Journal of Research High School
Vol. 2024 (9) 363 – 375
ISSN 2688-3651 [online]

Computerized Diagnostic and Therapeutic Strategies for Patients with ADHD: Artificial Intelligence and Computerized Games

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Received June 10, 2024; Revised July 6, 2024; Accepted July 19, 2024

Abstract

Attention deficit and hyperactivity disorder (ADHD) is a mental disorder that is characterized by obvious difficulty in concentration, short duration of attention, and hasty action. Traditional diagnosis mainly based on subjective report or questionnaire has the limitation of inconsistency and inaccuracy. Main treatment, pharmacology, is also criticized by irresponsiveness, overuse, side effects, or reluctance from patients. Recently, computerized methods have been developed and applied as diagnostic and treatment tools in various medical fields including psychiatry. This review was to describe computerized methods applying for diagnosis and treatment of ADHD that have been used. For this, articles were selected through extensive search of databases and reviewed with regard to diagnosis using machine learning (ML) and deep learning (DL) with extracted data from structural and functional magnetic resonance image, electroencephalography (EEG), and genetic study as well as treatment by computer games based on EEG feedback or not. Overall, the literatures included in this review stated that ML/DL techniques provided objective and reliable diagnostic tools with improved accuracy and computer games achieved better results in reduction of ADHD related symptoms than other traditional treatment. Computerized methods will be promising strategies to accurately select the patients with ADHD benefitted by treatment and provide the effective treatment method.

Keywors: Attention deficits and hyperactive disorder, Machine learning, Deep learning, Computer games, Diagnosis, Treatment

1. Introduction

Attention-deficit and hyperactivity disorder (ADHD) is a neurodevelopmental disorder characterized by impulsive disregard and an excessively agitated response to environmental disturbances(Puiu et al., 2018). This includes various cognitive and behavioral symptoms including the deficit or trouble of executive functioning, working memory, processing speed, finishing work, or emotional control(Ahire et al., 2023). The patients with ADHD have poorer educational and social outcomes, increased chance of injury during daily activities, and high tendency of association with other mental problems such as depression and anxiety(Dalsgaard et al., 2015; Rodriguez et al., 2024). These properties make the conditions more heterogenous and complicated, which ultimately prevents early diagnosis and further appropriate interventions.

With regards to diagnosis in clinical setting, physicians usually rely on subjective methods such as self-report or parent/teacher-based interviews focusing on cognitive and behavioral aspects. However, these subjective tests have faced criticism or controversies about their diagnostic validity resulted from inconsistency or contradictory response(Zelnik et al., 2012). Therefore, the necessities of diagnostic method with high consistency and accuracy are increasing.

Vol. 2024 (9) 363 – 375
ISSN 2688-3651 [online]

As to treatment, pharmacological treatment is regarded to be main treatment strategy and effective first-line treatments for ADHD. However, up to half of patients discontinue medication within the first 3 years of treatment due to adverse effects and treatment ineffectiveness(Nimmo-Smith et al., 2020). Also, there has been issues about overuse or misuse of medication, which in turn is frequently associated with dependence and diversion. A study reported that misuse and diversion of stimulation medication for ADHD treatment were common problems, with the prevalence believed to be approximately 5% to 10% of high school students and 5% to 35% of college students(Clemow & Walker 2014). Also, the emotional barrier for diagnosis or social stigma and adverse effects associated with medication often causes the patients to be reluctant to seek treatment, thus worsening their conditions. Therefore, non-pharmacological treatment methods including cognitive behavioral therapy, neurofeedback training, or mindfulness training were performed for substitute or additive to medication(Drechsler et al., 2020; Wakelin et al., 2023). Computer games were also assumed to be treatment option that had advantage of being enjoyed by patients more than any other treatment method.

Recently, as remarkable development of the computer science and its related fields, computer techniques and artificial intelligence (AI) is placed on the outstanding positions in various medical fields(Choi et al., 2020; Ramesh et al., 2004; Sarkar et al., 2023; Tran et al., 2021). Also, computerized techniques for the purpose of diagnosis and treatment of ADHD have been introduced and gained attention. This narrative review is to describe recently developed computerized diagnostic and therapeutic tools for ADHD that have been used and are expected to be promising strategies in the future, which assists the readers in obtaining up-to-date knowledges about forthcoming clinical approaches onto the patients with ADHD.

2. Materials and Methods

For this narrative review, a search of published literatures was conducted in the Medline (PubMed), Embase, Cochrane Review, and PsyInfo databases for articles published until May 31, 2024 using search terms. Search terms included "attention deficit disorder with hyperactivity", "artificial intelligence", "machine learning", "deep learning", "computational intelligence", "video games", and "computerized treatment." The literatures were selected regarding diagnosis of ADHD made by utilizing artificial intelligence, machine learning technique(ML), or deep learning(DL) techniques and treatment for ADHD by computerized serious games through reviewing title, abstract, and full text. The studies using only clinical diagnosis based on interview and/or questionnaire or treatment by non-computerized treatment method such as medication, psychotherapy, or brain stimulation were excluded. Among 2197 studies that were initially included after removing duplicates, selection of relevant studies was conducted on the basis of title and abstract review, followed by full-text screening. Finally, 29 studies were selected in this narrative review. (Figure 1)

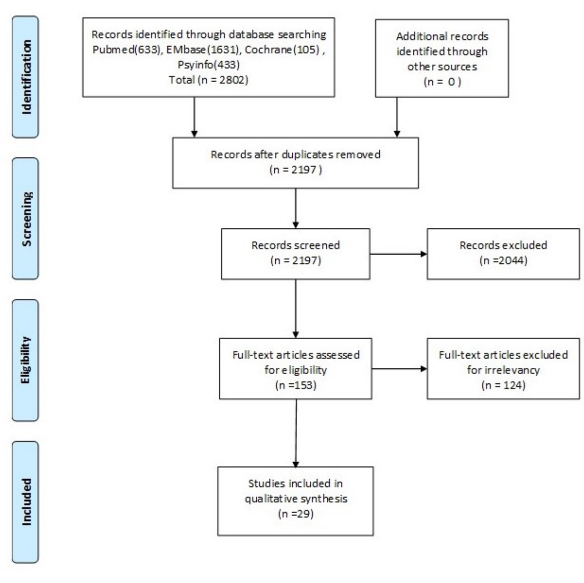

Figure 1. Flow diagram of study selection

3. Results

3.1 Diagnosis by structural magnetic resonance image (MRI) data

Chang et al.'s study (2012) used isotropic local binary patterns on three orthogonal planes (LBP-TOP) for extracting data from brain magnetic resonance images. They identified that gray matter gyrification data provided the

Vol. 2024 (9) 363 – 375
ISSN 2688-3651 [online]

higher discriminative power than other brain regions for separating ADHD from normal subjects. This results suggested that an ADHD classification model based only on anatomical data from structural MRI could be easier and not inferior in usefulness for ADHD classification in comparison with classification model by data from functional MRI(fMRI) necessitating complex preprocess(Chang et al., 2012). Peng et al. (2013) compared the diagnostic accuracy of ADHD between classical support vector machine (SVM) method and extreme learning machine (ELM) and revealed that ELM(90.18% of accuracy) was better than SVM(86.55% of accuracy). They also identified the brain regions, providing most remarkable different features between ADHD and healthy subjects; frontal lobe, temporal lobe, occipital lobe and insular(Peng et al., 2013). Iannaccone et al.'s study (2015) using SVM algorithm also indicated predictive brain region for ADHD, which were posterior cingulate, temporal and occipital cortex(Iannaccone et al., 2015). Johnston et al. (2014) using SVM accomplished 93% of diagnostic accuracy, supported by a region of reduced white matter in the brainstem, associated with pons volumetric reduction, adjacent to the noradrenergic locus coeruleus and dopaminergic ventral tegmental area nuclei. This result suggested that noradrenergic disconnection or dysregulation in brainstem was main pathophysiology of ADHD and hereby, medications to regulate dopaminergic and noradrenergic function could be useful(Johnston et al., 2014).

3.2 Diagnosis by fMRI data

AI using extracted data from fMRI had the characteristics of assessing the interconnection between brain regions that were not supported from structural MRI data, mainly focusing on relationship between specific brain region to ADHD. Du et al.'s (2016) performed discriminative subnetwork selection from whole brain networks in fMRI, extracted the features from selected subnetworks using graph kernel principal component (PCA), and then conducted ADHD classification by SVM. They stated that these methods could not only achieved high accuracy rate (94.91%), but discover the discriminative subnetwork in addition to discriminative brain regions, which were helpful to promote the understanding of ADHD (Du et al., 2016). Dey et al. (2014) constructed functional brain connectivity networks using resting state brain fMRI data and showed notable classification accuracies on the training (70.49%) and test data sets (73.55%)(Dey et al., 2014). Dai et al.'s study (2012) that applied SVM on functional connections using fMRI data, reported an 65.87% of ADHD classification accuracy(Dai et al., 2012). Hart et al. (2014) proposed pattern analysis of Gaussian process classifiers (GPC) based on task-based fMRI imaging data. This method achieved 90% sensitivity, 63% specificity, and 77% of diagnostic accuracy as well as identified regions of the discriminative network most predictive of controls and ADHD(Hart et al., 2014). Deshpande et al.'s study (2015), using fully connected cascade (FCC) artificial neural network (ANN) architecture from fMRI, obtained accuracy close to 90% for distinguishing ADHD from healthy subjects and accuracy close to 95% for differentiating the ADHD subtypes(Deshpande et al., 2015).

Yin et al. (2022), applying extreme gradient boosting (XGBoost) algorithm for fMRI data to differentiate subjects with ADHD from controls and predict ADHD severity of individuals, found that a degree of reduced neural flexibility was useful marker to identify children with ADHD, as well as to monitor symptom severity and treatment responses(Yin et al., 2022). Lie et al. (2021) proposed newly developed DL algorithm based on convolutional denoising autoencoder (CDAE) and adaptive boosting decision trees (AdaDT) and obtained improvement in its classification performance of ADHD(Liu et al., 2021).

Wang et al.'s study (2023) introduced a newly developed deep neural approach, independent component analysis with convolutional neural network(ICA-CNN) and correlation-autoencoder model, which outperform the classical methods such as logistic regression or SVM in terms of accuracy, sensitivity, and specificity of ADHD classification(Wang et al., 2023). Hu et al. (2024) employed two layer-graph CNN to identify specific brain regions and interconnections between them to significantly contribute to the ADHD classification. This study revealed the discriminative brain regions relevant to ADHD, if their interconnections were dysfunctional, were orbitofrontal gyrus, insula, temporal gyrus, basal ganglia, cerebellum, and the lingual gyrus of the occipital lobe(Hu et al., 2024).

Table 1. Summary of diagnosis by data from neuroimaging study

Author (year)	Neuroimaging study	Classifier	Accuracy
Chang et al. (2012)	Structural MRI(sMRI)	Support vector machines (SVM)	69.95%
Peng et al. (2013)	sMRI	SVM Extreme learning machine	86.55% 90.18%
Iannaccone et al. (2015)	sMRI	SVM	77.78%
Johnston et al. (2014)	sMRI	SVM	93%
Du et al. (2016)	Functional MRI(fMRI)	SVM	94.91%
Dey et al. (2014)	fMRI	SVM	73.55%
Dai et al. (2012)	fMRI	SVM	65.87%
Hart et al. (2014)	fMRI	Gaussian process classifiers	77%
Deshpande et al. (2015)	fMRI	Fully connected cascade artificial neural network	90-95%
Yin et al. (2022)	fMRI	Extreme gradient boosting(XG Boost)	77%
Lie et al. (2021)	fMRI	Convolutional denoising autoencoder & Adaptive boosting decision trees	75.64%
Wang et al. (2023)	fMRI	Independent component analysis with convolutional neural network(CNN) Correlation-autoencoder model	67% 69%
Hu et al. (2024)	fMRI	Two-layer graph CNN	83-85%

3.3 Diagnosis by electroencephalography (EEG) data

The data extracted from EEG has been utilized by artificial intelligence techniques as classification method for ADHD. Ahire et al.'s study (2023) using open eye EEG found that frontal, central, and parietal electrode sites were crucially relevant for ADHD classification and Naive Bayes classification algorithm accomplished better accuracy of 96% than any other methods such as K nearest neighbor(KNN), AdaBoost, and random forest(Ahire et al., 2023). A more recent study performed by same author groups observed that KNN produced the higher grade of accuracy than linear regression, random forest, and extreme gradient boosting (XGB), which was further improved by hyperparameter tuning. As well, this study suggested that ML techniques based on EEG could be used not only for ADHD classification but subgroup classification to identify the severity of the disorder(Ahire et al., 2024).

Esas & Latifoğlu (2023) compared sub-band data from EEG of ADHD and normal controls by robust local mode decomposition (RLMD) and variational mode decomposition (VMD). These subbands and the EEG signals were fed as input data to the DL algorithms. This showed 95.24% accuracy, 97% sensitivity, and 94% specificity and highest classification success was found in the frontal brain region(Esas & Latifoğlu 2023). According to Dubreuil-Vall et al.'s study (2020), CNN model achieved a greater accuracy compared to the recurrent neural network and the shallow neural network. Also, event-related potentials (ERP) spectrogram during performing experimental task provided a higher level of accuracy than resting state EEG spectrograms. Feature visualization techniques showed that the main features exciting the CNN nodes were a decreased and increased power in the alpha band and the delta-theta band respectively for ADHD patients compared to healthy controls, which was relevant to attentional and inhibition deficits, pathophysiologic sign of ADHD(Dubreuil-Vall et al., 2020).

3.4 Diagnosis by genetic data

ADHD is regarded to be genetic disorder with high tendency. Cervantes-Henríquez et al.'s study (2022) to investigate the association of genetic data to predict ADHD severity in families from a Caribbean community, revealed that single nucleotide polymorphisms (SNPs) harbored in DRD4, SNAP25, and ADGRL3 showed evidence of linkage and association to symptoms severity and a potential pleiotropic effect on distinct domains of ADHD severity(Cervantes-Henríquez et al., 2022). Liu et al. (2021) showed ML techniques with CNN identified EPHA5 as

Vol. 2024 (9) 363 – 375
ISSN 2688-3651 [online]

a potential risk gene for ADHD with an accuracy of 0.9018, AUC of 0.9570, sensitivity of 0.8980 and specificity of 0.9055(Liu et al., 2021). Wang et al. (2022) showed the expression level of mi RNA on white blood cell had the ability to predict ADHD and its treatment response (Wang et al., 2022). Liu et al. (2021) stated that the accuracy obtained by DL training and validation with variation intensity in each divided region from human genome sequencing data as feature vectors were higher than traditional k-mean clustering methods. The high weight regions included ADHD-associated copy number variation regions, including genes such GRM1 and GRM8, key drivers of metabotropic glutamate receptor neurotransmitter signaling. This result suggested that metabotropic glutamate receptor activator had the ability to control the ADHD symptoms(Liu et al., 2021).

Table 2. Summary of diagnosis by data from EEG and genetic study

Author (year)	Data source	Classifier	Accuracy
Ahire et al. (2023)	EEG	Naive Bayes classification algorithm	96%
Ahire et al. (2024)	EEG	K nearest neighbor	87%
Esas & Latifoğlu (2023)	EEG	Robust local mode decomposition, Variational mode decomposition, & CNN	95.2%
Dubreuil-Vall et al. (2020)	EEG	Four layer CNN	88%
Cervantes-Henríquez et al.(2022)	Genetic study	Logistic regression, Classification and regression tree, Random forest, SVM, & XGBoost	70-82%
Liu et al. (2021)	Genetic study	CNN	90.2%
Wang et al. (2022)	Genetic study	SVM	96.6%
Liu et al. (2021)	Genetic study	Multi-layer perceptron neuronal network	71-75%

3.5 Treatment

Computerized serious games utilized for treatment of ADHD is categorized into EEG based neurofeedback games and non-EEG based computer games.(Montaleão Brum Alves et al., 2022) EEG based neurofeedback games requires special devices which receives and transmits EEG signals to the software programs. This provides the patients with their attention status by visual feedback on computer screen, which consequently trains the patients to maintain and enhance the concentration or operates the games.

Computer-based cognitive games with EEG neurofeedback, performing the given tasks as well as trying to keep brain waves at the optimum level, produced the significant improvement of attention, impulsivity, and EEG findings(Rajabi et al., 2020). Brain computer interphase(BCI) based on EEG recording device, NeuroSky MindWave combined with video game, could be useful screening and therapeutic tool by visual feedback for attention status, showing the experimental result that ADHD group had a lower and more variable average attention than the control group across all levels of the games (Serrano-Barroso et al., 2021). A randomized controlled trial also indicated that BCI based attention training program with EEG feedback device achieved significant improvement of ADHD symptoms scale compared with control.(Lim et al., 2019) Another randomized trial showed that the computer game with EEG neurofeedback to induce decrease of theta wave accomplished the significant improvement of parents and teacher report than in cognitive training(Steiner et al., 2014).

Plan-It Commander, one example of non-EEG based games, was designed to promote behavioral learning in everyday life situations such as time management, planning, organizing, and prosocial skills known to be problematic for ADHD(Bul et al., 2015). García-Baos et al. (2019) assessed the improvement of attentional parameters after playing game by eye tracking controller in comparison with by mouse controller. This study showed that eye tracking group achieved significant improvement in impulsivity, reaction time, and fixation gaze control, while mouse group did not(García-Baos et al., 2019). A randomized controlled study comparing the children with ADHD treated by serious game with those with usual care showed that serious game group obtained significant improvement on parent rated management skills, parent rated social skill of responsibility, parent rated working memory, and parents and teachers reported social skills(Bul et al., 2016). Meanwhile, another randomized controlled trial comparing the computer game, ACTIVATE™, targeting multiple cognitive functions with usual care failed in achieving significant results(Bikic et al., 2018).

4. Discussion

4.1 Diagnosis

Diagnosis of ADHD based on Diagnostic and Statistical Manual of Mental Disorders(DSM) or International Classification of Diseases(ICD) criterion attributes an underlying cause to the various behavior or emotional difficulties without verifying underlying biological dysfunction. The evaluations for cognitive and behavioral aspects are based on reports or questionnaires subjectively written by patients themselves, parents, or teachers

The DSM-5 divides into three categories according to different presentations of ADHD: predominantly inattentive, predominantly hyperactive/impulsive, and combined presentation. Symptoms should be present for at least 6 months which is started before 12 years old and have to reduce or impair social, academic, or occupational functioning. DSM-5 changes the term "subtype" into "presentation" to emphasize the changeability of symptoms as patients are matured and developed(Drechsler et al., 2020; Posner et al., 2020). While, the ICD-10 distinguishes between hyperkinetic disorder of childhood and hyperkinetic conduct disorder, a combination of ADHD symptoms and symptoms of oppositional defiant and conduct disorders. The ICD-11 distinguishes five ADHD subcategories, which bring it into line with DSM-5: ADHD combined presentation, ADHD predominantly inattentive presentation, ADHD predominantly hyperactive/impulsive presentation and two residual categories, ADHD other specified and ADHD non-specified presentation(Drechsler et al., 2020; Posner et al., 2020).

Hereby, the objective tests such as neuroimaging and neurophysiological test are not routinely performed for diagnostic purposes. But their use is sometimes required as additional tools to exclude or identify other physical or neurological conditions to mimic ADHD symptoms.

Polanczyk et al. (2007) pointed out the limitation in diagnosis of ADHD through their systemic review, showing that ADHD prevalence estimates could be influenced by diagnostic criteria, information sources, geographic location or cultural background(Polanczyk et al., 2007). This condition raised the requirement of diagnostic method to yield consistent and objective result to exactly choose the patients to be helped by appropriate treatment. Exact diagnosis was absolutely important process to select the appropriate subjects that could be recovered by optimal treatment and further to prevent unnecessary waste of treatment resources and related adverse events. As neurobiological concepts are being stand out as a tool to explain the underlying mechanism of ADHD, the usefulness of the objective neurobiological tests become increasingly significant(Drechsler et al., 2020).

The advances in neuroscience paved the way for understanding the structure of the brain more in detail. As well, ML/ DL techniques have been developed and applied in many medical fields and these techniques were utilized for the diagnosis of mental illnesses by extracting and analyzing the structural neuroimaging data sources(Graham et al., 2019; Iyortsuun et al., 2023).

Aside from ML/DL provided the objective and quantitative way for diagnosis, which had been mainly dependent upon subjective measurements, ML/DL application to neuroimaging data improved understanding of patterns of neurobiological functioning that would not otherwise be detectable using other methods. These advances would ultimately improve not only our ability to diagnose these disorders but also augment our understanding of the mechanisms that contributed to their etiology(Eslami et al., 2020). ML/DL algorithm using the extracted data from structural brain MRI showed that specific brain regions were predictive of ADHD with high accuracy according to the reports mentioned in result of this review.

But this method had the limitation to identify interaction between various brain regions or contribution of specific brain region to different brain disorder. The association between ADHD and brain regions were related not only to individual brain sections but also to the interconnections among brain regions. In this regard, the conception of network-based diagnostics drew attention and ML/DL with fMRI data came into spotlight in classification of ADHD by identifying the interconnection between brain lesions(Du et al., 2016).

In addition to ADHD, ML/DL techniques with neuroimaging such as structural and functional neuroimaging have been utilized for diagnosing various psychiatric disorders such as depression, post-traumatic stress disorder, schizophrenia, Alzheimer's disease, and autism spectrum disorder(Iyortsuun et al., 2023; Lin et al., 2020). The diagnostic accuracy was reported to range from 60 to 80% for psychosis and autism(Woo et al., 2017). Particular phobia subtype was determined based on structural brain image with an accuracy of 89%(Lueken et al., 2015). ML techniques of SVM and graph CNN using fMRI data revealed that thalamic hyperconnectivity as a prominent neurophysiological signature of depression(Gallo et al., 2023).

Various kinds of ML/DL algorithm using structural and functional image sources, EEG, or genetic data were developed to improve diagnostic accuracy and eventually accomplished more reliable and regenerable results as compared with subjective interpretation. But the large amount of data was prerequisite for ML/DL to be more accurate diagnostic tool than now. Vabalas et al. (2019) stated that small sample sizes, prevalent in the mental health AI study due to the difficulty of data collection that required human participation, became important cause of bias(Vabalas et al., 2019). Although ML models might have resilience and not lose accuracy considerably even through training with a limited sample size, DL models required large amount of training data to avoid overfitting hazards(Iyortsuun et al., 2023). Overfitting, producing good predictions for data points in the training set but perform poorly on new samples, seriously had negative effects on performance of DL. Aside from model complexity or an imbalance in the training data, most important cause of overfitting was regarded as limited size of the training dataset. Although optimization of hyperparameters such as epochs, dropout, model regularization, activation function, and the number of hidden layers were tried to reduce overfitting, large sample size was critical to avoid overfitting(Pérez-Enciso & Zingaretti 2019).

4.2 Treatment

Pharmacological treatments are mainstay of ADHD treatment in most clinical settings. First line medications are two psychostimulants, methylphenidate(MPH) and amphetamines(AMP). Second-line medications include atomoxetine(ATX), guanfacine(GFC), and clonidine(CLO), prescribed when first line medications fail in successful outcomes or lead to side effects. The psychostimulants (MPH, AMP, and ATX) inhibit reuptake of and eventually increase dopamine and norepinephrine in the striatum and prefrontal cortex. The alpha-2 receptor agonists (CLO and GFC) stimulate alpha-2 noradrenaline receptors in the central nervous system(Caye et al., 2019).

The medications, despite their clinical usefulness and popularity, had serious issues regarding response, side effects, and reluctance to acceptance to be cared about. Overall, approximately 30% of ADHD patients responded poorly to the medication(Hodgkins et al., 2012). In addition, medication might not be equally effective across different ADHD subgroups. Approximately 73%–75% of children and adolescences group were reported to receive pharmacologic treatment, and only 58% were good responders(Quintero et al., 2018). Possible side effects of medication were sometimes problematic and included trouble falling asleep, loss of appetite, headaches, dry mouth, nausea, dizziness, and mood fluctuation(Drechsler et al., 2020). Also, the emotional barrier about social stigma associated with taking medication was another cause of reluctance for pharmacology, and further worsening their conditions. Therefore, the substitute of less side effects and well acceptance especially to children, main patient group were required.

Among non-pharmacological treatments, behavioral or psychological treatments were most frequently recommended and used in clinical setting. But their clinical benefits were not conclusive and evidence level was also conflicting, although they were not usually associated with side effects and, for this advantage, preferred by some patients and parents(Daley et al., 2014). A randomized study comparing between MPH plus behavioral treatment and MPH only showed no significant difference, suggesting behavioral treatment had no additional efficacy to medication(The MTA (Multimodal Treatment Study of children with ADHD) Cooperative Group 1999).

Nowadays, serious games usually based on computer platforms which were designed to educate, train, or change behavior rather than to entertain, have been used in numerous health problems including mental

Vol. 2024 (9) 363 – 375
ISSN 2688-3651 [online]

illness and showed clinical effectiveness for alleviating mental disorder related symptoms(Dewhirst et al., 2022). Also in the patients with ADHD, these games, consisting of series of tasks to facilitate executive functioning such as attention, working memory, reaction time, cognitive flexibility, or motor ability, succeeded in gaining improvement in cognitive functioning and reduction in ADHD symptoms(Drechsler et al., 2020; Montaleão Brum Alves et al., 2022).

Obtaining clinical efficacy by computerized serious games was explained by promoting cognitive function, which was based on theory of neuroplasticity and reorganization of neurological functions. Especially, the enhancement effects of restructuring neurobiological pathways were more prominent in children with increased neuroplasticity than adult(Granic et al., 2014; Shams et al., 2015).

In addition, computerized games had the advantage in high adherence because most of patients enjoyed games without feeling treated. Immediate feedback provided during playing games made the patients concentrate on games, which facilitated treatment process more efficiently. Interactive, visual, and immersive characteristics available in video games might make training more meaningful, interesting, and challenging than traditional teaching, which helped the patients to develop more creative problem-solving ability(Gamberini et al., 2008; Lau et al., 2016).

But there existed some concerns about determination of target age appropriate for each computerized serious game. Children with ADHD under 12 years of age enjoyed the games more, and therefore had more adherence than children with ADHD over 12 years of age. This suggested that certain game was not suitable for the older children, and a kind of game that gave something more interesting would be need for the older age group(García-Baos et al., 2019).

It was also important to identify which patients would benefit from computerized games. In one study of children with ADHD, the patients that dropped out had higher ADHD severity scores, suggesting that a serious game intervention might not be appropriate for those with severe symptoms(Bul et al., 2016). Furthermore, heterogeneous property of disorders in ADHD made it complex to determine which type of patients could achieve improvement by specific type of game. The patients with profound cognitive deficits had more difficulty in maintaining adherence on cognitive demanding games than those with other deficits(Bikic et al., 2018). Aside from selecting appropriate patient group in consideration of age and severity, development of computer games that met the specific needs of individual subgroup would be crucially required.

The adverse effects of computer games should not be underestimated. ADHD and game addiction possibly had bidirectional influences on each other. The patients with ADHD had the property to be indulged in computer games while computer game could aggravate the ADHD symptoms by escalating the exact disinhibition, quick responsiveness, need for immediate reward, and inattention(Weiss et al., 2011). This association was explained by the fact that ADHD was known as one of reward deficiency syndrome explained by lower dopaminergic activity in the brain's reward centers. Computer game might lead to addiction or aggravation of ADHD symptoms by increasing dopamine release and activating brain reward pathway(Blum et al., 2000; Weinstein & Weizman 2012). The dopamine increasing mechanism could help to supplement the reward deficiency, but might have hazardous effect to enhance the aggressiveness or inattention by abruptly increasing dopamine activity. The determinant factor was the property or context of games. The prosocial games showed positive effects on social behaviors, while violent games showed negative effects(Greitemeyer 2022). Computer games cooperatively played with multiplayers could be more beneficial to the patients with ADHD by enhancing interpersonal relationships and social behavior(Raith et al., 2021). The concerns for addiction and aggravating ADHD symptoms could be overwhelmed by the expected clinical benefits if computer games were prudently developed and applied in the way more beneficial to the patients with ADHD.

5. Conclusion

Computerized methods have been developed and applied in various medical fields including psychiatry. ML/DL techniques might be a useful objective, automated, and reliable diagnostic tools that could reduce variability in clinical practice and, ultimately, might help to improve diagnostic accuracy. Computer games achieved better improvement of ADHD related symptoms including attention, social skill, and impulsivity than other conventional treatment. Along with innate property of games being more interesting and challenging than conventional treatment, clinical benefits would make computer games more popularly used treatment tools. As progress of these techniques, the importance of interdisciplinary collaboration among experts of various fields including not only physicians and psychologists, but neuroscientists and computer scientists would be pronounced. By combining expertise from multiple fields, more sophisticated diagnostic and treatment approaches for ADHD were facilitated, which will further contribute to improvement of medical care for the patients with ADHD.

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Vol. 2024 (9) 363 – 375
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