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Review article

Brain computer interface based applications for training and rehabilitation of students with neurodevelopmental disorders. A literature review

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ABSTRACT

The aim of this article is to explore a paradigm shift on Brain Computer Interface (BCI) research, as well as on intervention best practices for training and rehabilitation of students with neurodevelopmental disorders. Recent studies indicate that BCI devices have positive impact on students' attention skills and working memory as well as on other skills, such as visuospatial, social, imaginative and emotional abilities. BCI applications aim to emulate humans' brain and address the appropriate understanding for each student's neurodevelopmental disorders. Studies conducted to provide knowledge about BCI-based intervention applications regarding memory, attention, visuospatial, learning, collaboration, and communication, social, creative and emotional skills are highlighted. Only non-invasive BCI type of applications are being investigated based upon representative, non-exhaustive and state-of-the-art studies within the field. This article examines the progress of BCI research so far, while different BCI paradigms are investigated. BCI-based applications could successfully regulate students' cognitive abilities when used for their training and rehabilitation. Future directions to investigate BCI-based applications for training and rehabilitation of students with neurodevelopmental disorders concerning the different populations involved are discussed.

1. Introduction

Brain Computer Interface (BCI) is the latest advancement of Human Computer Interaction (HCI). BCI enables either direct generated commands between external software applications and human brain (active BCI) or the communication between subjects and machines that lead to a seamless and beneficial experience for the user (passive BCI). With the help of BCI applications, the brain can interact seamlessly with a mechanical device and is therefore considered a fast-growing technology especially beneficial for fields such as Artificial and Computational Intelligence. There are many factors that have contributed positively to this development such as the increased knowledge of neurobiological processes and machine learning algorithms (Al-Nafjan et al., 2017). Human brain with more than 100 billion nerve cells is responsible for many complex executive functions, like reasoning, planning of tasks and processing thoughts (Haider and Fazel-Rezai, 2017). As a result, the brain generates a great amount of neural activity, that can be given as input in many BCI applications especially designed for non-disabled people. These applications can train higher integrative abilities such as thinking, learning, production, and understanding of speech, memory, emotion. BCI applications exist mainly as an alternative to natural communication and control by processing the activity, which derives directly from brain generated activity and not from the interaction with the peripheral nervous system. For example, they can serve as a medium of communication for people who are not able to control manually a PC, by converting their thought, intention, or decision to a command for an external machine, such as a computer or phone. Moreover, subjects' mental states being monitored using an Electroencephalogram (EEG) can be analyzed with the help of a motor imagery BCI. The users can then learn to control their physiological and psychological states (Yang et al., 2017). Additionally, scientists have analyzed this ongoing brain activity to extract brain patterns, based on the International 10–20 System, in order to

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accurately position electrodes (Figure 1). The system comprises tasks such as pattern recognition and signal processing that are usually delivered automatically (Graimann et al., 2009). The up to 256 electrodes that are placed on the user's scalp make the detection of signals an easy as well as a portable way for psychometric or cognitive research (Ramadan et al., 2015). Furthermore, BCI applications can be utilized in painting, smart home controlling, attention training games, stroke rehabilitation, lie detection and they can replace common control devices like mice or joysticks (Finke et al., 2009; Fazel-Rezai and Ahmad, 2011).

According to Ramadan and Vasilakos (2017) BCI is a compact system that includes software and hardware tools to extract useful information from human signals that are able to provide control output for several communication devices and computers. Definition presented in the literature describes the whole range of functions of a BCI in terms of receiving, editing, sorting and utilizing brain wave signals from a human brain with neuromuscular deficiencies and degenerative nerve diseases (Schwartz, 2004; Wolpaw and Wolpaw, 2012). BCI detects a plethora of brain signals, namely Delta within the frequency scale of 0.5–3.5 Hz, Theta within 3.5–7.5 Hz, Alpha within 7.5–12 Hz, Beta within 12–30Hz and Gamma signals with frequency range of 31 and up. Oscillatory Electroencephalography (EEG) output that is generated by a vast network of neurons and Event-Related Potentials (ERPs), the brain generated feedback that is noticed after a specific event, are of particular interest to BCI. EEG activity can be captured from the very beginning of providing a stimulus, which can generate with a time-delay a noticeable electrical wave in EEG, up until the end when the EEG will settle down. Forming a BCI system requires the following steps: signal acquisition, signal pre-processing, signal classification and data manipulation (Rao et al., 2012, Ramadan et al., 2015; Haider and Fazel-Rezai, 2017; deCharms et al., 2005; Strehl et al., 2006). BCIs primarily facilitate communication for people with severe motor disability that cannot communicate otherwise but may provide useful communication and rehabilitation of different disorders even for healthier people or people with less critical movement disorders. BCI research can capitalize on advances in cognitive neuroscience when dealing with training tasks, feedback analysis, accessibility, concentration, exhaustion, stimulation and distress among others (Allison et al., 2007; Allison, 2009). Li et al. (2009) present a general BCI system including data acquisition, preprocessing, feature extraction and translation algorithms, (Figure 2).

BCI applications classify mainly the following target populations: patients lacking any motor control, patients who barely have voluntary movements and those with significant neuromuscular control. BCI use is also for people suffering from psychiatric disorders such as schizophrenia and depression. Considerable advances in the field of EEG-based BCI offer an acceptable signal quality that combines low cost and easy-to-use equipment allowing their users new means of communication and control without any interference of peripheral nerves and muscles. Moreover, neuromarketing and video games industry use increasingly BCIs to extract healthy people's affective information, bypass physical interaction, and develop new levels of control. BCIs make you more relaxed and focused as well as make things easier for the end user if they manage to control the BCI (Abdulkader et al., 2015; Bos et al., 2010; Lotte, 2011; Lotte and Jeunet, 2015; van de Laar et al., 2013). EEG studies are well suited to characterize developmental attention disorders such as ADHD (attention deficit hyperactivity disorder) and can measure brain function reliably in a wide age range, even in infants, and during both wakefulness and sleep (Banaschewski and Brandeis, 2007; Yang et al., 2017). A broad variety of neurofeedback applications use BCI systems to improve healthy individuals' cognitive performance, speech skills, affection, and pain management and for the treatment of attention deficit, learning disabilities, depression and autistic disorders (Angelakis et al., 2007; Monastra et al., 2006; Nicolas-Alonso and Gomez-Gil, 2012; Rota et al., 2009; Sitaram et al., 2011; Yang et al., 2017).

However, there are many challenges that are linked with the BCI system, which are classified as technology related and/or user related and are being discussed in section 5. BCI technologies require multidisciplinary skills from fields such as neuroscience, engineering, computer science, psychology and clinical rehabilitation to lead to a natural and effective user experience (Al-Nafjan et al., 2017).

2. Research methodology and process

BCI is categorized into three main groups; Invasive, partially invasive and non-invasive. In this paper, we investigate only non-invasive BCI type of applications since we consider this type the safest and the cheapest (Ramadan et al., 2015). This paper is an evidence-based research upon representative, non-exhaustive and state-of-the-art studies and aims to present the use of BCI applications for training and rehabilitation of students with neurodevelopmental disorders according to their new classification in DSM-5 (APA, 2013; Harris, 2014; Ismail and Shapiro, 2019; Reed et al., 2019; WHO, 2018). To our knowledge this study is the only one to highlight aspects in the field of BCI-based intervention applications for training and rehabilitation of students with neurodevelopmental disorders. The manuscript selection process includes a designated set of articles from important journals within the field, according the criteria exhibited in Table 1.

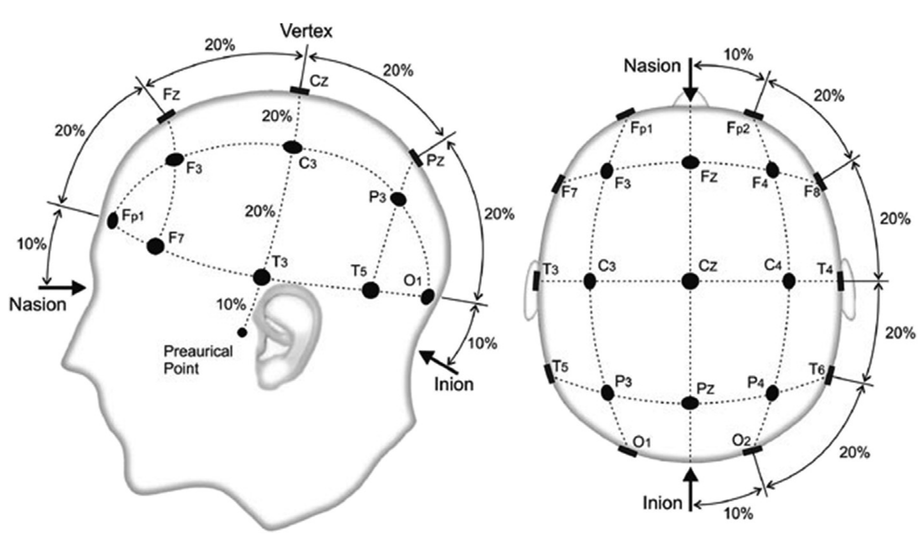

Figure 1. The International 10–20 System. The first letters of each label denote the region of the brain over which each electrode should be positioned: Fp – prefrontal, F – frontal, C – central, P – parietal, O – occipital, T – temporal.

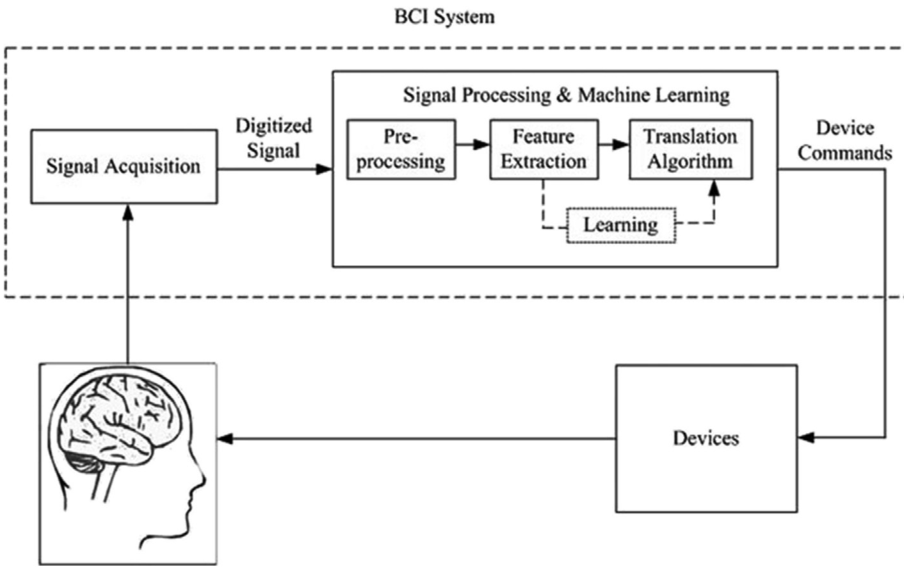

Figure 2. Basic layout and process of a BCI system.

3. Experimental design and performance evaluation

3.1. BCI for learning, memory and attention

A common BCI application, combined sometimes either with eye movements or thoughts, is neurofeedback intervention to boost attention, executive functions and memory (Ramadan et al., 2015). BCI-based neurofeedback training engages learning structures in the brain that require repeated training with feedback and reward, e.g. when users manage to move through a computer screen with the cursor by controling their brain signals, through mental imagery strategies (Gruzelier et al., 2006; Gruzelier and Egner, 2005; Heinrich and Strehl, 2007; Lotte and Jeunet, 2015; Neuper and Pfurtscheller, 2009). In order to increase BCI reliability to a higher level, it is necessary to make learning tasks more fascinating and stimulating by challenging the user through multi-player/collaborative game versions, the use of tactile/sensory modalities, and a user cognitive profile creation related to their mental imagery BCI performances (Leeb et al., 2013; Lotte et al., 2013; Lotte and Jeunet, 2015). Other issues that need investigation concern how EEG enrichment of attention and memory achieved by healthy participants can be extended to clinical groups and who is most likely to benefit from the training (Gruzelier and Egner, 2005).

EEG neurofeedback through either Virtual Environments or Video Game based Learning is a promising approach. It is both diagnostic and prognostic, for attention-training tasks that can improve users' attentional abilities which in turn improve BCI performances (Arns et al., 2013; Brandmeyer and Delorme, 2013; Jeunet et al., 2016; Martínez et al., 2016; Monastra et al., 2006; Rohani and Puthusserypady, 2015; Yang et al., 2017). EEG-based neurofeedback is considered a promising alternative communication and control channel for improving the cognitive skills of children with ADHD (Gevensleben et al. 2009, 2010; Heinrich et al., 2004; Lévesque et al., 2006; Qian et al., 2018; Wang et al., 2007; Vernon et al., 2004). A practical issue concerns the design of new protocols that can make BCI applications more user-friendly as well as the roles of the researcher and experimenter concerning the demystification of the BCI technology, the writing of informed-consent forms and the social presence and trust relationship with the user (Jeunet et al., 2016).

In a pilot study, a progressive series of training games using EEG-based BCI, which could train users to improve their concentration, was developed. The characters that Children with ADHD had to control in the game, moved in a speed equivalent to the childrens' level of concentration, so they needed to put all their attention on the game in order to finish it in the given time. This form of attention training showed reduced children's ADHD symptomatology (Jeunet et al., 2016; Lim et al. 2010, 2012). In another research experiment, an EEG-based neuro-feedback game using motor imagery for the treatment of ADHD was developed. Analysis of the band power results showed that users were not only entertained and relaxed throughout the game, but they also seemed to improve their level of attention. Thus, BCI neurofeedback system proved to be particularly effective for ADHD (Yang et al., 2017). Neuro-feedback effects are substantial revealing a superiority of the NFT in reducing ADHD symptoms by approximately 25% after Slow Cortical Potentials, even under strict control conditions (Gevensleben et al. 2009, 2010; Heinrich et al., 2004). Novel approaches, which use 2D/3D games in conjunction with BCI technology, provide a promising process in training attention for ADHD patients. Also, facilitate brain maturation, regularize the salience processing and boost their cognitive skills including the ability to sustain the attention for longer duration (Jiang et al., 2011; Martínez et al., 2016; Shenjie et al., 2014; Thomas and Vinod, 2016; Qian et al., 2018). Qian et al. (2018) showed that BCI-based intervention significantly improved ADHD inattentive

Table 1. Inclusion and Exclusion criteria.

Inclusion criteria	Exclusion criteria
a. The studies must contain BCI-based intervention applications regarding memory, attention, spatial, visuospatial, learning, collaboration and communication, social, creative and emotional skills.	a. Articles before 2004.
b. The article is only referring to primary, secondary and/or tertiary education students	b. Locked-in state and complete locked-in state students
c. It is also referring to BCI value added on students with anxiety, ASD, ADHD or Dyslexia.	c. Students with ALS (Amyotrophic Lateral Sclerosis); history of medical diseases; psychiatric disorders (e.g. bipolar and tic disorders); head trauma; brain injury, neurological disorder (e.g. multiple sclerosis, stroke); drug/alcohol addiction; and a family history of genetic disorder.
d. Articles are referring to users with less severe disabilities, and even healthy users.	

Table 2. Summary of articles on BCI-based applications for students with learning, memory and attention disabilities.

Study (year)	Sample	Study contents/method	Key findings
Arns et al., (2007)	19 children with dyslexia average age 10.33 and 19 control children average age 10.34	qEEG data were acquired from 28 channels: Fp1, Fp2, F7, F3, Fz, F4, F8, FC3, FCz, FC4, T3, C3, Cz, C4, T4, CP3, CPz, CP4, T5, P3, Pz, P4, T6, O1, Oz and O2. Neuropsychological assessment made using a touch screen monitor with EO.	qEEG results showed an increased (left) frontal and right temporal slow activity in the Delta and Theta bands and increased Beta 1 power at F7 in children with developmental dyslexia. No important correlations between the EEG power data and the EEG coherence data within frequency bands was found.
Arns et al., (2013) Meta-Analysis	1253 ADHD children and 517 control children. 6–18 years group and. 6–13 years Group	TBR data during EO from location Cz were investigated from children-adolescents between 6-18 years old with or without ADHD.	The grand mean ES obtained in this meta-analysis is rather misleading and was considered an overestimation. An increased TBR cannot be considered a reliable measure used for the diagnosis of ADHD at this time. The ESs obtained were 0.75 for the 6- to13-year-olds and 0.62 for the 6- to 18-year-olds.
Breteler et al., (2010)	Experimental Group of 10 children and a Control Group of 9 children who were diagnosed with dyslexia	QEEG data were acquired from 28 channels: Fp1, Fp2, F7, F3, Fz, F4, F8, FC3, FCz, FC4, T3, C3, Cz, C4, T4, CP3, CPz, CP4, T5, P3, Pz, P4, T6, O1, Oz, O2. Neuropsychological measurement was completed using a touch screen monitor with EO.	The main effect is a large and clinically relevant progress in spelling, whereas no progress in reading abilities was found. Cohen's 3.02 d value, implies an important enhancement in spelling of the neurofeedback group
Gevensleben et al., (2009)	102 children (Neurofeedback Group $N = 59$, Control group $N = 35$, dropouts = 8) with ADHD aged 8–12 years.	Children performed either 36 sessions of NFT or a computerised attention skills training within two blocks of about four weeks each.	For parent and teacher ratings, improvements in the NF group were superior to those of the CG. A significant effect was found for the inattention subscale ($t(60) = 1.94$; $p < .05$) and a trend for the hyperactivity/impulsivity subscale ($t(60) = 1.59$; $p < .1$).
Heinrich et al., (2004)	22 children with ADHD aged 7–13 years. (n = 13 Training Group, n = 9 Waiting-List Group)	25 sessions of 50 min duration in 3 weeks. 100–120 trials of 8 s duration (2 s baseline, 6 s feedback) per session	Significant effects for the SCPs training group only: ADHD rating scale – total score: 25% decrease after training
Jeunet et al., (2015)	18 participants, aged 21.5 ± 1.2, were instructed to learn to control an EEG-based MI-BCI by performing 3 MI-tasks. 2 of them were non-motor and they spanned over 6 training sessions, on 6 different days.	The EEG signals were recorded using 30 scalp electrodes (F3, Fz, F4, FT7, FC5, FC3, FCz, FC4, FC6, FT8, C5, C3, C1, Cz, C2, C4, C6, CP3, CPz, CP4, P5, P3, P1, Pz, P2, P4, P6, PO7, PO8). Each participant took part in 6 sessions, on 6 different days spread out over several weeks.	In this study, it was shown how users' profiles can influence their MI-BCI control levels. It therefore creates a path for designing new protocols that involve MI-BCI techniques, that can be adjusted to each user's specific profile.
Leins et al., (2007)	Two EGs groups included 19 ADHD children each, with ages between 8–13 years.	This study worked toward answering whether: (i) children manage to improve their cortical self-regulation, (ii) if treatment can work in favor of their behavioral and cognitive skills (ii) the two groups show differences between the skill amelioration outcomes.	Self regulation of SCPs: between sessions 2 + 3 and 29 + 30 ($t[18] = 3.51$, $p = .006$, ES = 1.09) as well as 2 + 3 and 32 + 33 ($t[14] = 3.07$, $p = .016$, ES = 1.05). Amplitudes of SCP in activation and deactivation tasks: sessions 2 + 3 and sessions 29 + 30 had a notable difference ($t[18] = 3.67$, $p = .004$, ES = 1.03). The same is observed between sessions 2 + 3 and sessions 32 + 33 ($t[15] = 5.28$, $p < .001$, ES = 1.07). Theta/Beta-ratios were also notably different for the two tasks, at the end of treatment (sessions 29 + 30) for the feedback ($t[36] = 4.224$, $p < .001$, ES = 1.37) and transfer condition ($t[36] = 3.003$, $P = .010$, ES = 2.25). Only the Theta/Beta group showed a substantial progress in Tests for the full scale IQ ($t[17] = 3.26$, $p = .015$, ES = .62).
Lévesque et al., (2006)	20 ADHD children aged 8–12 randomly assigned to either an experimental (EG $N = 15$) or a control (CG $N = 5$) group.	Before the study began, participants in both groups were treated with methylphenidate. No participant underwent cognitive training before the experiment. Psychostimulants were not allowed over the course of the experiment.	Neutral Trials: For the EG group, this score was significantly greater ($P < 0.05$) at Time 2 (67%, S.D.: 18.3) than Time 1. Interference Trials: For the EXP group, this score was significantly higher ($P < 0.05$) at Time 2 (68%, S.D.: 13.9) than Time 1.
Lim et al., (2010)	10 ADHD children aged 7–12 as EG and 10 ADHD children as controls	20 sessions of therapy over a 10-week period. Three-channel EEG signals are recorded from the frontal (Fp1, Fp2) and parietal (Pz) positions, covering theta, alpha, beta 1, and beta 2 waves.	Effect size for parental ratings was about –0.95 SD (95% C.I. –1.92 to 0.01 SD), and that for teachers' ratings was –0.85 SD and (95% C.I. –2.14 to 0.44 SD).
Lim et al., (2012)	20 unmedicated ADHD children with significant inattentive symptomatology (combined and inattentive subtypes).	A BCI-based attention training game-system tracked attention with a headband with dry electrodes for EEG sensing in	Results show significantly improved inattentive and significantly improved hyperactive-impulsive symptoms of ADHD

(continued on next page)

Table 2 (*continued*)

Study (year)	Sample	Study contents/method	Key findings
		order to control a feedforward game. The treatment's design included 8 weeks of training that comprised of 24 training sessions in total, with 3 follow-up booster training sessions once a month.	respectively for inattentive and combined subtypes, according to parents' behavioural ratings.
Martínez et al., (2016)	The population sample includes children that were invited directly to the study as well as children that receive therapy for reasons concerning their communication and behavior.	A case-based study aiming to examine and study the attention, cognition and memory of children with ADHD. Children were invited to play the Stroop and Flanker tests and other games that require the use of memory, practicing skills related to memory, attention and reasoning.	EEG and video analysis data as well as childrens' scores during the game were used to code their affective states relevant to engagement, frustratio and excitement.
Nan et al., (2012)	32 students aged 20–29 years (Neurofeedback group N = 16, control group N = 16)	20 sessions of NFT	The increases in forward and backward digits of the NFT group were significantly larger than those of the control group ($t(30) = 2.944$, $p < 0.005$ in forward increase; $t(30) = 4.091$, $p < 0.001$ in backward increase).
Qian et al., (2018)	66 boys with ADHD, combined or inattentive subtypes, were split in a random manner in two groups (ADHD-Intervention group N = 44 and ADHD-Non Intervention group N = 22)	The ADHD-I participants went through three BCI-based therapy interventions every week, throughout eight weeks. Two dry EEG sensors were placed at the frontal sites FP1 and FP2. The BCI-based attention training game included a headband with mounted dry EEG sensors that transferred EEG readings to the computer through Bluetooth-enabled protocol.	The ADHD-I group had significantly greater reduction in the ADHD-RS clinician inattention scores compared to the ADHD-NI group ($p = 0.038$). Intra- and inter-network FC showed significant group and time interaction effect ($p < 0.05$). The results show that BCI-based therapy sessions can be useful in improving the behavioral skills of children with ADHD, by modifying salience network processing.
Shenjie et al., (2014)	Four healthy subjects.	Attention estimated from the signals recorded from 4 EEG channels namely O1, O2, AF3, and AF4. Subjects played the game with three difficulty levels for three consecutive days.	The proposed control mechanism in the designed video game is capable of enhancing attention and brain functions including the ability to sustain the attention for a longer period.
Walker and Norman (2006)	12 subjects aged 7–16 years	A QEEG and a reading difference Topograph is obtained. Next, the therapists, train down the irregularities that show an important increase and train up the ones that show a notable decrease.	Each of the 12 subjects that underwent treatment, showed an improvement by more than two grade levels after 30–35 ten-minute sessions each.
Wang et al., (2007)	2 ADHD subjects aged 8 and 11 years	The 2 children were examined by an IVA – CPT, with 3 electrodes, Cz, Fp1 and Fp2 that were placed on their head in positions specified by the International 10–20 system.	The BCI–NFB-VR system can lengthen the attention span of children with ADHD.
Yang et al., (2017)	10 university students	Creation of a brain controlled game, that involves motor-imagery with an original BCI and game design. EEG output is generated by the Neuroscan device with 27 different channels of electrodes.	The bandpower analysis findings showed that participants' attention level improved during the experiment.
Zoefel et al., (2011)	24 students (14 in the NFT group aged 23.7 $\pm$ 2.3 years old and 10 in the control group aged 22.1 $\pm$ 3.8)	For each student, the treatment included one training session for each day from Monday to Friday. On the first and the fifth session, cognitive skilles were examined with a mental rotation test.	The UA amplitude during the first base rate showed a significantly higher amplitude than the first base rate of the first session ($t(10) = 3.59$, $p = 0.003$). Cognitive performance was significantly increased for the NFT group ($t(16) = 2.21$, $p = .029$) Independence was significant in the trained UA range between IAF and IAF+2 Hz ($t(10) = 2.39$, $p = 0.019$).

EEG: electroencephalogram; qEEG: Quantitative electroencephalogram; EO: Eyes Open; ADHD: attention-deficit/hyperactivity disorder; TBR: Theta/Beta Ratio; ES: Effective Size; EG: experimental group; CG: control group; VR: virtual reality; NF: neurofeedback; NFT: neurofeedback training; TOVA: Test of Variables of Attention; SCPs: Slow Cortical Potentials; 3D: 3 dimensional; BCI: brain computer interface; MI: motor imagery; T/B: Theta/Beta; ADHD-I: ADHD-Intervention; ADHD-NI: ADHD-Non-Intervention; ADHD-RS: ADHD-Rating Scale; EOG: electrooculography; IVA: Integrated Visual & Auditory; CPT: Continuous Performance Test; FC: Functional Connectivity.

symptoms after an 8-week training. Specifically, The ADHD-Intervention group had significantly greater reduction in the ADHD-Rating Scale clinician inattention scores compared to the ADHD-Non Intervention group. It is however noted that further research may need to examine ADHD patients that have undertaken BCI-based treatment for a longer period with long-term reexaminations, as well as the creation of adaptive educational tools that can take into account users' affection states (Martínez et al., 2016).

The progress of BCI studies with regard to computer game applications, show that BCI can provide several benefits when adapting them to the design principles of a game application. The impact of neurofeedback in the context of a simple computer game controlled by attention based brain signals are promising for boosting the attention level and cognitive skills of healthy as well as disabled people (Thomas and Vinod, 2016). Thomas et al. (2013) proposed a neurofeedback based game to improve the working memory and attention skills of five healthy subjects. The

Figure 3. Subjects must focus on a particular letter they want to write. Left, mid boards: row/column speller. Right board: single character speller.

user of the game should first concentrate on a 3 × 3 matrix consisting of numbers, memorize each number and then refill correctly each matrix box. The experimental analysis showed statistically significant performance improvement in increasing players' concentration and memory skills. BCI/EEG-based computer game interaction is best suited for gaming because of its high temporal resolution, affordability, portability, non-intrusive access, safety and enriching of experience of able-bodied and physical impaired users (Marshall et al., 2013). BCI video game-based neurofeedback enables subjects/patients to improve their attention spans, regulate their physiological and psychological states and enhance significantly the cognitive performance of the neurofeedback group in relation to the control group (Yang et al., 2017; Zoefel et al., 2011). However, results would be more informative to evaluate the impact of EEG based games if higher number of subjects are used to every group, more robust methods, precise treatment protocols and more imaginative gaming environments (Thomas and Vinod, 2016).

Meditation practicing has also been proved to improve concentration, attention and level of consciousness which are critical factors to drive BCI activities reducing experience of anxiety and inducing different states of consciousness and ‘thoughtless awareness’ during the performance of a mental task (Eskandari and Erfanian, 2008; Mahmoudi and Erfanian, 2006). BCI-based EEG neurofeedback showed good results on the level of focus and orientation, attentional control, implicit procedural memory and recognition memory among others (APA, 2013; Gruzelier, 2014; Shenjie et al., 2014; Leins et al., 2007). As a result, interesting breakthroughs have been produced in EEG-based BCIs and subjects are encouraged to maximize effort and help enhance performance (Coyle et al., 2011; Jiang et al., 2011; Kerous et al., 2017; Nijholt et al., 2009).

Moreover, neurofeedback has high potential to diagnose dyslexia and improve spelling disorder (Fadzal et al., 2011). In a study conducted to compare a group of dyslexic children with a matched control group significant correlation between the obtained EEG outcomes and the tests (articulation, rapid naming of letters, spelling and phoneme deletion) were revealed contributing to the diagnosis of subtypes of dyslexia and to the theory that neurobiological deficits may suggest dyslexia (Arns et al., 2007). Besides, memory performance improved by individual alpha neurofeedback training associated with electroencephalogram alpha activity (Nan et al., 2012; Zoefel et al., 2011). In a randomized controlled study on neurofeedback training of children with dyslexia, they noted a clinically significant advancement in spelling, but no similar

Table 3. Summary of articles on BCI-based applications for students with spatial and visuospatial disabilities.

Study (year)	Sample	Study contents	Key findings
Hammer et al., (2012)	83 healthy BCI novices (range 17–65, 79% of them were students)	The psychological test-battery included performance, personality and clinical tests and the vividness of movement imagery questionnaire. Brain signals were recorded from the scalp with a 128-channel EEG amplifier using 119 Ag/AgCl electrodes.	It is concluded that visuo-motor coordination, concentration and μ-peak when relaxed are greatly important determinants of success with an SMR-BCI that is mostly using machine-learning processes.
Hammer et al., (2014)	33 healthy participants aged 19–32 (most of them were students)	A considerable number of clinical, personality and performance tests were collected. EEG was acquired from 16 passive Ag/AgCl electrodes, mounted into a 64-channel cap at positions FP1, FP2, F3, Fz, F4, T7, C3, Cz, C4, T8, CP3, CP4, P3, Pz, P4, Oz.	Visuo-motor coordination ability and impulsivity were positively correlated with SMR feedback performance. Mean SMR-BCI performance across all feedback sessions was M = 79.00%
Jeunet et al., (2015)	18 participants, aged 21.5 ± 1.2,	The EEG signals were recorded using 30 scalp electrodes (F3, Fz, F4, FT7, FC5, FC3, FCz, FC4, FC6, FT8, C5, C3, C1, Cz, C2, C4, C6, CP3, CPz, CP4, P5, P3, P1, Pz, P2, P4, P6, PO7, PO8). Each user took part in 6 sessions, on 6 different days spread out over several weeks, performing 3 MI-tasks, 2 of which were non-motor tasks.	The study showed the way that a user's profile can influence their MI-BCI control skills. Therefore, they proposed a novel method of designing new protocls for MI-BCI training, that are adjusted to each user's profile.
Wang et al., (2007)	2 ADHD subjects aged 8 and 11 years	Both participants underwent assessment by an IVA - CPT. Three electrodes (Cz, Fp1, Fp2), were placed on their head as described in the International 10–20 system.	It is argued that the BCI–NFB-VR system helps ADHD subjects recover their cognitive function visualizing EEG signals techniques for restoring the movements.
Yang et al., (2017)	10 university students	A brain-controlled game based on MI is created. Both the BCI system and the game were designed. EEG output was obtained by Neuroscan using 27 different channels of electrodes.	The analysis of bandpower outcomes showed that participants' attention level increased throughout the experiment performing MI tasks.

EEG: electroencephalogram; ME: Motor execution; EO: Eyes Open; MIK: kinesthetic motor imagery; MIV: visual–motor imagery; OOM: observation of movement; ADHD: attention deficit/hyperactivity disorder; VR: virtual reality; NF: neurofeedback; BCI: brain computer interface; MI: motor imagery; IVA: Integrated Visual & Auditory; CPT: Continuous Performance Test; SMR: sensorimotor rhythms; Ag/AgCl: Silver/Silver Chloride.

improvement in reading skills was observed, potentially because many of them receive remedial teaching (Breteler et al., 2010). Other studies' findings suggest that neurofeedback treatment and clinical experience, as evidenced by the case examples is likely to result in remediating reading disability effectively over relatively short time periods (Thornton and Carmody, 2005; Walker and Norman, 2006). Research findings assist in the detection of several dyslexia subtypes and establish a link between EEG parameters and dyslexia relevant constructs. There remains skepticism among the researchers that BCI can lead to a great amount of exhaustion having a very low information transfer rate. This emphasizes the priorities of designing simple and precise devices along with suitable development platforms, meeting also ethical and legal implications (Kerous et al., 2017).

The details of the articles covered are outlined in Table 2.

3.2. BCI for spatial and visuospatial skills

Mental training and concentration is beneficial for spatial skills and performance in many fields such as sports, surgical performances and music (Jeunet et al., 2016). Research suggests that the developing brain is susceptible to alterations when fafcing environmental stimuli that affects the physical structure of the brain (Rabipour and Raz, 2012). BCI-based applications can become useful therapeutical tools to help patients enhance their cognitive skills either by using EEG signals and visualizing techniques for restoring their movements and communication or by utilizing Virtual Reality (VR) to produce useful response information to stay in certain brain state (Wang et al., 2007). Spatial ability, namely the capacity to understand, reason and remember the spatial relations among objects or space have shown significant improvement of

Table 4. Summary of articles on BCI-based applications for students with collaboration, communication and social disabilities.

Study (year)	Sample	Study contents	Key findings
Bakhshayesh et al., (2011)	35 children with ADHD aged 6–14 years (therapy group $N = 18$, CG $N = 17$)	Participants were randomly assigned to either the therapy or the control group. Training phase lasted 10–15 weeks (30 sessions-30 min each).	Analysis of Variance showed a significant effect of Time for Inattention (NF:Mpre = 1.42 ± 1.12; Mpost = 0.92 ± 0.81; BF:Mpre = 1.06 ± 0.78; Mpost = 1.06 ± 0.53; F(1,33) = 6.91; p = .013), Hyperactivity(NF:Mpre = 1.17 ± 0.96; Mpost = 0.69 ± 0.64; BF:Mpre = 1.01 ± 0.81; Mpost = 0.86 ± 0.59; F(1,33) = 6.48; p = .016) and total mean scores (NF:Mpre = 1.38 ± 0.74; Mpost = 1.04 ± 0.53; BF:Mpre = 1.38 ± 0.57; Mpost = 1.31 ± 0.57; F(1,33) = 5.86; p = .021).
Coben and Padolsky (2007)	EG N = 37 children with ASD, CG $N = 12$	Non-randomized controlled study. NFT period of 20 sessions. 32 channels including F8–F7, Ft8-Ft7, T4-T3, F7–F8, F6–F5, F4–F3.	Significant reductions in ASD behaviors, executive deficits, representing a 40% reduction and 89% success rate in ASD symptoms. Following NFT a considerablereduction in ASD symptomatology was reportedon the ATEC (F (1, 40) = 18.360, p = .000)
Drechsler et al., (2007)	30 children with ADHD. 17 children participated in the EC and 13 children in the CG.	Non-randomized study. NF training consisted of 2 weeks Daily double sessions, 5 weeks Transfer with cards and 3 weeks of 5 double sessions. Group Therapy consisted of 12–15 weeks of 14–15 double sessions (90 min).	According to parents' ratings, both groups showed behavioural improvements over time which seems to account especially for changes in behavioural control. On the neuropsychological tests both groups showed significant improvement. Effects were moderate to large in the neurofeedback group and small to moderate after group therapy.
Gani et al., (2008)	23 children aged 8–13 years, SCP group $N = 11$, T/B group $N = 12$	Randomized long-term follow-up study. 30 sessions. Electrodes were affixed on Cz, C3f, and C4f. Each session consisted of 3–5 runs. Each run included 39 trials.	Children improved in behavior and attention after being treated with NF. These effects were stable or even more improved 2 years after the last training session had taken place. Theta/Beta group children showed significantly more above-average achievements (t_{10} = -4.755, p = 0.003, ES = 0.39) at 2 year follow-up compared to screening.
Kouijzer et al., (2009)	14 children with ASD, EG $N = 7$, CG $N = 7$, aged 8–12 years	40 sessions of NF. Data were acquired at Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2 scalp locations.	NF treatment resulted in clear improvements in children's executive functioning as reflected in a wide range of executive function tasks. Auditory selective attention (F (1,11) = 8.437, p = .014, η = .434). Cognitive flexibility (F (1,11) = 5.602, p = .037, η = .337). Complex sequential problems, F (1,11) = 7.198, p = .021, η = .396. General communication, F (1,12) = 5.379, p = .039, η = .310, but not for pragmatics, F (1,12) = .036, p = .852, η = .003.

EEG: electroencephalogram; ASD: Autistic Spectrum Disorder; ADHD: attention-deficit/hyperactivity disorder; ATEC: Autism Treatment Evaluation Checklist; NF: neurofeedback; NFT: neurofeedback training; BCI: brain computer interface; SB: social behavior; CSs: communication skills; TB: typical behavior; EG: experimental group; CG: control group; SCP: Slow Cortical Potential (a special type of event related potentials reflecting the excitation threshold of the upper cortical layer); T/B: Theta/Beta.

Table 5. Summary of articles on BCI-based applications for immersion, creativity and emotional skills.

Study (year)	Sample	Study contents	Key findings
Dennis and Hajcak (2009)	20 children 5–10 years old, younger children (aged 5–6) N = 10 and older children (aged 7–10) *N* = 10 with 5 boys and 5 girls in each age group.	30 developmentally appropriate pictures were selected from the International Affective Picture System while EEG was being recorded using a BCI system appropriately designed. 64 electrodes were placed on the scalp based on the 10–20 system in addition to 2 more electrodes on the left and right mastoids to generate the reports.	No significant gender differences emerged. The study demonstrates that a strategy that controls cognitive emotion could moderate childrens' LPP. Significant interaction between Interpretation Type and Child Gender $F(1,16) = 5.32$, $p < .05$, partial $\eta^2 = .25$. Significant Interpretation Type by Child Gender and by Child Age interaction. $F(1,16) = 5.05$, $p < .05$, partial $\eta^2 = .24$
Friedrich et al., (2015)	13 children with ASD (6–17 years old) Group1 *N* = 6, Group2 *N* = 7	16 1h NFT sessions 2–3 times per week during 6–10 weeks. Subjects were pseudo-randomly assigned to one of two training groups. During these sessions the children played a Social Mirroring Game, controling the game by enhancing mu power.	Overall, the Social Mirroring Game was successful at engaging children with ASD during NFT and produced positive effects on all measures. Children displayed significantly more correct responses in the emotion recognition task. Mu Power: F1,11 = 52.6, $p < .01$, $\eta^2 = .83$ Theta and Beta: F1,11 = 57.4/38.3, $p < .01$, $\eta^2 = .84/.77$
Gruzelier et al., (2014a)	33 11-year olds were randomised to 10 sessions and divided into three groups (N = 11 in each): A/T training, SMR training and a non-training control group.	For SMR training the active scalp electrode was placed over sensory-motor cortex at Cz, the standard placement for the process. For A/T training children relaxed with their eyes closed and an active electrode at Pz, a standard placement for measuring alpha and theta.	Rehearsed performance: Group X Time $F(2, 27) = 3.313$, $p = 0.05$; A/T $t(9) = 2.18$,$p = 0.057$; SMR $t(8) = 0.39$; control $t(10) = 0.89$. Creativity scale: Group X Time ($F(2, 27) = 6.224$, $p = 0.006$. Communication subscale: Group X Time $F(2,27) = 11.326$, $p = 0.001$) Decrease in commission errors ($F(2, 26) = 20.36$, $p = 0.001$; A/T $t(8) = 4.47$, $p = 0.002$; SMR $t(6) = 1.98$, $p = 0.095$; controls $t(9) = 1.71$, ns)
Gruzelier et al., 2014b	64 conservatoire students in their first year of BA contemporary dance. Four groups: Alpha–theta neurofeedback (AT) *N* = 18, Heart-rate variability (HRV), Choreology Studies, No-intervention control.	Randomised study. Four groups: A/T NF, HRV, Choreology Studies, No-intervention control. 10-session 20 min long protocol.	Linear decrease in alpha values (F 1,9 = 9.2, $p < 0.05$) and linear increase in theta values (F 1,9 = 9.8, $p < 0.05$). Heart rate variability: (Linear, F 1,8 = 6.227, p 0.037 < Quadratic, F = 2.10, ns). Dance performance ratings ratings ranged between r = .54 to r = .67, p's < .001. Mood: the only group difference was in Anxiety (F3,60 = 2.82, $p < .04$; Depression, F = 0.39; Stress, F = 1.37). Cognitive creativity: t-tests confirming a greater increase for the AT group compared with the CG (t30 = 3.2, $p < .01$).
Leventon et al., 2014	46 school age children 5–8 years old. Children were divided into two age groups: younger *N* = 24 11 girls; Mage = 6.23 years, range = 5.42–7.50 years and older *N* = 22 13 girls; Mage = 8.08 years, range = 7.58–8.92 years	164 child-appropriate images were selected from the International Affective Picture System. Study consisted of two sessions separated by 24 h. EEG data in Sessions 1 and 2 were collected using an EEG cap with 32-shielded Ag/AgCl electrodes.	For valence ratings, a main effect of emotion condition was observed, $F(1.38,37.35) = 43.56$, $p < .001$, $p\eta^2 = .617$, emotion condition significantly influenced heart rate responses to the images, $F(2,68) = 4.21$, $p = .02$.
Martínez et al., 2016	The study observed children specifically invited to this study as well as children currently undergoing behavioral therapy.	A case-based study conducted to examine and gain an understanding of the emotions expressed by children with ADHD, which were invited to play physical and digital game forms of the Stroop and Flanker tests as well as memory-based games, practicing memory, attention and reasoning skills.	Affection states related to engagement, frustration, meditation and excitement were decoded from EEG data, video analysis and scores obtained from the gameplay. Implementing neurofeedback in the everyday school environment school showed to be achievable with great educational potential.
Schoneveld et al., 2016	750 children 7–13 ys old. Randomized controlled study *N* = 136. Mindlight group *n* = 69 Max group n = 67 Younger girls (grade 3 and 4), older girls (grade 5 and 6), younger boys (grade 3 and 4) and older boys (grade 5 and 6).	Children use Microsoft Xbox 360 controller and a one-channel dry-sensor EEG headset that transforms the raw EEG values and converts them to gradations in a light placed on the head of the avatar's game (Mindlight). The 'mindlight' shines brighter, the more relaxed the user feels.	Pretest anxiety scores (total anxiety: $t(132) = -4.18$, $p = 0.000$; personalized anxiety: $t(132) = -2.55$, $p = 0.012$; maternal report: $t(115) = -2.12$, $p = 0.036$; paternal report: $t(92) = -1.51$, $p = 0.135$), all posttest anxiety scores (total anxiety: $t(122) = -3.47$, $p = 0.001$; personalized anxiety: $t(122) = -2.89$, $p = 0.005$; maternal report: $t(60) = -2.24$, $p = 0.029$; paternal report: $t(53) = -2.13$, $p = 0.038$)

(*continued on next page*)

Table 5 (*continued*)

Study (year)	Sample	Study contents	Key findings
Verkijika and De Wet 2015	36 participants 9–16 years old The average age of the participants was 14.06 years with a standard deviation of 2.08.	Each subject was expected to complete two sessions. The research edition of the Emotiv EPOC BCI device was used. The scope was to determine whether using a BCI mathematics educational game could help students to reduce effectively math anxiety. The participants had to play two levels of the Math-Mind Game.	The effect of math anxiety can be trained and decreased with a BCI-based mathematics educational game providing a home based solution for reducing math anxiety.

LPP: Late Positive Potential; A/T: Alpha–theta; HRV: Heart-rate variability; EEG: electroencephalogram; ASD: Autism Spectrum Disorder; ADHD: attention deficit/hyperactivity disorder; NF: neurofeedback; NFT: neurofeedback training; BCI: brain computer interface; SMR: sensorimotor rhythms; ERPs: Event-Related Potentials; BA: bachelor of arts; Ag/AgCl: Silver/Silver Chloride; CG: control group.

participants in speed, memory, attention, flexibility and problem solving while performing an EEG spatial activity using a lightweight EEG device (Promsorn et al., 2017). BCIs based on visual stimuli can be implemented with two different approaches, which are named according the brain patterns they produce: P300 potentials and steady-state visual evoked potentials (SSVEP). P300 based BCI stimuli are usually letters or symbols which elicit a brain pattern about 300 ms after the presentation of the stimulus that control a cursor, robot arm, or mobile robot Figure 3 (Guger and Edlinger, 2009). Similarly, a SSVEP based BCI requires several visual stimuli that flicker continuously with different frequencies eliciting a SVEP in the visual cortex which generate as output signals relevant to a user's intention (Bell et al., 2008; Citi et al., 2008; Graimann et al., 2009; Li et al., 2009). Important precondition for good performance in the modulation of sensorimotor rhythms (SMR) BCI performance is the ability to sustain attention and control impulsive movements throughout the BCI experiment (Hammer et al. 2012, 2014; Jeunet et al., 2015). To improve motor-imagery based BCI control, experimental conditions should support 'real' motor imagery that involves kinesthetic experiences instead of visual representations of actions (Neuper et al., 2005). Additionally, operation of BCI devices involves learning mechanisms in the brain such as when someone learns to ride a bicycle. A well-defined training method and useful response signals offer the user feedback on how well their strategy works and facilitates their learning process. Combining BCI and VR with a rich virtual representation of the feedback signal can result in lifelike BCI response schemes improving a person's brain activity skills (Neuper and Pfurtscheller, 2009).

There is an increasing number of BCIs studies presenting 2-D pointer movement control, which generate from the brain using Evolutionary algorithms and adapting to each user and each session without the participation of peripheral nerves and muscles (Citi et al., 2008; McFarland and Wolpaw, 2011). Moreover, other studies showed a significant correlation between spatial abilities and surgery, mathematics or engineering and anatomy education (Promsorn et al., 2017). A BCI system based on different brain mechanisms, such as number multiplication, visual counting and letter composing can teach humans how to change their brain electrical activity to restore communication or motor function (Wang et al., 2007). In addition, the users were able to increase their attention span by examining EEG features produced from motor imagery (Yang et al., 2017). The optimal way of representation of brain signals or other EEG activity depends on both the user who should feel motivated and does not become bored and frustrated, and on the task that should be challenging to augment the brain's capacity to regulate itself (Neuper and Pfurtscheller, 2009). Psychological parameters have a moderate, but notable importance in overcoming the BCI inefficiency phenomenon and improve user's capacity to combine visual and motor integration (Hammer et al., 2012).

Information of the articles covered is in Table 3.

3.3. BCI for collaboration, communication and social skills

Neurofeedback BCI treatments proved to be effective approaches for the modulation of brain activity, cognition and behavior (Bakhshayesh et al., 2011; Drechsler et al., 2007; Huster et al., 2014). In addition, in another study after a 2-year follow-up, all improvements in behavior proved to be stable indicating that these children were still able to control effectively their brain activity (Arns et al., 2009; Gani et al., 2008). Friedrich et al., (2014) have designed an innovative game that included social interactions, provided neural and body-based feedback for children on the autism spectrum, and highlighted the importance of using NF Training and Biofeedback to reinforce their neurophysiological and peripheral physiological behavior in social situations. Following neurofeedback treatment, ASD chidren showed further improvement in their typical behavior and communicative skills as well as during social interaction, compared with matched controls (Coben and Padolsky, 2007; Kouijzer et al., 2009; Pineda et al., 2014). BCI technology manages to decode the silent codes of human brain signals in applications that need spelling, identify semantic categorization, or silent speech communication and help individuals with normal/moderate/severe motor and communication disorders to express their intention and thoughts (Abdulkader et al., 2015; Brumberg et al., 2010; Lelievre et al., 2013; Wang et al., 2011). Mind reading and remote communication through BCI systems build a communication bridge between human brain and the external world. These systems are designed to treat users with disabilities to improve their motor substitution, motor recovery, and communication skills, but also as a modal tool for healthy people (Abdulkader et al., 2015; Bonnet et al., 2013; Morioka et al., 2014; van de Laar et al., 2013).

It would be interesting to analyze from a neuroscience perspective how collaboration and motivation among teams can influence task performance and benefit BCI design when specific feelings of frustration,

Table 6. Main results of the review.

Main results of the review of BCI-based applications for training and rehabilitation of students with neurodevelopmental disorders.
• are used as promising approach, both diagnostic and prognostic • provide attention-span training • improve motor imagery classification results • achieve better cognitive scores in terms of attention skills and memory power • dyslexia appears as the main learning disorder that can be treated • cognitive skills such as speed, memory, attention, flexibility and problem solving showed significant improvements • improve ASD children's social interaction and communicative abilities • proved to be particularly effective for ADHD • foster students' immersion, creativity and emotional skills • reduce experience of anxiety • improve a human's ability to control their brain signals

hesitation, shyness, or irritability are exhibited (Bonnet et al., 2013). Even without perfect control BCI games can bring value added to a modern game that gets users curious and interested in this new modality although control and involvement might be lower in the BCI condition (van de Laar et al., 2013). Also, it would be interesting to conduct a randomized assignment of treatment and control groups to exclude any possible interaction between the treatment effect and subject selection when treatment is selected by patients (via parents). Furthermore, it would be beneficial to explore the connectivity between the frontal, temporal, central, parietal, and occipital lobes in Autism and other conditions as well as a long-term follow-up to demonstrate that BCI training has a substantial impact on individuals with ASD affecting their social, emotional and cognitive function (Coben and Padolsky, 2007).

The details of the articles covered are summarized in Table 4.

3.4. BCI for immersion, creativity and emotional skills

The proliferation of wireless EEG technology advances in computational techniques and machine learning reflected a considerable growth of EEG-based emotion detection journal publications. BCI emotion-based recognition systems improve the communication between users and machines. Similarly, lead to a natural and effective user experience detecting levels of meditation, engagement, frustration, excitement and stress (Al-Nafjan et al., 2017; Dennis and Hajcak, 2009; Friedrich et al., 2015; Gruzelier et al. 2014a, 2014b; Leventon et al., 2014). Moreover, a novel emotion elicitation technique based on the Mirror Neuron System has revealed the potential of robust emotion recognition method from EEG contributing to improve Human Machine Interface (HMI). The implemented technique enabled advanced monitoring of user status regarding six basic emotions namely happiness, surprise, anger, fear, disgust and sadness (Petrantonakis and Hadjileontiadis, 2010). Martínez et al. (2016) conducted a case study where they created a computational system namely KAPEAN that adapted content and resources depending on ADHD childrens' emotional responses. The researchers pose the issue on how detectable a humation emotion can be when using automated methods. According to their experiment, emotions (affective states) that have to do with a children's level of contentration, fatigue, excitement and meditation were detected from analysing the EEG outputs from their interaction with a game. During the sessions, children practiced their cognitive, attention and reasoning skills. It is concluded that the KAPEAN setting enabled the researchers to better interpret a number of affective states that a child with ADHD may exhibit when undertaking a task. Liberati et al. (2015), state that affective BCI field is in constant development combining a wide variation of neuroimaging techniques to recognize a subject's affective state, concluding that the gap between what is tested in laboratory settings and the translation of the findings to everyday situations, still needs to be filled. Schoneveld et al. (2016) evaluated a game developed on evidence-based practices for reducing children's anxiety and proposed to maximize dedication, emotional strength and commitment. Multiple evidence-based strategies for minimizing stress by changing users' state of mind were embedded in the game. The 'mindlight' shines brighter, in proportion to the user's feeling of relaxation. If a user feels anxious, the light weakens and they are made to shift their mind in a more relaxed state through neurofeedback reinforcement mechanics. Children demonstrated great relief of anxiety after 3 months, according to the children/parent reports. Similarly, Verkijika & De Wet (2015) conducted a study whose central aim was to determine whether a BCI-based mathematic educational game could be used to reduce math anxiety in students between the age group of 9–16 years. The study showed that a BCI math mind game could effectively train all participants to reduce math anxiety.

There are various elements that positively contribute to the development of improved EEG-based emotion detection technology namely the increased neurobiological knowledge, faster computational processing, more available and reliable devices for recording brain signals and more powerful machine learning algorithms (Al-Nafjan et al., 2017). Technical challenges concerned with the system obstacles related to the recorded electrophysiological properties of the brain signals and usability challenges which affect the level of human acceptance can contribute in EEG signals variability Abdulkader et al., (2015).

The details of the articles covered are summarized in Table 5.

4. Results and discussion

Al-Nafjan et al. (2017) predicted that mainstream adoption of Brain Computer Interface would occur in more than 10 years, as appeared in the Gartner's Hype Cycle report for Emerging technologies, 2016. BCI is gaining more attention from people with less severe disabilities than those in the locked-in and complete locked-in state and even healthy individuals for improving cognitive skills like memory, attention, communication and emotion or entertainment (Ramadan et al., 2015). Lotte and Jeunet (2015) stated that in order to bring BCI reliability to the next level, it is necessary to build a comprehensive training framework, in order to teach anyone to gain BCI control and study what the impact of current BCI training protocols on BCI performance and illiteracy/deficiency is. Poor EEG signal-to-noise ratio and non-stationarity of the signals are some of the reasons why a given subject may not gain BCI control among many others.

Moreover, dyslexia seems to be one of the learning disorders that could be treated by BCI EEG neurofeedback training as it has been shown by studies identifying the different activities of the brain of dyslexics and non-dyslexics when using mental activity to generate control command in BCI device (Fadzal et al., 2011). In addition, BCI spatial abilities training has shown significant improvements in cognitive skills such as speed, memory, attention, flexibility and problem solving (Promsorn et al., 2017). The relationship between BCI performance and motor processes are mediated by spatial ability levels related to the personality and cognitive profile of the user (Jeunet et al., 2015).

BCI's training value added for students' immersion, creativity and emotional skills has been well documented in studies related to ADHD/ASD students' affective states. Qian et al. (2018) presented evidence that BCI-based intervention improved ADHD symptoms, regularized the salience processing in ADHD and facilitated brain maturation of children with ADHD. Neurofeedback training compared to biofeedback (BF) training (aiming at forehead muscle relaxation) in ADHD children improved hyperkinetic symptoms. The effect sizes showed larger improvements for the NF group (aiming at theta/beta ratio reduction) than for the BF group (Bakhshayesh et al., 2011). BCI studies demonstrate promising findings in both cognitive assessment and training contexts according both to the different populations involved (ADHD, ASD, dyslexia) and to the specific target of cognitive interventions (attention, memory, language and visuospatial abilities) (Carelli et al., 2017). Neuro-feedback game systems process signal methods yielding improved motor imagery classification results, which prove the feasibility of the BCI game systems to provide attention-span training and achieve better cognitive scores in terms of attention skills and memory power (Yang et al., 2017). It is noted that more studies should consider ADHD's clinical heterogeneity and examine patients with ADHD that underwent BCI-based therapy sessions for a longer time and with long-term reexaminations. Another important issue is that in order to evaluate the efficacy of BCI-based training program in treating ADHD and to avoid an exaggerated treatment effect, a well-designed controlled trial is needed (Qian et al., 2018). In our opinion, there are still many challenges to be solved namely the generalization of effects to subgroups of individuals with ADHD, methodological limitations including small samples and low number of NF training sessions.

There are unsolved issues that prevent BCI systems' widespread use in practice namely the speed and accuracy of current devices and the ease of obtaining high-quality recordings by home users including adaptation to the needs and the profile of the user (Coyle, 2016; Jeunet et al., 2015). Hammer et al. (2014) estimated that there is a population up to 50% not able to manage BCI control effectively. Moreover, some other factors seem to impact BCI performance such as demographic characteristics (age, gender), experience/habits (playing a musical instrument, video games, sports, typing) and user's environment (Jeunet et al., 2016).

Role-playing game mechanics track and modulate behavior changes. Moreover, they provide novel insights about the physiological correlates of ASD and link appropriate behavior in social situations (Friedrich et al., 2014). The findings of a single-blind randomized controlled trial imply that the specific version of NF of the BCI design or other extraneous factors may be the factors that result in a change in behavior such as behavioural contingencies, self-efficacy, relaxation, structured learning environment and routines (Bakhshayesh et al., 2011). NFB may hold particular value for ASD treatment comparable with the effects found to children with ADHD (Kouijzer et al., 2009). van de Laar et al. (2013) showed the importance of using BCI Neurofeedback Training to improve students' collaboration, communication and social skills related to ASD children's social interaction and communicative abilities. BCI games can be an appropriate tool to improve behavior, cognition and emotional regulation in children with ASD using neurofeedback based on imitation and emotional responsiveness (Friedrich et al., 2015).

Although the results show constraints on cognitive generalization, when considering the effect on creativity, neurofeedback training did have as an outcome a notable development in levels of creativity in domains of music, dance and acting and divergent thinking (Gruzelier et al., 2014b). Findings indicate that in the early school-age years, emotional stimuli is less well integrated with memory processes thus, further work should examine the developmental trajectory of the emotion effect (Leventon et al., 2014). However, there are still questions to answer as for the level of detection of possible human mental states when using digital instructional resources (Martínez et al., 2016). These questions are related to subject elicited versus event elicited emotions, laboratory design versus real world, expression versus feeling, open recordings versus hidden recordings and emotion-purpose versus other-purpose (Petrantonakis and Hadjileontiadis, 2010). BCI games show a significant potential for improving both mental and emotional innovative approaches (Schoneveld et al., 2016). For example, research findings showed that an educational BCI game focused on mathematics could effectively train and help in math anxiety (Verkijika and De Wet, 2015).

In Table 6 main results of the review of BCI-based applications for training and rehabilitation of students with neurodevelopmental disorders are presented.

5. Conclusion

This paper focuses on exploring and highlighting representative and non-exhaustive studies about BCI-based applications regarding memory, attention, visuospatial, learning, collaboration and communication, social, creative and emotional skills. Moreover, it draws attention to BCI systems that are non-invasive and develop new levels of control for students with anxiety, ADHD or Dyslexia. This paper illustrates that BCI technology has potential applications for users having less severe disabilities, or even healthy users. According to the project ‘BNCI Horizon 2020: The Future of Brain/Neural Computer Interaction’ the possible changes of BCI in the future can be viewed with regard to “user”, “industry” and “research” (Brunner et al., 2015). BCI studies demonstrate auspicious findings in both cognitive assessment and training contexts according to the different populations involved (ADHD, ASD, dyslexia) and to the particular target of cognitive interventions (attention, memory, language and visuospatial abilities) (Carelli et al., 2017). Possible future directions in the BCI technology will be contingent on the development of appropriate software combined appropriately for all subjects in line with their needs and desires (Alamdari et al., 2016). Further studies are needed towards a more systematic investigation of the BCI efficiency in relation to cognitive skills namely memory, attention, visuospatial, learning, collaboration, and communication, social, creative and emotional. Thus, it is critical to investigate the longstanding results of BCI-based applications for training and rehabilitation of students with neurodevelopmental disorders in a longitudinal study. Future research could further examine the phonological or orthographic deficits and ADHD using EEG data either for prognostic purposes or for treatment module (Arns et al. 2007, 2013; Breteler et al., 2010; Gevensleben et al., 2009). In future studies the role of age, ability to concentrate on the task and visuo-motor coordination have to be investigated to elucidate their influence to overcome the BCI inefficiency phenomenon without long-lasting user-training (Hammer et al., 2012). Future work will consist in developing BCI training protocols to improve the users' spatial abilities related to BCI performance providing a user-specific support namely cognitive, emotional and social (Jeunet et al., 2015). A cautious training of users with a motor-imagery-based BCI system that involves a set of kinesthetic or visual representation of actions is vital to improve BCI control (Neuper et al., 2005). To summarize, further investigations are needed to study the connection between cognitive and spatial abilities and BCI effectiveness (Jeunet et al., 2016).

BCI tools need experts to deal with them and face challenges such as low BCI signal strength, low data transfer rate and high error percentage due to high brain signal variability (Rao et al., 2012; Ramadan et al., 2015). The system's accuracy is reduced due to the inability of the subjects to retain identical intellectual states during different sessions as it is found that long periods of usage introduces cognitive fatigue. Besides, BCI signals are affected by the person's eye blinks, muscular movements, suddenly hearing sound etc (Soman et al., 2012). The usage of BCI systems is limited in clinical settings due to the accuracy and reliability of sensory interfacing and translation algorithms of these technologies that involve time constraints, the number of electrodes, and the number of recognized emotions with regard to the low-to-noise ratio in noninvasive EEG systems (Al-Nafjan et al., 2017). Challenging factors that affect the EEG recording while a BCI recording is performed could be cognitive load, practice and attention, training time, and mental or emotional states such as frustration, depression, fatigue, distractions, motivations and desire (Alamdari et al., 2016). Further improvements in the design of a methodology is vital that involve bette controlled studies, larger samples, and a more accurate collection of the samples' characteristics and the data from their follow-up sessions (Kouijzer et al., 2009). Many other features of BCIs also demands considerable thought such as the need to be faster and inexpensive and the user's comfort in using a BCI system (Haider and Fazel-Rezai, 2017). The BCI system needs to have a faster speed and accuracy when it comes to the signal processing and translation algorithms used, under the effort of an interdisciplinary team of engineers, computer programmers, psychologists, neuroscientists, and neurohabilitation specialists in order to be successfully improved and developed (Alamdari et al., 2016). Other BCI challenges could be classified as followed: A lack in developing principles for a BCI system, participants might get exhausted and less motivated to continue participating in the long training, Non-linearity and Non-stationarity in EEG that devalue the performance of the BCI system as a whole, Information transfer rate to measure the effectiveness of BCI applications, The development of invasive and non-invasive sensors, Real-life effective and low-cost applications, Ethical and security issues, Difficulty to distinguish a common perspective among all BCI key players on future trends and policies of BCI technologies (Ramadan and Vasilakos, 2017).

In this review, we have referred to state-of-the-art BCI studies, analyzing the contribution of BCI technology methods as intervention practices for training and rehabilitation of students with neurodevelopmental disorders. BCI effectiveness is evidenced, notwithstanding important constraints and limitations regarding the generalization and the user acceptance of the techniques and the laboratory design of the studies. Brain signal acquisition and monitoring provide numerous solutions for self-regulation, social, emotional and cognitive function and entertainment where BCI systems may apply in fields such as education and psychology for training and rehabilitation of students with neurodevelopmental disorders.

Declarations

Author contribution statement

George Papanastasiou: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Athanasios Drigas: Conceived and designed the experiments; Performed the experiments.

Charalabos Skianis: Contributed reagents, materials, analysis tools or data.

Miltiadis Lytras: Analyzed and interpreted the data.

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Additional information

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