

Online ISSN

3007-3197

Print ISSN

3007-3189

<http://amresearchreview.com/index.php/Journal/about>

ADHD and Executive Functioning in Adolescents

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ABSTRACT

The problem of Attention-Deficit/Hyperactivity Disorder (ADHD) in teens is a burning topic to neuroscience and computational modeling due to its complicated impact on the executive functioning (EF) a system of cognitive procedures regulating attention control, working memory, and impulse control. Growing more recent advances in the field of computer science, particularly in areas such as artificial intelligence (AI), machine learning (ML) and computational cognitive modeling, have enabled new possibilities to quantify, model and project such executive deficits with a new degree of precision. The intersection of ADHD and executive functioning and concepts of computational science, how data-driven algorithms and neuroinformatic tools can be applied to understand more about the cognitive processes of adolescents will be the subject of this review. According to the multimodal data, i.e., the functional MRI, EEG, and behavioral task data, machine learning frameworks may be made more efficient at identifying the type of ADHD, predicting the level of symptoms, and plotting the EF-related neural activities. Besides that, simulation-based explanations of cognition and reinforcement learning systems give lead on the deviation of executive regulation in ADHD bringing virtual test beds in the examination of neurocognitive processes. Besides diagnostics, digital interventions, including

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3007-3197

Print ISSN

3007-3189

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adaptive neurofeedback and training via a mobile device, and brain-computer interface (BCI) applications that are utilized to record attentional states in real-time are generated by AI-based systems. Despite being a promising one, problems of generalizability of data, ethical issues, and interpretation of the model still exist. The syncretism of the accuracy of computations and neurocognitive theory makes this review single out the likelihood of the AI-based methods to change the manner and manner in which the executive functioning associated with ADHD is analyzed, evaluated, and treated in the adolescents.

Keywords: Attention-Deficit Hyperactivity Disorder, Executive Functions, Computational Neuroscience, Machine Learning, Cognitive Modeling And Neuroinformatic, Artificial Intelligence, Adolescent Brain.

1. INTRODUCTION

Attention-Deficit/Hyperactivity Disorder (ADHD) is a very common neurodevelopmental condition which is typified by pervasive tendencies towards inattention, hyperactivity and impulsivity that disrupt the functioning in several areas of life [1]. ADHD affects between 5 and 8 percent of a worldwide population of children (and between 2 and 5 percent of adolescents), and has attracted a great deal of interest within neuroscience, psychiatry and to a growing extent, even within the area of computational disciplines [2]. Although the basic behavioral symptoms of ADHD have been known, the cognitive and neural processes underlying the disorder are an essential problem to be addressed. Among the few reliable results in the decades of studies, it can be noted that executive functioning (EF) deficits (or impairment) a set of higher-order cognitive processes that regulate goal-directed behavior is at the center of ADHD symptoms. Executive functioning involves selection of abilities like attention, working memory, cognitive flexibility, and inhibitory control that are crucial in keeping track of focus, preventing irrelevant impulses, and behavior planning based on long-term objectives [3]. The disorders in EF are particularly decisive in adolescence, when post frontal cortex and other related neural systems are still in the fast track. The EF losses in this developmental phase can have implications

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on the academic performance, emotional regulation, risk-taking, and adjustment to socialization, and therefore it is a crucial stage to research the cognitive deficiencies of ADHD [4]. Recent advancements in computational neuroscience and artificial intelligence (AI) have provided resources that are game-changing and with which ADHD can be studied without having to exist within the usual behavioral and neuropsychological paradigms [5]. Machine learning (ML) and computational cognitive modeling can create new opportunities to quantify the impairments of the EF, identify neurobiological subtypes patterns, and predict the patterns of symptoms on an individual basis. Such computational frameworks represent a way in which the researcher can model detailed dynamic interactions of neural systems and cognitive processes of control via the integration of multimodal data, that is, functional data of the MRI (fMRI) and electroencephalography (EEG) data and performance on behavioral tasks [6].

Most of the traditional diagnostic methods which are used to identify ADHD rely on subjective rating scales, and observation on the part of the clinician and tend to be very low in specifications and also poor in respect of reproducibility in the setting [7]. The heterogeneity in the ADHD presentations is further predisposed by the genetic, environmental and developmental factors, which have made the disease hard to assess. These weaknesses are also supposed to be overcome by the use of computational techniques that will enable the objective and data-driven descriptions of the ADHD phenotype and the profile of executive functioning [6]. Besides this, digital technologies are changing how EF impairments related to ADHD are measured and fixed as well [8]. An AI-constructed neurofeedback system, an adaptive mobile cognitive training, as well as a brain-computer interface (BCI) application can now monitor the attention state of any particular individual in real-time and provide an intervention based on the activity of the brain of that particular individual [9]. Those developments connect the theory and clinical practice and introduce the concept of precision medicine to the domain of neurodevelopmental disorders [10]. The given review will attempt to synthesize the available information about the

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3007-3197

Print ISSN

3007-3189

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intersection of ADHD, executive functioning, and computational science. In particular, it examines the way, which data-driven algorithms and computational models are transforming our knowledge regarding cognitive control among adolescents with ADHD. The review will include a review of the conceptual theories of EF, the neurobiological processes of executive dysfunction in ADHD, and the current use of AI and ML in the field of executive modeling, diagnosis, and intervention. The final goal is to outline how the computational strategies can be used to complement the conventional neurocognitive studies, and provide more detailed understanding of adaptive and maladaptive executive functions of the adolescent brain.

1.1 Fundamental Building Blocks of the Executive Functioning

Executive functioning is a general term used to describe a set of cognitively interconnected processes that control behavior, thoughts, and feelings. EF is not a single skill but a system of functions that facilitates goal-oriented behavior which is flexible. The major components of it are the working memory, cognitive flexibility, inhibitory control, and planning [11]. Working memory is an ability to process and store the information within the short-term periods. The working memory of the adolescents is efficient in learning, understanding, and reasoning. The weaknesses of working memory are one of the strongest cognitive signs of ADHD, which present themselves as forgetfulness, disorganization, and inability to maintain mental activity [12].

Set-shifting or cognitive flexibility helps people to adjust to the needs of the changing environment, alternate tasks, and change strategies when new information is presented. Rigidity, distractibility, and poor adjustment is one of the possible reasons that impaired flexibility can explain in adolescents with ADHD. The other basic EF component is inhibitory control which enables an individual to suppress impulsive behavior or insignificant stimuli. Failure in this area causes hyperactivity, impulsivity and lack of self-control-some of the fundamental characteristics of ADHD. The pathophysiological basis of this inhibitory deficit has a strong connection with the

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3007-3197

Print ISSN

3007-3189

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dysfunctions of the right inferior frontal gyrus and basal ganglia, which are part of the top-down control and suppression of responses [13, 14].

EF processes are facilitated by a distributed network of areas, most notably, the prefrontal cortex (PFC), anterior cingulate cortex (ACC), basal ganglia and parietal areas. The PFC, especially the dorsolateral and the ventromedial parts, are the control centers that combine sensory, emotional, and motor input in order to direct adaptive behavior. The basal ganglia is also involved in the selection and initiation of correct motor and cognitive responses as well as the monitoring and detection of errors is mediated with the help of the ACC. Goal-oriented behavior and attention control, which are mechanisms that are highly impaired in ADHD, are supported by the efficient interaction between these circuits [15, 16]. Figure 2.1 gives a conceptual point of view on the association between the deficits of executive functions and ADHD symptomatology. It lays emphasis on how the characteristic symptoms of the ADHD inattention, hyperactivity and impulsivity can be attributed to impairment of working memory, inhibition, flexibility and planning which are some of the key executive functions regulated by the prefrontal cortex and basal ganglia. The feedback loops help understand that the behavioral dysregulation might lead to additional executive dysfunction and that the cognitive and behavioral disturbances are mutually affected.

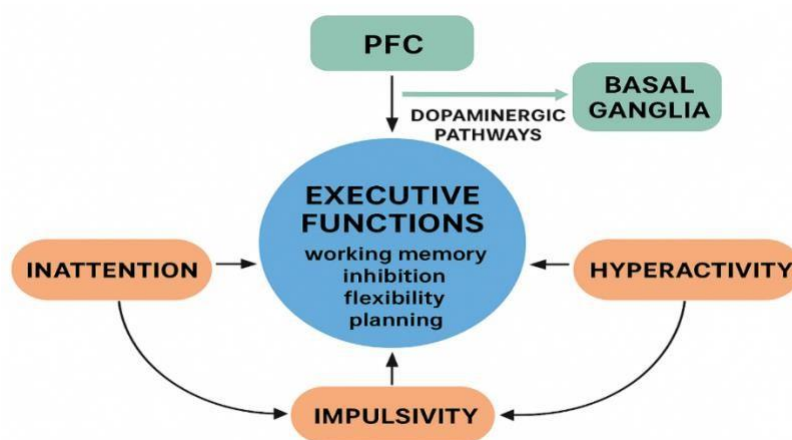


Figure 1.1. Deficits in executive functions (working memory, inhibition, flexibility, and planning) contribute to core ADHD symptoms.

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1.2 Executive Dysfunction and ADHD

The conceptualization of ADHD as a disruption of executive control has been widely used, and the impairments include working memory, inhibition, and sustained attention. Executive dysfunction model This is based on the assumption that the disruption in the above cognitive processes is due to abnormalities of fronto-striatal circuitry and disorganization of neurotransmitter systems, especially dopamine and norepinephrine. These are neurotransmitters which play critical roles in regulating arousal, motivation and cognitive flexibility which is crucial in the optimal functioning of EF [17]. Neuroimaging investigations are always some of the studies that indicate structural and functional changes in areas that support EF. Adolescents affected by ADHD show a low cortical thickness of prefrontal cortex, atypical activation of anterior cingulate and parietal regions and cortical slowness in maturation as compared to their normal developing counterparts. Figure 2.2 illustrates the major neural pathways involved with the executive dysfunction in people with ADHD. The diagram focuses on highlighting how structural and functional defects in the prefrontal cortex, anterior cingulate cortex, parietal locales and basal ganglia are involved in the impairments in attention management, inhibitory control, and cognitive adaptability. Mesocorticolimbic and nigrostriatal dopaminergic systems depicted as green projections are involved in motivation and arousal mechanisms that tend to be dysregulated in ADHD and result in poor executive control and behavioral regulation.

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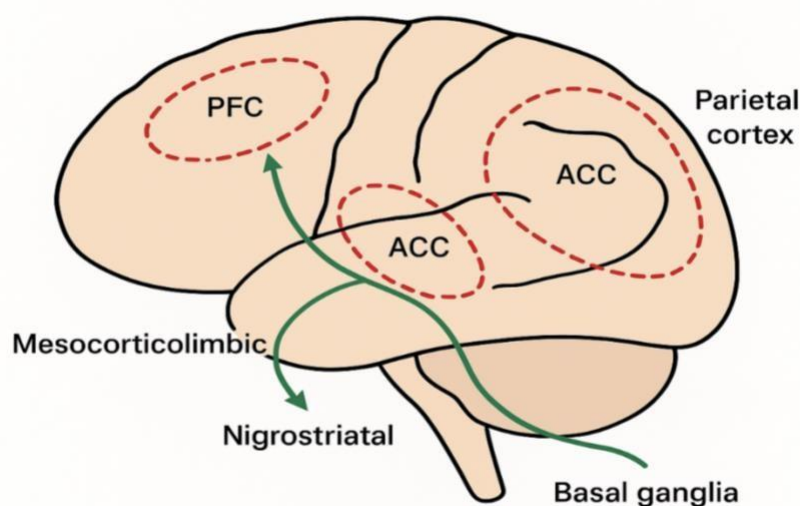


Figure 1.2 Neural Circuitry Underlying Executive Function in ADHD

A network that is active at rest and inactive at task engagement Abnormal connectivity is observed in the default mode network (DMN), which signifies the loss of attentional control and the reduction of distractibility [18]. Neurochemically, motivation and attentional problems are caused by the lack of dopaminergic release in the mesocorticolimbic and nigrostriatal systems. Drugs like methylphenidate are stimulant drugs that attempt to boost the level of dopamine in the brain, and in the short term, stabilize the functions of the EF. Nevertheless, these pharmacological treatments fail to deal with the heterogeneity of the executive dysfunction in ADHD subtypes comprehensively. Phenotypes of ADHD (inattentive, hyperactivity-impulsive, and combined) are characterized by different executive profiles. The inattentive type is usually marked by severe working memory and sustained attention deficit and hyperactive-impulsive type is typified by inhibitory control and impulsive decision-making. Combined subtype has a more complicated cognitive portrait of attentional and inhibitory disorders [19, 20]. Simulation models of such variations have started to demonstrate that subtype-specific pattern could be attributed to a differential weighting of neural parameters (dopamine gain, signal-to-noise ratios, etc.). The course of EF development during adolescence is in a dynamically

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intertwined interaction with the development of the symptoms of ADHD. In the normal course of things, the prefrontal cortex keeps developing until the third decade of life, perfecting the inhibitory control and strategic thinking. This is not the case in the typical maturation in adolescents with ADHD which causes an incongruity between the stimulative forces (mediated by the limbic system) and regulation capabilities (mediated by the PFC). Such developmental asynchrony contributes to the risk-taking behaviour, emotional turmoil and academic difficulties which typified this developmental stage. Outside neurobiology, there is interaction between environmental and genetic factors that come in to have effects on EF outcomes [4, 21]. The absence of EF is a result of genetic differences in the genes involving the dopamine transporter (DAT1) and receptor activity (DRD4, DRD5). The genetic differences in dopamine transport genes (DAT1) together with the genes of receptor activity (DRD4, DRD5) also causes the execution dysfunction and environmental stressors such as haphazard parenting, sleeplessness, or chronic stresses. The multifactorial interactions are impossible to conceive without data-driven techniques capable of integrating heterogeneous variables in that respect, computational neuroscience and machine learning are the only fields in which this can be done [22]. Overall, the core of the ADHD cognitive pathology is executive dysfunction. It is an indicator of a complicated interplay of neural, chemical, and developmental processes, which weakens the capacities of the adolescent brain to control attention and behavior. These nonlinear dynamics cannot be captured by traditional cognitive and clinical models which are still informative but lack precision. Computational methodologies, using neuroimaging information, reinforcement learning theory, and AI-based pattern recognition can provide the opportunity to quantitatively map these mechanisms [6, 23, 24]. Figure 2.3 shows that the conventional clinical rating scales (around 45%) and moderate accuracy of neuropsychological testing (around 60) are limited in the precision and moderate accuracy, respectively. By contrast, machine learning models give higher reliability (almost 75%), and hybrid neurocomputational models, that is, behavioral,

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3007-3197

Print ISSN

3007-3189

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neuroimaging, and computational data, have the highest diagnostic accuracy which exceeds 80%.

By conceptualizing EF deficits as an emergent property of interconnected neural networks, researchers can get a step closer to a mechanistic conceptualization of ADHD that has connections between cognition, neurobiology, and computational theory.

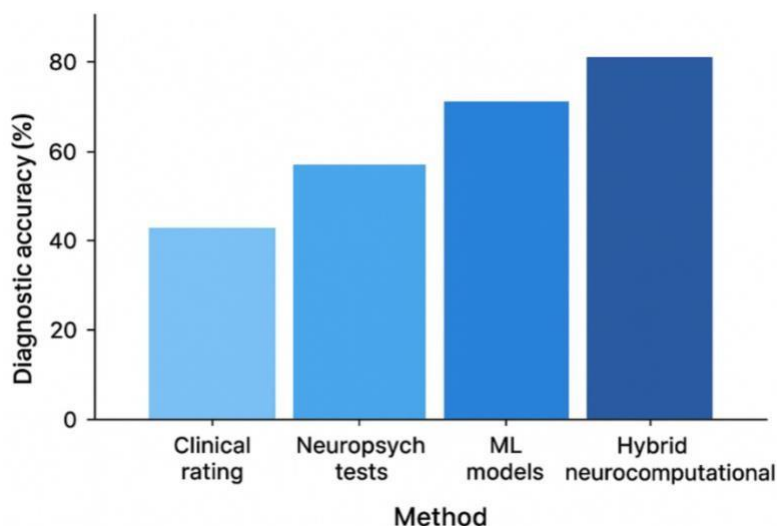


Figure 1.3 Comparative Diagnostic Accuracy of ADHD Assessment Methods

2. Functional and Structural Neuroimaging

Neuroimaging has made major contribution to understanding of the neurobiological basis of ADHD and its effects on executive functioning (EF). Functional magnetic resonance imaging (fMRI), diffusion tensor imaging (DTI), and electroencephalography (EEG) are some of the techniques that have played a major role in defining neural correlates of attentional control, inhibition, and working memory among adolescents [25, 26]. The hypoactivation of the parts of the prefrontal cortex (PFC), specifically, the dorsolateral prefrontal cortex (DLPFC), ventrolateral PFC, and anterior cingulate cortex (ACC) of the brain are consistently demonstrated in functional MRI (fMRI) studies as they are the important areas of the brain that are

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critically involved in the executive control. When performing tasks that involve the inhibition of activity (e.g., go/no-go or stop-signal paradigms), adolescent ADHD victims have weaker activation of these networks, with compensatory hyperactivation of posterior structures, including the parietal cortex. These trends imply the ineffective distribution of neural resources and the impaired top-down control [27, 28]. Intended to measure the white matter integrity, DTI is complemented with information on structural connectivity underlying EF processes. Fractional anisotropy (FA) and mean diffusivity (MD) increases and decreases have been detected in fronto-striatal and fronto-parietal tracts that indicate myelinization and impaired communication between the regions respectively [29, 30].

Interestingly, the dysfunction of the superior longitudinal fasciculus and corpus callosum is significantly correlated with functional impairment of attention and working memory, and the impaired structural connectivity of the brain structures is a source of functional impairment in ADHD. EEG is very temporal and is used to investigate neural oscillations that are related to EF [30, 31]. The ADHD is characterized by an increased theta power (4-8 Hz) and a decreased beta power (13-30 Hz) and high ratio between theta/ beta, which is a well-established electrophysiological biomarker of attentional dysregulation. ERP reports also show reduced P3 activity when engaged in an inhibitory control and target detection experiment, which demonstrates a lack of resource allocation and cognitive processing slowing.

The other important discovery in modalities is the default mode network (DMN), a cluster of brain areas that comprise the medial prefrontal cortex and posterior cingulate that are active even when one is resting [32, 33]. In ADHD the DMN does not effectively deactivate when performing a task and this leads to a constant lapse of attention mind-wandering. Functional connectivity results indicate that the DMN and task-positive networks (e.g., fronto-parietal) have a weakened synchronization, which means lack of dynamical coordination between internally and extrinsically oriented attention. All these imaging studies define ADHD as a network

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disorder and not a focal deficit. Disturbed fronto-striatal, fronto-parietal, and limbic circuit activity and connectivity upsets the coordination involved in executive control, emotion regulation, and motivation [18, 34]. The knowledge of these distributed patterns has led to the development of computational models that could describe multiscale interactions, which are dynamic and cause EF deficits. The fusion of multiple data modalities across various systems at any given moment is known as multimodal data integration.

2.1 Multimodal Data Integration

Multimodal data integration is the fusion of multiple data modalities across different systems at a single point in time. One of the biggest developments in the research of ADHD has been the combination of multimodal neuroimaging, behavioral, and cognitive evidence to offer a more encompassing depiction of the executive dysfunction. ADHD is too complex to be described by any type of data on its own; but by integrating fMRI, EEG, DTI, as well as behavioral performance measurements, richer and more interpretable models of the correlations between the brain and behavior can be obtained [35]. Canonical correlation analysis (CCA), joint independent component analysis (jICA) as well as graph-theoretical modeling are multimodal fusion techniques being used to align structural and functional data. To give an example, basing the interpretation of microstructural impairment on the combination of DTI-based connectivity maps and fMRI activation maps can be used to determine how microstructural impairments are reflected in abnormal network dynamics during executive tasks. In the same spirit, EEG-fMRI integration provides researchers with the capability to relate real time oscillatory activity with hemodynamic responses which can provide temporal and spatial resolution of EF processes. The appearance of neuroinformatic and big data platforms, e.g. the ADHD-200 Consortium, OpenNeuro, have enabled faster cross-site analyses through standardized pipelines. Such large-scale repositories support machine learning techniques that could classify subtypes of ADHD along with its higher or lower degrees of severity using multidimensional and intricate data [36]. Notably, such data sets enable the researcher to detect reproducible

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3007-3197

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biomarkers, which enhances the external validity of the models of computation. Nevertheless, multimodal data present complications in terms of dimensionality, harmonization of data and interpretation. Deep learning architecture, computational frameworks are being used to learn latent feature characteristics across modalities with biological interpretability, usually using deep learning architectures (autoencoders, graph convolutional networks (GCNs)). These neuroimaging discoveries combined with computational modeling are the basis of new diagnostic and predictive systems in the next generation [37].

3. Executive Processes as Computational Models

Computational modeling offers some theoretical contribution between neural patterns of observation and the cognitive mechanisms of EF. Simulation models based on reinforcement learning (RL), neural networks, and Bayesian learning are models that endow individuals with ADHD with information-processing and feedback-reward behavior, and attention regulation, over time. The conceptualizations of reinforcement learning theory put ADHD into the framework of altered reward sensitivity and missing prediction error signals [38]. Normally during learning, the dopaminergic neurons store differences between anticipated and actual results, which is a component in guiding adaptive behavior. This process in ADHD is interrupted by attenuated dopamine signaling, which results in poor reinforcing decisions and impulsive decision-making. These behavior patterns have been replicated by RL models, which demonstrated that adolescents with ADHD have a tendency to overweight instantaneous rewards and underweight delayed consequences -the same behavioral patterns in the real world reflected in impulsivity. A further point of illumination is demonstrated by neural net simulations of the inhibitory control and working memory. The Leaky Competing Accumulator (LCA) and the Dynamic Neural Field (DNF) models are used to model the dynamics of the development of competing cognitive representation over time. These models produce ADHD-like behavior of premature response initiation and high variability of performance by modulating connection weights, or by modulating noise parameters [39, 40]. Computationally, it

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has been further demonstrated that minor changes in prefrontal-striatal gain control can cause large scale breakdowns in the control of attention, replicating behavioral studies of both fMRI and EEG. These computational models do not only make descriptions but also predications- they allow testing of hypotheses regarding the causation of executive dysfunction [41]. Through comparison of simulated results with empirical data, the various theories about EF can be optimized by researchers to suit better with the neural reality of ADHD.

3.1 Machine Learning in ADHD Classification and Prediction

Machine learning (ML) has become a game changer in the field of ADHD research, and can be used to process high-dimensional neuroimaging and behavioral data to detect diagnostic measures, forecast the severity of symptoms, and subtypes. Compared to traditional methods of statistics, the ML models are able to model nonlinear relationships and intricate interactions of features that neurocognitive data have [42]. The selection of neurobiological or behavioral indicators that are most predictive of outcomes associated with ADHD is a very important initial step that is known as feature extraction. As an example, resting-state fMRI connection values, EEG spectral values, or cognitive performance values may act as the input vectors. Classification studies to date using support vector machines (SVMs), random forest classifiers, and deep neural networks (DNNs) have been able to classify ADHD patients versus controls with an average classification accuracy of 70-85% -a order of magnitude better than the traditional diagnostic heuristics [43]. This field has further been developed by the deep learning architectures, and the most common neural networks are convolutional neural networks (CNNs) and recurrent neural networks (RNNs). CNNs on fMRI and DTI volumes are able to discover spatially localized patterns gold in ADHD, whereas RNNs can process temporal data of EEG or behavioral time series to discover temporal always of attention dynamics [44].

Symptom severity prediction has also been done through machine learning

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models, and the personalization of the executive deficits in models can be modeled. Multimodal data can then be used to predict clinical scores (e.g., inattention or hyperactivity indices) with regression-based ML models (e.g. elastic net or Gaussian process regression) which can be quantitative relationships between brain activity and behavior. However, in spite of these achievements there still exist issues as to validation, generalizability and interpretability. Most ML research works use small sample sizes or imbalanced populations resulting in overfitting and lower external validity [45, 46]. Furthermore, deep learning models are not very transparent regarding their biological interpretation of features due to their black-box nature. To handle this, scholars are turning to more and more use of Explainable AI (XAI) approaches that disclose connections between how model choices are linked to underlying cognitive processes [47].

3.2 Neurocognitive Research Explainable AI (XAI)

The application of AI in neuroscience requires interpretability especially when the computational results should be translated to a clinical understanding. Explainable AI (XAI) models seek to render insights into the necessity of the ML model decision-making process by associating the algorithmic output with recognizable neurobiological characteristics [48]. Layer-wise Relevance Propagation (LRP), SHAP (Shapley Additive Explanations), and Grad-CAM (Gradient-weighted Class Activation Mapping) are methods that enable visualizing what part(s) of the brain (or the EEG) make the strongest contribution to a classification choice. Indicatively, with the help of XAI, it is possible to point out that the changes in the patterns of DLPFC or ACC connectivity are the major cause of ADHD classification, which neuroscientifically validates the result of the model [49]. XAI also promotes a two-way integration in the cognitive modeling cases: computational predictions are used to inform theory, and theory restricts model interpretation. This synergy promotes credibility and interdisciplinary communication of computer scientists and clinical neuroscientists. A transparent AI will enhance interpretability but more importantly it will help to establish clinical trust, which is a precondition of the real-world

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implementation of AI-based diagnostic systems [50]. Figure 8 illustrates the application of Explainable AI (XAI) in interpreting ADHD-related neuroimaging data. The brain heatmap highlights key regions—the dorsolateral prefrontal cortex (DLPFC) and anterior cingulate cortex (ACC)—that contribute most to the machine learning model's diagnostic predictions. The accompanying SHAP and Grad-CAM panels demonstrate how computational models can map feature relevance and spatial activation patterns, thereby linking algorithmic outcomes to neurobiological substrates. This interpretive transparency bridges the gap between AI decision-making and cognitive neuroscience, reinforcing the credibility of computational diagnostics.

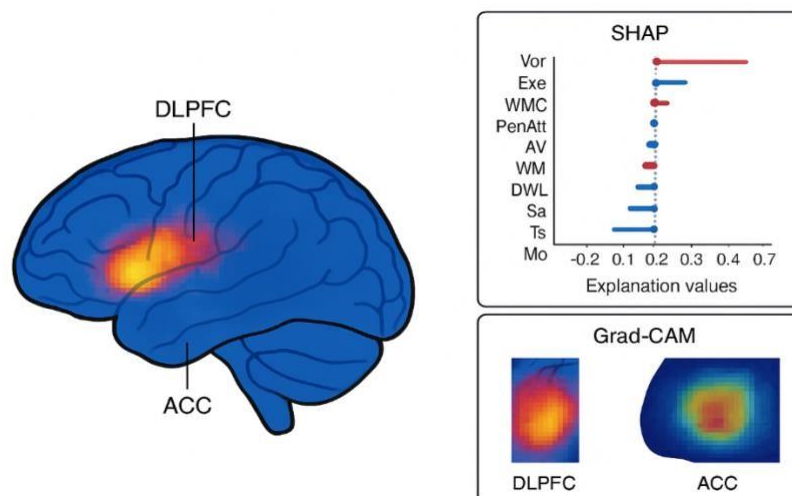


Figure 3.1. Explainable AI (XAI) Interpretation in ADHD Neuroimaging

4. Computational Biomarkers and Diagnostics

The application of computational models and machine learning together with digital health technologies is changing the traditional subjective symptom checklists used to diagnose ADHD to quantitative and data-driven models. A radical step towards the accuracy of psychiatry has been the advent of digital biomarkers, objective, algorithm-based measures of cognitive or neural activity.

4.1 AI-Based Assessment Tools

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The integration of behavioral and neurophysiological data to identify EF deficits with AI-driven diagnostic platforms is more accurate [51]. As an example, machine learning systems can be used to interpret eye-tracking recordings of eye-directed attention tasks or EEG microstates of rest to suggest cognitive control effectiveness. This type of tools can categorize the ADHD types in real time, which allows to detect them early and keep track of them.

4.2 Individualized Digital Biomarkers

Longitudinal modeling can be used to recognize personalized neural phenotypes revealing distinct processes of executive dysfunction in AI. These biomarkers allow continuous EF measurements in the ecological context by integrating wearable sensor measurements, interactions with the mobile application, and brain imaging. Digital phenotyping of behavioral measures, such as smartphone use, speech, or movement can be used to offer additional data streams that can be used to measure attentional variability and impulsivity in the field [52].

4.3 Mobile Interventions and Remote Monitoring

Attentional states in naturalistic settings are now achievable, due to the integration of wearable EEG headsets, smartwatch sensors, and devices that are compatible with BCI. Cognitive training or neurofeedback Mobile applications that use adaptive algorithms can provide customized feedback using neural activity patterns identified. In adolescents who have ADHD, these closed-loop systems facilitate engagement and self-regulation, and reduce the use of clinic-based intervention [9].

5. Simulation based Cognitive Modeling

The use of cognitive modeling based on simulation provides a strong model to formalize and test hypotheses on the mechanisms of executive dysfunction in ADHD. In contrast to descriptive behavioral studies, computational simulations can be used to give mechanistic accounts of the ways neural mechanisms result in cognitive control failures. These models combine neuroscience, psychological, and computer science results in order to recreate under controlled conditions the human-like behavior of attention, decision-making, and impulsivity [39]. Reinforcement learning (RL) is one

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3007-3197

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of the most important frameworks of this field since it describes the behavior as an optimization problem that minimizes reward prediction errors. The defective modulation of dopaminergic pathways involving cortico-striatum influences the encoding of reward contingency in ADHD [53]. Temporal-difference (TD) learning algorithm simulation studies have established that ADHD-like agents have increased sensitivity to instant rewards and less ability to learn delayed rewards. This is a computational phenotype that is replicated as an empirical finding of impulsivity and a lack of delay tolerance in adolescents with ADHD [54]. Outside the paradigm of reinforcement, there have been computational models that have been used to model cognitive control tasks, including ACT-R (Adaptive Control of Thought-Rational) and SOAR. The architectures simulate the working memory load, attentional changes, and the inhibitory processes through the allocation of cognitive modules with numeric parameters. These models can reproduce typical ADHD-related neural parameter effects, such as elevated neural noise or reduced working memory capacity, in predicting characteristic behavioral patterns, such as errors in responding frequently, decreased response times, and poor performance on executive tasks. Also, before clinical trials, intervention hypotheses can be tested through simulation-based methods [55]. As an example, virtual testbeds can be used to model the effect of pharmacological modulation (e.g. stimulant dose) or cognitive training on neural efficiency [56]. The critical benefit of the cognitive simulation is that it represents the capability of integrating multi-scale data, including neuronal firing dynamics and behavioral results. Dopamine-mediated plasticity at the prefrontal cortex and basal ganglia can be simulated using computational models like the spiking neural networks (SNNs) to study the effect on signal propagation. When integrated into more complex artificial neural systems, these biologically motivated systems can replicate such processes of EF as switching to a different task and maintaining attention [57]. Not only are such simulations able to enhance theoretical knowledge, but they also inform the development of bio-inspired AI systems that have both adaptive control and decision-making abilities comparable to those of human cognition.

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6. Artificial Intelligence-Based Interactions and Digital Therapeutics

Even though computer models and machine learning algorithms have had considerably impactful contribution to the understanding of ADHD and its diagnosis, its integration with therapeutic effects is a ground-breaking strategy of patient-oriented data-driven intervention-based approaches. The AI-based digital therapeutics uses real-time data to customize the cognitive training, neurofeedback, and behavioral control interventions to the specific users, particularly the adolescent demographic, who will be more benefited by the adaptive and interactive environments. According to the author, adaptive neurofeedback systems involve the use of an adaptive algorithm that establishes the optimal time required to carry out a specific activity within a given time [58].

Adaptive Neurofeedback Systems Adaptive neurofeedback systems consist of subsystems that participate in neural processes like learning and modifying behavior.

6.1 Adaptive Neurofeedback Systems

Adaptive neurofeedback systems are composed of subsystems that are involved in neural processes such as learning and behavior modification. The traditional neurofeedback consists in the training of people to control the brain activity through the EEG or fMRI. This process can be enhanced by the neurofeedback systems based on AI expansion that rely on machine learning algorithms capable of updating the feedback parameters according to the neural profile of a particular participant [59]. The training thresholds can be adjusted according to the real-time changes in the attentional state to ensure that the level of difficulty remains at an optimal level, as in the case of the AI algorithms that are developed based on the principles of reinforcement. It has been shown that adaptive neurofeedback leads to the fact that the attention span, impulse control and working memory is increased to a stronger extent than the protocols, which are not adaptive [60]. Moreover, the current versions of neurofeedback include a cloud-based data aggregation system, and learners are capable of learning at all times. Over time, the system is better as it tends to have more accurate predictive depictions of attentional lapses or hyperactivity. It can also be used

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together with the BCI (Brain-Computer Interface) technology, and, as long as that is done, neural activity can be translated into interactive feedback and, assuming that, given the opportunity to control digital worlds, i.e. games or virtual activities, through concentrated mental activities, adolescents can do it. Such gaming transforms it into more motivating and compliant which is crucial in the success of the adolescence intervention [61, 62].

6.2 Cognitive Training and Behavioral Interventions Mobile-Based

Mobile technologies are one of the ways of scaling solutions of cognitive training out of clinical setting. The AI-based mobile applications are grounded in the reinforcement learning algorithms that optimize the difficulty of the task, the time of feedback, and the reward mechanisms, in accordance with the trends of the personal performance. As an illustration, attention training games can be dynamically tuned to the speed, accuracy and consistency of a reaction of a user to give a user specific learning curve, which replicates the cognitive development of a user [63]. In addition, it can be noted that the monitoring of executive functioning through the use of mobile sensing technologies can be carried out by counting dynamic varying behavioral information through the use of smartphone use patterns, physical activity, and sleep measurements in the real world [64]. Machine learning models are used to analyze these streams of data so as to identify the early signs of attentional drop or impulsivity and trigger early feedback or intervention alerts. Such kinds of digital phenotyping allows a clinician and a caregiver to track the progress of treatment remotely and vary the treatment plans dynamically [65].

7. Virtual Reality and Immersive Technologies

The other new frontier in the field of ADHD intervention is the combination of the virtual reality (VR) environment with augmented reality (AR) with AI analytics. Cognitive training in VR immerses users in multisensory scenarios that are realistic and require focus on long periods, switching tasks, and inhibiting [58]. AI programs interpret the responses (behavioral and physiological) to feedback on the behavior (gaze patterns, reaction time, and heart rate variation) and offer personalized feedback.

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Early experiments indicate that simulations of immersive digital environments are potentially useful in generalizing training outcomes to real-life attention and self-control capabilities [66].

7.1 AI in Pharmacology Optimization and Precision Treatment

Besides the behavioral interventions, AI is also being introduced to optimize the pharmacological interventions of ADHD. Predictive models of individual reaction to stimulant drugs would potentially be done through clinical and genetic-based predictor models and would save the waste of trial and error prescribing. In the same way reinforcement learning algorithm can be used to simulate dose-response curves which could then be used to recommend an optimum medication regimen based on the modeled drug efficacy and side effects. These applications are congruent with the larger vision of precision psychiatry, in which the decision making regarding the treatments is based on the forecast made by the data rather than the generalized rules [67, 68].

8. LIMITATIONS AND CHALLENGES

Although there have been major improvements in computational and AI-based studies regarding ADHD and executive functioning, there remain a number of limitations and challenges. Remnants of data heterogeneity heterogeneity behaviors of the imaging and behavioral studies still pose challenges to cross-validation and modeling generalizability. The risk of overfitting is further complicated by the lack of representative samples and the presence of patients rated inconsistently involved in data acquisition, which minimizes the level of reproducibility. Most computational models are also simplistic with the complexity of executive control and are interested in aspects of executive control which are usually abstract parameters that might not be a true reflection of neurobiological processes. Ethical implications are still considerably high, especially regarding the issue of privacy of data and the bias of the algorithm and the informed consent among teenagers. Besides, there are no standardized frameworks of clinical validation to support the integration of AI-based diagnostic tools in the everyday clinical practice. The solution to these challenges will

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entail coordinated datasets, plain algorithms and an interdisciplinary interaction of neuroscientists, computer scientists and clinicians.

9. FUTURE DIRECTION

In the future, the future of ADHD research is to come up with integrative, evidence-based models that entail neuroimaging, electro physiological, genetic and behavioral data to come up with personalized diagnosing and interventions. Recent development in deep learning, federated modeling, and explainable AI will also allow scalable and privacy-conscious analyses, and at the same time, be interpretable. The precision of the therapeutic interventions will be achieved further through real-time brain-computer interface and adaptive neurofeedback systems that connect computational predictions to real time neural feedback. The future aim is to construct predictive models that can determine the pathways of the risks and lead to the optimal treatment interventions before cognitive impairments take roots.

10. CONCLUSION

In conclusion, computational neuroscience and artificial intelligence are transforming the understanding of ADHD and executive functioning from descriptive observation to mechanistic precision. These interdisciplinary approaches enable objective assessment, individualized treatment, and continuous monitoring of cognitive control in adolescents. However, achieving sustainable impact requires balancing innovation with ethical responsibility, ensuring that technology complements rather than replaces human clinical judgment. The integration of computational modeling with neurodevelopmental theory promises a future where ADHD diagnosis and intervention are both scientifically rigorous and personally adaptive, an essential step toward precision psychiatry in adolescent mental health.

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