic

1 Introduction

Brain–computer interfaces (BCIs) are systems which provide an alternative communication pathway between users' brain activity and a computer system [1]. The most common signal acquisition technology in BCI is the non-invasive electroencephalography (EEG). EEG has low spatial but high temporal resolution in signal acquisition, using electrodes which rest over the scalp of the user. Through EEG, the acquired signal represents a macroscopic measurement of brain activity over a layer of bone and tissue, susceptible to interference from a variety of artifacts such as physiological (electromyographic (EMG) from muscle movement, electrocardiographic (ECG) from heart beat and electro-oculographic (EOG) from the eye movement) and electrical (power-line noise or other electronic equipment).

In an EEG system, brain modulation patterns can be extracted and analyzed to determine the mental state of the user, either through emotion recognition [2] or in body control and sense of ownership [3]. In a BCI, these mental states can be translated, within a processing pipeline including signal processing algorithms and machine learning to extract a control signal that could act as an artificial input to computers or external devices (e.g., robots). These patterns can be triggered by an exogenous source through visual, auditory or sensory stimulus, like Steady-State Visual-Evoked Potentials (SSVEP) and P300. SSVEP is caused by visual stimulation of flashing lights and can be captured at the primary visual

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cortex of the brain [4]. Instead, P300 responses are generated by measuring the brain-evoked responses 300 ms after stimulus onset [5]. In contrast, a BCI paradigm of an endogenous source is motor-imagery (MI) BCI. Motor-imagery makes use of the visuo-motor imagination (mental visualization of upper and/or lower limb movement) and has been widely used as the main BCI paradigm in research for users with high degree of motor disability. To date, MI is proven useful in a wide area of applications ranging from accessibility tools for disabled users with paralysis or severe neuromuscular disorders [1], for restoration of active movement [6], to human–computer interaction research [7], and virtual reality and video games [8].

During the past few years, and with the launch of low-cost EEG devices, BCI games (also known as neurogames) have become increasingly more advanced by incorporating immersive virtual reality [9]. Virtual Reality (VR) can simulate an artificial environment inside the virtual space giving the user the illusion of physical presence inside the virtual world [10]. In the last few years, VR technology has improved substantially with the help of modern hardware and software into the design of immersive environments, getting the attention of major technology companies [11]. Furthermore, augmented reality (AR) technology is able to enhance the real world by merging it with the virtual world in real time [12]. Going a step further, the fusion of BCI with VR and AR applications allows a wide range of experiences where participants can control various aspects of a virtual world or by superimposing digital information directly onto the real environment only by thought [13]. This direct brain-to-VR communication can produce induced illusions, enhancing the sense of presence [14] mostly relying on the sensorimotor contingencies between perception and action [15]. Direct manipulation of virtual environments without the mediation of interfaces that require motor control have been investigated in the past [16,17] showing that the combination of VR and BCI offers radically new experiences. Since this field is relatively young, there are very few data available assessing the psychological impact and user experience [18].

BCIs in games and virtual environments (VEs) can be grouped into three main categories: passive, reactive and active [19]. Passive BCIs are not used for controlling the games directly, but just as an implicit input by monitoring user's mental state. Reactive BCIs embed information with respect to the user's intention in the response signal of an exogenous source through SSVEP or P300 stimuli and are used as explicit input. Another type of explicit input to games are the active BCIs which are typically used as a direct control in games and VEs through the use of motor-imagery. In one of the earliest examples, users controlled the movement of First-Person Shooter (FPS) game by modulating low and high Mu (μ) rhythms to turn left or right [20]. Results showed that users learn to control the modulation of the μ rhythm levels very quickly, but especially when this learning involves producing similar μ levels (whether high or low) over each hemisphere.

The Berlin brain–computer interface (BBCI) presented a setup with intuitive control strategies in plausible gaming applications which employs advanced signal processing and machine learning technology for training the computer rather than the human subject [21]. The BBCI used motor-imagery (MI) to play Pacman and Pong and similar familiar games such as Tetris. A one-channel EEG-based controlled 'Run and Jump' game to allow subjects to get pulse width-modulated control was also implemented [22]. The training procedure allowed subjects to produce one brain pattern, elicited by motor-imagery, of two different durations. Results with 5 users showed that they were able to jump with a high accuracy (about 94.5 %) over hills having low number of false positives (39 %) between the hills. Another example is a pinball BCI game that controlled the left and right paddles [23]. The system was designed to examine two classes of motor-imagery (left- and right-hand movement). Later, the use of low-cost commercial BCIs was evaluated with the same game. Results indicated that both BCI technologies offer the potential of being used as alternative game interfaces after some familiarization with the device and in some cases some sort of calibration [24].

Unfortunately, the fundamental issue of BCI illiteracy is always presented in users that are unable to have a stable control, with an estimated 15–30 % of users unable to use effectively a BCI system [25,26]. This limitation occurs more frequently with MI-BCI paradigms [27]. MI can also be affected by insufficient attention due to user distraction or frustration [28]. As frustration is presented within many video games (triggered either from mechanics within the game design or player's limited skill), maintaining the entertainment and gameplay challenges within a brain-controlled game is a challenge. Moreover, feedback presentation is also related with EEG synchronization patterns by increasing the hemispheric asymmetry [29], interconnected with increased performance of fine motor tasks, and with left hemisphere changes being linked to motor learning [30]. A recent approach to increase user performance adopted in MI-BCI games is making use of tutorial levels with training elements to "disguise" or encapsulate user training inside the game so as to enhance the user's experience [31].

Despite the increased attention that BCI's have with the launch of low-cost EEG devices for gaming, it is hardly used outside laboratory environments [32]. Current BCI systems lack reliability and good performance in comparison with other types of gaming interfaces [33]. As a result, long training sessions can contribute in user fatigue and reduced performance. In addition, prolonged training is problematic in generating EEG oscillatory rhythms modulated during MI, such as Mu (μ) and Beta (β) rhythms [34]. Therefore, it is essential to identify new strategies for a successful MI-BCI training and control.

To date, it has been shown that users regularly exposed to video games have improved over time their visual and spatial attention, memory, mental rotation abilities [35,36] and enhanced sensorimotor learning, enabling better performance in tasks with consistent and predictable structure [37]. Extensive video game practice improves the efficiency of movement control brain networks and visuo-motor skills of the users [38]. However, there is a limited understanding on how these factors affect the activity patterns of motor-related areas during a motor-imagery task. Since these type of skills are used in current mental tasks used to control a BCI (e.g., mental rotation of geometric figures, motor-imagery, remembering familiar faces [39]), this suggests that users might improve their mastery of BCI by performing training tasks that do not involve the BCI system. This includes playing various video games and improving in an indirect way their visuo-motor capabilities. So far, the relationship between video game practice, player profile and BCI performance has been observed for BCI based on Steady-State Visual-Evoked Potentials (SSVEP) [40] but not in MI and still there is currently no available literature to support this hypothesis [32]. Having BCI users practicing video games might be a promising indirect training method to improve their BCI control skills and minimize the overall training time.

The aim of this paper is to examine the effect that gaming experience has in brain pattern modulation capacity during motor-imagery training and to identify the elements that contribute to high BCI control. Our hypothesis is that experienced gamers could have better performance in MI-BCI training due to enhanced sensorimotor learning derived from gaming [41]. An experimental study with 20 participants undergoing MI-BCI training and followed by online control through abstract feedback (Graz-BCI paradigm) [42] was performed to identify EEG correlates of user gaming profile and differences between gaming-experience groups. Further, an extended study was performed to identify possible changes over time and learnability. Overall, this research attempts to identify if an enhanced sensorimotor capability of experienced gamers can be reflected in MI-BCI training and traits in user profile that influence EEG rhythms activation. For this, an experimental setup for assessing the following hypotheses was designed: (a) examine if player profile can influence EEG rhythms activity patterns during a motor-imagery task and (b) assess the relationship between video game practice and player profile with BCI performance.

The rest of the paper is structured as follows. Section 2 describes the methods used in the experiment such as the experimental design, the questionnaires and the participants. Section 3 presents the analysis of the experimental data and Sect. 4 the most significant results. Finally Sects. 5 and 6 present our discussion and conclusions.

2 Methods

2.1 Experimental design

This experiment is divided into two parts. In the first part, a between-subject design was used for the comparison of two different groups and in the second part a within-subject design but over different BCI sessions. The training protocol of the sessions was the same across both parts of the study and amongst all sessions. In the first part, only one BCI session took place and in the second part, a subset of users performed two additional BCI sessions, one per day, completing all BCI sessions in three days.

The setup was composed by a desktop computer (OS: Windows 8.1, CPU: Intel® Core™ i5-4440 at 3.3 GHz, RAM: 8GB DDR3 1600MHZ, Graphics: Nvidia GT 630 1GB GDDR3), running the BCI training task and the Vuzix iWear VR920 (Vuzix, NY, USA) head mounted display (HMD) for displaying the BCI feedback (Fig. 1a). The HMD includes 640 × 480 twin LCD displays, 32-degree field of view (FOV), 3/4″ eye relief and 5/16″ eye box. The BCI setup comprised 8 active electrodes equipped with a low-noise biosignals amplifier and a 16-bit A/D converter (256 Hz). The spatial distribution of the electrodes followed the 10–20 system configuration [43] with the following electrodes over the sensory-motor areas (Fig. 1b). The g.MOBIlab biosignal amplifier (g.tec medical engineering GmbH, Graz, Austria) was connected via bluetooth to the desktop computer for the EEG signal acquisition and processing through OpenVibe platform [44]. For all sessions, a Common Spatial Patterns (CSP) filter was used for feature extraction and Linear Discriminant Analysis (LDA) for classifying the two classes (left | right-hand imagery). The classified data were transmitted to the RehabNet Control Panel (Reh@Panel) [45] through the Virtual Reality Peripheral Network (VRPN) protocol [46] to log the data and send the control signal to the online feedback module.

The feedback was based on the Graz-BCI paradigm [42], which uses standard bars-and-arrows sequence (Fig. 2c). When an arrow appears on screen (left or right direction), the user has to perform mental imagery of the corresponding hand and this could involve mental grasping, throwing, waving, etc. The visualization should remain consistent during the whole duration of the training session to train the linear classifier that distinguishes left- from right-hand imagery. Each session included 5 main blocks (Fig. 2): (1) 10–15 min of equipment setup and instructions; (2) subjects were exposed to an 8-min MI-BCI training block followed by (3) a 5 min rest; (4) an MI-BCI task of 8 min; (5) finally, subjects

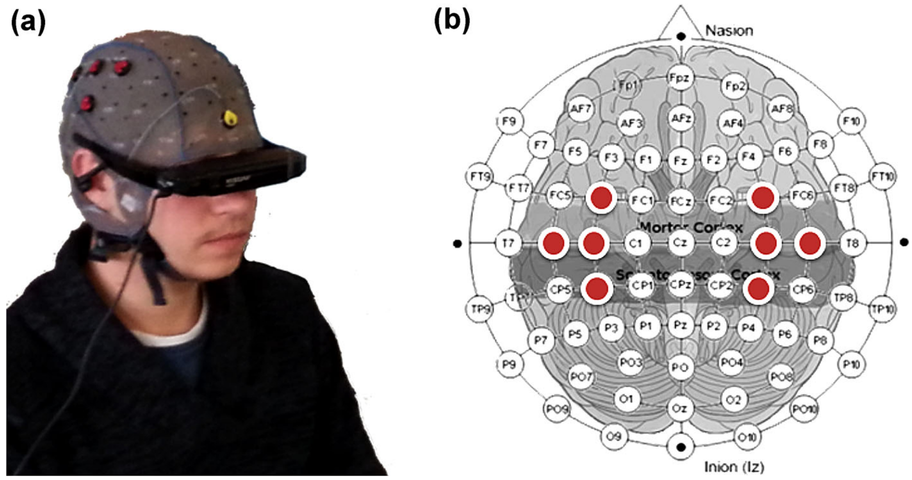

Fig. 1 **a** User setup with EEG cap and HMD, **b** 10–20 configuration diagram of the electrodes over the motor and sensorimotor cortices: frontal–central (FC3, FC4), central (C3, C4, C5, C6), and central–parietal (CP3, CP4)

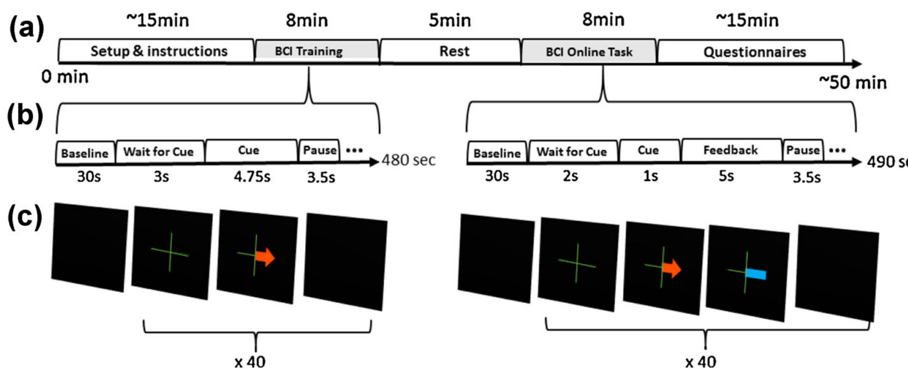

Fig. 2 Experimental protocol overview. **a** Experiment protocol, starting with a 15-min briefing and setup, followed by 8 min of BCI training, 5 min of rest, 8 min of online task, and questionnaires. **b** BCI calibration and motor-imagery task blocks. **c** Visual feedback stages with the Graz feedback for motor-imagery training

answered a set of self-report questionnaires. In total, each condition lasted approximately 50–60 min with 16 min of overall BCI exposure. During all blocks in all sessions, EEG data were logged synchronously and time stamped including the different stimulation codes (Start of trial, End of trial, Left, Right, Feedback, Cross on screen) for offline analysis.

2.2 Questionnaires

Before the BCI training session, demographics and user data were gathered through three questionnaires:

1. The Edinburg handedness inventory classifies users based on their handedness. It assesses left handed (−100 to −40 %), ambidextrous (−40 to 40 %) and right handed (40–100 %), with a higher score corresponding to higher level of handedness either left or right [47].
2. The Vividness of Movement Imagery Questionnaire-2 (VMIQ2) [48] was used to assess the feeling of the participant to perform an imagined movement (Kinesthetic Imagery). The Kinesthetic Imagery (KI) questions involve both upper and lower limb movements ranging from 1 (‘no kinesthetic sensation’/‘no image’) to 5 (‘as clear as executing an action’/‘image as clear as seeing’).
3. For assessing gaming experience, we used the Gamer Dedication (GD) questionnaire, a 15-factor classification questionnaire as assessed though a Likert scale between 1 and 5, in which participants were asked whether they “strongly disagree”, or “strongly agree” with a series of statements [49].

2.3 Participants

The study consisted of a total of 20 participants with a mean age of 28 ± 2 years, 16 male, 4 female. Participants were a voluntary sample, recruited based on their motivation to participate to the study, with no previous known neurological disorder. All subjects signed an informed consent to participate in the study and to publish their data. To group users based on their gaming experience, the GD questionnaire was used. Through this method the GD score was calculated based on the following formula:

$$\mathrm{GD} = \frac{\sum_{j=1}^{n} w_j s_j}{\sum_{j=1}^{n} 5 w_j} \tag{1}$$

where s = self-ranked score; w = weight

Since the GD score has not yet been validated for measuring gamer dedication, we gathered all 15 questions and we performed a principal component analysis (PCA) to assess the consistency of the GD scores. PCA is a well-known technique for dimension reduction and aims in reducing a larger set of variables into a smaller set of 'artificial' variables (called 'principal components') [50]. The extracted components account for most of the variance in the original variables. From the PCA analysis, the principal component was highly significantly correlated with the GD final score ($r = 0.98$, $p < 0.001$), meaning that the GD score is a sufficiently representative scale of gamer dedication for our sample. Following the scoring, the two-step cluster analysis procedure was used to form gamer dedication groups based on the GD answers. Two-step cluster analysis is an unsupervised machine learning task of inferring natural groupings or clusters within a dataset. From the clustering results we defined 2 balanced groups (10 users per group). These groups are further referred as 'Hardcore' and 'Moderate' gamers in the following sections.

3 Data analysis

3.1 EEG signal processing

EEG signals were processed in Matlab (MathWorks Inc., Massachusetts, US) extracting the Power Spectral Density (PSD) following an Independent Component Analysis (ICA) for removing major artifacts related with power-line noise, eye blinking, ECG and EMG activities with the help of the EEGLAB toolbox [51]. The power spectrum was extracted every 500 ms using Welch's method with windows of 128 samples for the following frequency rhythms: Alpha (8–12 Hz), Beta (12–30 Hz), Theta (4–7 Hz), and Gamma (25–90 Hz). For the current analysis, and because we were only measuring from sensory-motor areas, data were averaged for all the channels for each experimental condition. Left and right hemisphere electrodes were also aggregated to assess hemispheric asymmetries between groups (left hemisphere minus right hemisphere. From the extracted PSD, the Engagement Index (EI) was computed for all participants during both training and online sessions. EI is a metric created at NASA Langley for evaluating operator engagement in automated tasks, and was validated by Prinzel et al. through a bio-cybernetic system for Adaptive Automation [52] and is widely used in EEG studies for assessing engagement [53]. The engagement index was computed from the EEG power spectrum according to Eq. (2).

$$\mathrm{EI} = \beta/(\alpha + \theta) \qquad (2)$$

where α is the Alpha rhythm, β Beta rhythm and θ Theta rhythm.

3.2 Statistical methods

Normality of all data was assessed using the Shapiro–Wilk (S–W) normality test. For classifier performance, non-parametric statistical tests were used for the analysis because data deviated from normality. For the assessment of overall differences between three BCI sessions, a Friedman test was used on each dependent variable. For further pairwise comparisons, the Wilcoxon signed-rank test on each of our combinations was used. On EEG rhythm data, the S–W test revealed normality of the data ($p > 0.05$). The data were analyzed using a repeated measures ANOVA with a Greenhouse–Geisser correction due to Mauchly's Test of Sphericity violation. For all pairwise comparisons, a Bonferroni correction was used to account for the number of comparisons. Effect sizes were computed on pairwise comparisons. For all statistical comparisons, the significance level was set to 5 % ($p < 0.05$). Spearman correlations were performed between electrophysiological (EEG), demographics and questionnaire (GD, KI, and their sub-domains) data, with significance level set to 5 % ($p < 0.05$). All statistical analyses were done using IBM SPSS 20 (SPSS Inc., Chicago, IL, USA). Moreover, a stepwise regression modeling approach was used to identify predictors that provide a good fit in the regression line based on their R-squared values and their statistical significance ($p < 0.05$) between questionnaire, demographics and EEG data. The set of variables that were used for the multivariate linear regression includes (a) the subjective as reported through the questionnaires against (b) the EEG rhythms and the Engagement Index. The stepwise coefficient estimation of the models was done using Matlab (MathWorks Inc., Massachusetts, USA).

4 Results

The primary goal of this study was: (1) to understand how population data (gaming experience and user demographics) can affect performance in an MI-BCI task and the modulation of different EEG rhythms and (2) to investigate the electrophysiological correlation of user experience (how well users were associated with the demographic data, and identify all elements that contribute to high BCI control). Acquired data from consequent BCI sessions were also used to investigate EEG modulation over time.

4.1 EEG activity inference through population data

To assess the strength and direction of association that exist between the EEG data (*EEG rhythms, EI, hemispheric asymmetry*), LDA classification score and the population data (*Demographics, KI and GD answers*), the Spearman rank-order correlation coefficient was calculated. Subsequently, a multilinear regression modeling analysis was used to identify predictors that can describe the relationship between dependent and independent variables.

4.1.1 What is the relationship between user profile and EEG activity?

(A) EEG activity in training session

Demographic data EEG rhythms generated during training, Alpha, Beta, Theta, Gamma positively correlated with gender as age group correlated only with Gamma and handedness only with Theta rhythms (Table 1).

Kinesthetic imagery data From the reported KI ability, a significant correlation between the classification performances was found during training with the reported KI ability for "swinging on a rope". In addition, a reverse correlation between the Engagement Index during training and the KI of the participant of "bending to pick up a coin". Finally, users with increased KI of "walking" formed a reverse correlation of the Engagement Index and with the hemispheric asymmetry of Theta rhythm during training (Table 1).

Gamer dedication From the GD answers, the " preference towards violent/action games" correlates significantly with Alpha, Beta, Theta during training. "Discussing games with friends/bulletin boards" and users that have "comparative knowledge of the industry" have a significant correlation with high Engagement Index. On KI, significant reverse correlations are formed only for scores from users that are "technologically savvy" and "willing to pay" for games. Furthermore, users that "play games over many long sessions" have increased hemispheric asymmetry in Gamma. Those

Table 1 Significant correlations between demographic data and subjective answers (rows) with extracted EEG-related data (columns) and kinesthetic imagery for both training and online session

	Alpha training	Beta training	Theta training	Gamma training	Alpha onine	Beta onine	Theta onine	Gamma onine	EI training
GD: I prefer violent/action games	0.599**	0.496*	0.664**		0.571*	0.477*	0.680**		
GD: I discuss games with friends/bulletin boards							0.472*		0.566*
GD: I have comparative knowledge of the industry									0.635**
GD: I have the latest high-end computers/consoles									
GD: I am technologically savvy									
GD: I am willing to pay									
GD: I play games over many long sessions									
GD: I have the desire to modify or extend games in a creative way									
GD: i play for the exhilaration of defeating (or completing) the game									
GD: I am engaged in competition with myself, the game, and other players									
KI: Swinging on a rope									
KI: Walking					−0.647**		−0.517*		−0.486*
KI: Bending to pick up a coin									−0.520*
Gender	0.495*	0.566*	0.566*	0.471*	0.542*	0.613**	0.519*	0.566*	
Age Group				0.523*					
Education					0.550*	0.520*			
Handedness		0.539*		0.587**	0.702**	0.662**	0.662**		
Sport Gym									

Table 1 continued

	EI Online	KI	Theta hemi. asymm. training	Gamma hemi. asymm. training	Alpha hemi. asymm. online	Beta hemi. asymm. online	Theta hemi. asymm. online	Gamma hemi. asymm. online	LDA training
GD: I prefer violent/action games									
GD: I discuss games with friends/bulletin boards	0.484*								
GD: I have comparative knowledge of the industry	0.553*								
GD: I have the latest high-end comput-ers/consoles	0.635**					0.498*		0.649**	
GD: I am technologically savvy		−0.489*							
GD: I am willing to pay		−0.501*							
GD: I play games over many long sessions				0.489*				0.467*	
GD: I have the desire to modify or extend games in a creative way					0.669**	0.733**	0.722**	0.567*	
GD: i play for the exhilaration of defeating (or completing) the game					0.459*	0.512*	0.472*		
GD: I am engaged in competition with myself, the game, and other players					0.612**	0.580**	0.567*		
KI: Swinging on a rope									0.484*
KI: Walking			−0.456*						
KI: Bending to pick up a coin									
Gender									
Age Group									
Education									
Handedness						0.461*		0.527*	
Sport Gym					−0.478*	−0.498*	−0.498*		

who have the "desire to modify or extend games in a creative way" have increased hemispheric asymmetry in all rhythms, namely for Alpha, Beta, Theta, Gamma. Scores from users that "play for the exhilaration of defeating (or completing) the game" have increased hemispheric asymmetry in Alpha, Beta, Theta. Similarly, score from users which are "engaged in competition with themselves, the game, and other players" have stronger and increased hemispheric asymmetry in Alpha, Beta, Theta (Table 1).

Finally, classification score from the training session is significantly reverse correlated with the hemispheric asymmetry of Alpha, Beta, and Theta.

(B) EEG activity in online BCI session

Demographic data EEG rhythms produced during the online session: Alpha, Beta, Theta, Gamma form a significant relationship with gender and education with Alpha and Beta rhythms. Furthermore, participants involved in a sport or frequent gym visits have a significant reverse correlation with the hemispheric asymmetry that occurred during the online session, namely in the Alpha, Beta and Theta rhythms. For handedness, a strong positive significant correlation is found for all EEG rhythms during the online session (Alpha, Beta, Theta, Gamma), and also with the hemispheric asymmetry in Beta and Gamma. Overall, gender, education and handedness affect EEG rhythm modulation with sports and handedness to strongly affect also the hemispheric asymmetry in EEG rhythm activation (Table 1).

Kinesthetic imagery data The KI of the participant with increased KI of "walking" formed a reverse correlation with the produced Alpha and Theta rhythms, similar to the training session (Table 1).

Gamer dedication Similar as in training session, the " preference towards violent/action games" correlates significantly with all EEG rhythms except Gamma during the online session. In addition, "Discussing games with friends/bulletin boards" correlates significantly with the Engagement and additionally with increased Theta rhythms. Score from users that have "comparative knowledge of the industry" has a strong correlation with high Engagement Index. Users which have the "latest high-end computers/consoles" form a strong correlation with the online Engagement Index and with hemispheric asymmetry for Beta and Gamma. On KI, significant reverse correlations are formed only for scores from users that are "technologically savvy" and "willing to pay". Furthermore, users that "play games over many long sessions" have increased hemispheric asymmetry in Gamma rhythms similar as in the training session. In addition, those who have the "desire to modify or extend games in a creative way" have increased hemispheric asymmetry in all rhythms. Scores from users that "play for the exhilaration of defeating (or completing) the game" have also increased hemispheric asymmetry in Alpha, Beta, Theta and finally, score from users which are "engaged in competition with themselves, the game, and other players" have stronger and increased hemispheric asymmetry in Alpha, Beta, Theta (Table 1).

4.1.2 Can EEG activity be predicted from user profile?

A stepwise regression modeling approach was used to identify predictors of GD and KI from EEG activity through the different rhythms, Engagement Index and hemispheric asymmetry and also the overall performance (see Table 2).

The most significant predictor for the online performance ($R^2 = 0.243$) is the score related to the level of tolerance or frustration as reported through the GD questionnaire. The Alpha rhythm modulation during training ($R^2 = 0.327$) is related with the users which prefer violent/action games as well as the Alpha during the online session ($R^2 = 0.524$), combined with the user score related with the exhilaration of defeating (or completing) the game. Beta rhythm ($R^2 = 0.564$) during the online session is related with the preference to violent/action games, comparative knowledge of the industry, and engagement in competition with themselves the game, and other players. Finally, Theta activity in the online session ($R^2 = 0.418$) is related with score of users that prefer violent/action games.

For KI ($R^2 = 0.261$), the score of users that are *technologically savvy* is a significant predictor. Engagement index during training ($R^2 = 0.609$) is related with users that have comparative knowledge of the industry and with users that have a hunger for gaming-related information. Engagement index during the online session ($R^2 = 0.612$) is related to the score of users that have the latest high-end computers/consoles and the score of them that have a hunger for gaming-related information.

Concerning hemispheric asymmetry, from training data, the hemispheric difference of Theta ($R^2 = 0.230$) is related with the score of users that are technologically savvy and for Gamma ($R^2 = 0.242$) is related with the score of them which play games over many long sessions. From the hemispheric asymmetry as recorded during the online session, asymmetry of Alpha ($R^2 = 0.583$) is related with the score for those which play games over many long sessions and have the desire to modify or extend games in a creative way. For Beta ($R^2 = 0.579$), users which play games over many long sessions and have the desire to modify or extend games in a creative way have a significant relationship. For Theta ($R^2 = 0.455$), users which have the desire to modify or extend games in a creative way are significantly related, and for Gamma ($R^2 = 0.419$), the score of users which have the latest high-end computers/consoles is related with the hemispheric asymmetry. Finally, training classification performance ($R^2 = 0.292$) can be better predicted by the hemispheric asymmetry of Theta.

Table 2 Stepwise linear regression between gamer dedication answers (columns) and extracted EEG data and kinesthetic imagery (rows)

Dependent variable (R square) / independent variables (coeff.)	GD: I am much more tolerant of frustration	GD: I am technologically savvy	GD: I prefer violent/action games	GD: i play for the exhilaration of defeating	GD: I have comparative knowledge of the industry	GD: I am engaged in competition with	GD: I have the latest high-end	GD: I have a hunger for gaming-related	GD: I am willing to pay	GD: I play games over many long sessions	GD: I have the desire to modify or extend games in a creative way
LDA online (0.243)	−1.759										
KI (0.261)		−4.753									
Alpha training (0.327)			2.029								
Alpha online (0.524)			3.093	1.266							
Beta online (0.564)			3.305		−1.748	1.227					
Theta online (0.418)			2.518								
EI online (0.609)							0.012	−0.009			
EI training (0.612)					0.009				−0.007		
Theta hemi. asymm. training (0.230)		1.099									
Gamma hemi. asymm. training (0.242)										1.268	
Alpha hemi. asymm. online (0.583)										1.2	2.344
Beta hemi. asymm. online (0.579)										1.244	2.231
Theta hemi. asymm. online (0.455)											2.651
Gamma hemi. asymm. online (0.419)							2.068				

4.2 Group differences in EEG activity

From the two gaming groups derived from the GD clusters as explained in the Sect. 2.3 paragraph, the differences between 'Hardcore' and 'Moderate' gaming groups were assessed for the LDA classification score, the Engagement Index, the KI, all EEG rhythms and finally the hemispheric asymmetry for both the training and the online session.

4.2.1 Are there differences between gamer dedication groups?

(A) LDA classification

The LDA classification (Fig. 3a) is higher on training for the 'Hardcore' group (Mdn = 65.6, IQR = 8.06) compared to the 'Moderate' (Mdn = 63.7, IQR = 7.23). During the online session, 'Hardcore' group (Mdn = 49.9, IQR = 8.40) performs lower than the 'Moderate' group (Mdn = 50.4, IQR = 4.78).

(B) EEG rhythms

A Wilcoxon signed-rank test showed that during training, Alpha rhythm has only 0.3 dB difference between 'Hardcore' (Mdn = −61.5, IQR = 6.45) and 'Moderate' groups (Mdn = −61.8, IQR = 5.36). For Beta rhythms, 'Hardcore' group (Mdn = −65.6, IQR = 6.87) is lower than 'Moderate' group (Mdn = −64.8, IQR = 6.22). Theta rhythm is lower for 'Hardcore' group (Mdn = −61.5, IQR = 5.9) compared with the 'Moderate' group (Mdn = −59.8, IQR = 6.57). Finally, Gamma is lower for 'Hardcore' (Mdn = −69.2, IQR = 6.84) compared to 'Moderate' (Mdn = −69, IQR = 6.98).

During the online session. Alpha rhythm is lower in 'Hardcore' group (Mdn = −60, IQR = 7.03) compared to 'Moderate' (Mdn = −63.5, IQR = 5.03). For Beta, only 1 dB difference during online, with 'Hardcore' (Mdn = −65.8, IQR = 6.05) and 'Moderate' (Mdn = −65.9, IQR = 6.82) at the same median values. Theta is increased for 'Hardcore' (Mdn = −59.3, IQR = 8.44) and decreased for 'Moderate' (Mdn = −62.1, IQR = 4.64). Finally, Gamma for 'Hardcore' (Mdn = −70.3, IQR = 6.83) is lower than 'Moderate' (Mdn = −67.3, IQR = 7.79).

(C) Engagement index

The EI stable across both groups in both training and online session is not statistically significantly different ($Z = -1.125$, $p = 0.260$). The engagement index during training for 'Hardcore' has a median of 0.54 (IQR = 0.03) and in 'Moderate' the median is 0.53, (IQR = 0.02). The engagement index during the online session ($Z = -0.059$,

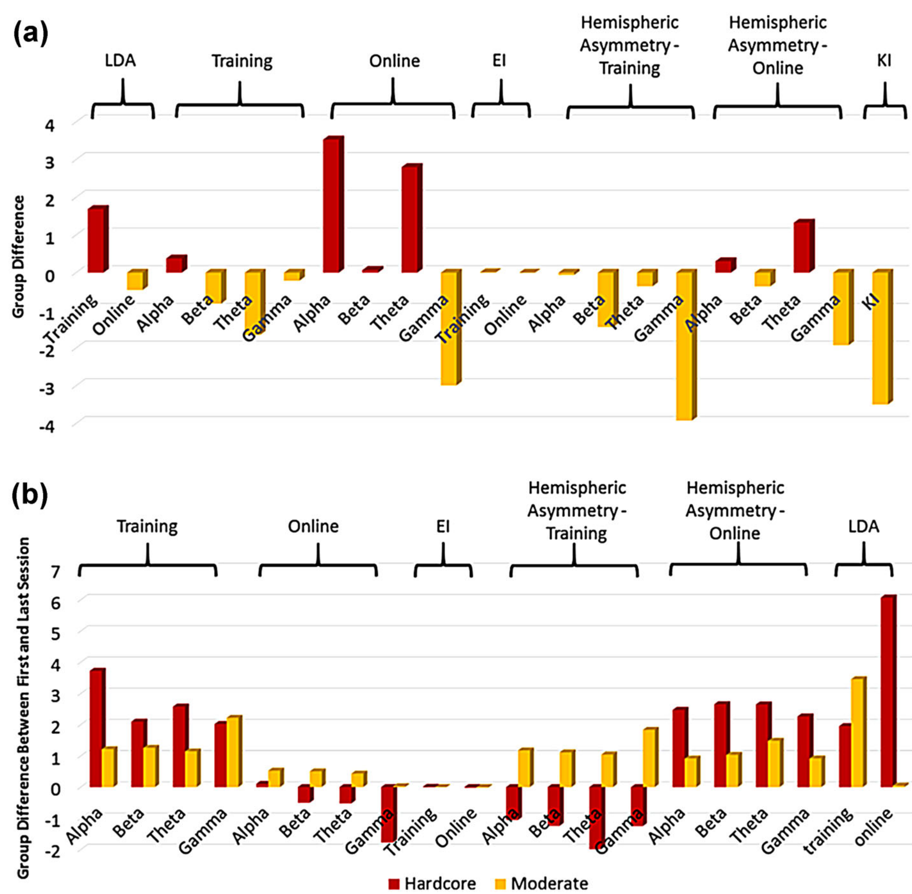

Fig. 3 **a** Differences between 'Hardcore' and 'Moderate' groups in all EEG rhythms (for training, online task, hemispheric asymmetry), LDA classification performance, Engagement Index and Kinesthetic Imagery. **b** Contrasts between first and last BCI session for both groups for the same type of data

$p = 0.953$, in both for 'Hardcore' (Mdn = 0.54, IQR = 0.03) and 'Moderate' (Mdn = 0.54, IQR = 0.04) groups remains similar.

(D) Kinesthetic imagery

For KI, there are not any significant differences between groups but 'Hardcore' group (Mdn = 21, IQR = 21) has a lower median value than 'Moderate' group (Mdn = 24.5, IQR = 9.5).

(E) Hemispheric asymmetry

Finally, hemispheric asymmetry between the two groups has no significant differences, namely for Alpha training ($Z = -0.415, p = 0.678$), online ($Z = -0.296, p = 0.767$), Beta training ($Z = -0.770, p = 0.441$), online ($Z = -0.059, p = 0.953$), Theta training ($Z = -0.533, p = 0.594$), online ($Z = -0.296, p = 0.767$) and Gamma training ($Z = -1.244, p = 0.214$), online ($Z = -0.770, p = 0.441$). 'Hardcore' group shows the higher hemispheric asymmetry only during the online session for Alpha (Mdn = 0.87, IQR = 6.25) compared with 'Moderate' (Mdn = 0.56, IQR = 8.87) and Theta with 'Hardcore' median at 0.99 (IQR = 6.27) and 'Moderate' at −0.33 (IQR = 10.55).

4.2.2 How do different groups progress over time?

Results (Fig. 3b) revealed a statistically significant difference only between the hemispheric asymmetries of the two groups. In particular, Theta rhythm ($t(10) = -0.956, p < 0.05$) and Gamma ($t(10) = -0.831, p < 0.05$) have a significant difference during the online session between the 'Hardcore' and 'Moderate' groups. Specifically, for Theta, the 'Hardcore' group ($M = 2.64$, SD = 1.05) presents an increased hemispheric asymmetry as compared to 'Moderate' ($M = 1.48$, SD = 4.45). For Gamma, the 'Hardcore' group also showed increased asymmetry ($M = 2.26$, SD = 2.49) as compared to the 'Moderate' group ($M = 0.91$, SD = 4.28). Overall, the 'Hardcore' group indicates a distinct pattern in terms of EEG modulation and hemispheric asymmetry with increased modulation in all EEG rhythms during training but reduced in the online session. This is reflected in the hemispheric asymmetry, being decreased in training and increased during the online session.

5 Discussion

From current results, we have identified the following: (1) relationship between electrophysiological data with gaming experience, KI ability and demographic data, and (2) differences between gamer groups based on their dedication, and (3) differences of different groups over time.

From the demographic data, gender-related correlations can be identified, strongly associated with all EEG rhythms in both training and online task. Handedness was related mostly with EEG activity modulation and asymmetry through the online session. Based on previous research, asymmetry in the Alpha rhythm is task dependent and extends to a broader range of tasks [54], also to be depended upon gender and familial handedness [55]. It was also identified that users which exercise frequently have reduced hemispheric asymmetry, which is consistent with previous findings that show differences in all EEG rhythms in users with increased physical activity [56]. Finally, the level of education correlated significantly with the amplitude of online Alpha and Beta rhythms, important for motor-imagery training, which are modulated during sensorimotor activation.

For KI, the training performance is correlated with the *swinging on a rope* KI score, and engagement index is correlated during training with *bending to pick a coin* score. The most important KI relationship was between users with increased walking KI score and a reverse correlation with online Alpha and Theta, engagement index during training and hemispheric asymmetry on Theta rhythms. Interestingly, similar correlations occurred for users performing sports, suggesting a relationship between physical activity and KI ability of lower limbs.

For GD, multiple correlations related to hemispheric asymmetry were identified, for users that play games for long sessions, modify games creatively, are very competitive and truly engaged to the competition in general. Previous studies have shown that hemispheric asymmetries enhance the performance of fine motor tasks and trigger changes in motor learning [30]. Therefore, users engaged in a competitive manner and in long sessions of gameplay could present enhanced motor-related EEG modulation, leading to increased motor learning. Finally, users which prefer violent and/or actions games have an increased ability to modulate all EEG rhythms in both training and online sessions.

Through linear regression modeling, we identified that competitiveness and preference to violent/action games are significant predictors for the EEG rhythm modulation that is mostly activated during MI (i.e., Alpha and Beta rhythms). Furthermore, increased addiction (play games over long hours) is a predictor for increased hemispheric asymmetry that could lead in increased BCI performance.

Between different groups we observed an increased modulation and hemispheric asymmetry for the 'Hardcore' group mostly on Alpha and Theta rhythms. Interestingly, during training, only Alpha band—responsible for relaxation and sensory idling [21]—was higher than the 'Moderate' group. Theta also might be responsible for increased memory encoding [57], which can be related to increased asymmetry between hemispheres.

Concerning the progress over time—between first and last session— of the score and the evolution of the EEG activity, both groups have increased their EEG rhythm activity during training. However, the 'Hardcore' group showed higher EEG modulation and the training score was lower than for the 'Moderate' group. In addition, hemispheric asymmetry seems to be reduced for 'Hardcore' group during training. In contrast, during the last session of online control, EEG rhythms are reduced for the 'Hardcore' group but the hemispheric asymmetry and final scores increase. Based on these data and the previous correlations of training score with the hemispheric asymmetry of Alpha, Beta and Theta, and with Theta also acting as a predictor for performance, we can conclude that there is a clear relationship between the scores and hemispheric asymmetry.

6 Conclusions

Experimental results of this study indicate that demographic traits such as gender, handedness, experience of action and violent games affect the activity patterns of sensorimotor-related EEG rhythms during an MI task. Concerning BCI performance, results showed that increased performance is related with higher tolerance to frustration, and also to users with increased KI of rope swing and bike riding. Moreover, long gaming sessions and addiction seem to increase hemispheric asymmetries—related from previous research to increased performance of fine motor tasks—and it was showed that increased hemispheric asymmetry can be a more valuable predictor of BCI performance than specific EEG rhythm modulation. Although both groups have similar engagement indices, the 'Hardcore' group increased faster their performance over time and also their hemispheric asymmetry compared to the 'Moderate' group. Therefore, increased gaming experience might not directly increase the performance in an MI-BCI paradigm, but it can provide faster learning.

Summarizing, with current results we can link the impact of demographics in EEG modulation during a motor-imagery session, identifying a clear influence of the user profile in EEG rhythms activity patterns. Moreover, a relationship between video game practice and BCI performance was identified. This will help us not only to identify possible causes of BCI illiteracy but also to provide inclusion criteria for BCI training and adaptation of current BCI training protocols. Consequently, current results provide a first step into user-centered neurogame design using EEG-based motor-imagery as a primary input but also to open a way into exploring the effect in augmented/virtual reality applications and its effect on embodied cognition. This underexplored possibility for BCI training has a great potential not only for games in the entertainment domain but also for utilizing these techniques in the health domain for users with neurological disorders through with the use of virtual tools and serious games. Overall, since we know which traits of player profile can influence EEG rhythm activity patterns during a motor-imagery task and we have modeled the relationship between video game practice and player profile with BCI performance, we can embed current findings in neurogame design for enhanced performance.

In terms of future work, new studies need to be extended by including participants with lower or no gaming experience. This will allow us to generalize the findings to a greater extend and provide stronger statistical outcomes. In addition, a 3D immersive environment (including an HMD with a higher resolution) will be used to assess the impact of gaming experience in immersive VR-based MI-BCI rather than abstract feedback. Moreover, the use of an EEG system with additional electrodes would allow us not only to gain higher spatial resolution over the somatosensory area but also to improve the quality of the feature selection before training the classifier. These steps are considered necessary to gain further insights into how different brain activity is elicited on 'Hardcore' players and how this information can be used to optimize the BCI Game experience.

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Athanasios Vourvopoulos is a Ph.D. Candidate at the University of Madeira (Portugal) and a member of NeuroRehabLab group at the Madeira Interactive Technologies Institute (M-ITI). His doctoral research involves the development of neuroscience-based interactive systems for stroke rehabilitation with his main area of interest in Brain–Computer Interfaces (BCI) and Virtual Reality (VR) for neurorehabilitation. He has assessed various BCI prototypes during his undergraduate and postgraduate studies at Coventry University, UK, and Serious Games Institute (SGI). He is a member of the IEEE Brain Community, the International Society for Virtual Rehabilitation (ISVR), and the International BCI Society.

Sergi Bermudez i Badia is an Assistant Professor at the University of Madeira and a research fellow at the Madeira-ITI and member of the NeuroRehabLab group. He received his M.Sc. in telecommunications engineering from the Universitat Politècnica de Catalunya (Barcelona) and a Ph.D. in neuroscience from the ETHZ (Zürich). In the past, he has also pursued research at the EPFL (Lausanne), the Universitat Pompeu Fabra (Barcelona), and at Carnegie Mellon University (Pittsburgh). He is an Associate Editor of the Journal of NeuroEngineering and Rehabilitation (JNER) and the IJ of Advanced Robotic Systems (ARS), as well as reviewer for several international conferences and journals. For the past years, he has been involved in the development and clinical validation of several motor and cognitive stroke neurorehabilitation systems using interactive technologies such as Virtual Reality, Brain–Computer Interfaces, and haptic interfaces.

Fotis Liarokapis is an Associate Professor at the HCI Laboratory at Masaryk University, Faculty of Informatics at Brno. Before, he was the Director of Interactive Worlds Applied Research Group (iWARG), Faculty of Engineering and Computing at Coventry University and a research fellow at the Serious Games Institute (SGI). He has contributed to more than 90 refereed publications in the broad areas of virtual and augmented reality, procedural modelling, serious games, and brain–computer interfaces. He has organised multiple conferences and workshops, and he is the co-founder of VS-Games international conference.