Received 6 March 2024, accepted 23 March 2024, date of publication 2 April 2024, date of current version 10 April 2024.

*Digital Object Identifier 10.1109/ACCESS.2024.3383847*

APPLIED RESEARCH

# Open-Loop Neuroadaptive System for Enhancing Student's Cognitive Abilities in Learning

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This work was supported by the Academic Leadership Program "Priority-2030" of Immanuel Kant Baltic Federal University of Ministry of Science and Education of Russian Federation.

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Independent Ethical Committee of the Clinical Research Center in Immanuel Kant Baltic Federal University under Approval No. #32, 04.07.2022.

**ABSTRACT** Neuroeducation seeks to implement knowledge about neural mechanisms of learning into educational practice and to understand the impact of learning itself. The crucial tasks in this field are to evaluate and to enhance cognitive abilities, that are used in monitoring educational performance, but also known to greatly impact learning process. Contemporary neuroscience achieved significant progress in measuring brain cognitive abilities through mental state assessment. Popular approach to this task based on brain-computer interface can be difficult to implement in the context of education, but general concept of neuroadaptation is still plausible. In this study, we propose open-loop neuroadaptive system for enhancing student's cognitive abilities in learning. Assessment of cognitive abilities is based on the concept of executive functions. We design EEG study with special tests and use combined analysis of behavioral and brain activity to assess the level of development of cognitive abilities. Feedback in this system is implemented in the form of recommendations aimed to develop and enhance underdeveloped cognitive abilities and skills. Recommendations have form of various types of extracurricular activities and are based on extensive literature search. This is the system with open-loop adaptation, as it can assess cognitive abilities, provide feedback aimed to enhance these abilities and then after a period of time it can assess cognitive abilities again as a part of the next loop. We believe that developed neuroadaptive system has a potential to be used in educational institutes.

**INDEX TERMS** Neuroadaptive system, open-loop, cognitive abilities, executive functions, decision support system, educational neuroscience, behavioral characteristics, neurophysiological characteristics, electroencephalogram.

## I. INTRODUCTION

Learning is the cognitive process of acquiring knowledge and skills through education. One fundamental purpose of education is to provide students with the cognitive abilities (CAs), also known as cognitive functions or cognitive skills, related to problem-solving, logical and creative thinking, that generally help to succeed in life. Measuring CAs is essential for monitoring student's educational performance and personal growth. However, the reverse is also true: CAs and other individual factors have a great impact on learning process [1]. Studying CAs is one of fundamental

The associate editor coordinating the review of this manuscript and approving it for publication was Yiqi Liu.

domains of neuroscience, so education could potentially benefit from findings in this area of knowledge. This naturally leads to the concept of educational neuroscience (or neuroeducation) as an interdisciplinary field of study, that seeks to implement knowledge about neural mechanisms of learning into educational practice and to understand the impact of learning process on the student's brain [2], [3], [4]. However, a certain gap remains between the fundamental findings and their application in the classrooms, and some aspects of neuroeducation are still a subject of a heated discussion [5], [6], [7]. On the one hand, methods developed for strict lab conditions may be inappropriate to use in classrooms [8], [9]. On the other, implementation of poorly justified results often leads only to spreading and reinforcing neuromyths in education [10], [11]. This explains the active usage of neuroscientific approach for solving tasks in education [12], [13], for instance in the context of distance learning [14]. Thus, proper neuroeducational technology should combine robustness of execution with scientific soundness of approach.

A traditional approach for assessing CAs comes from psychology and implements various tests and questionnaires. While some researchers suggest that psychological studies provide enough results to build scientifically sound concepts for education [15], neuroscientific approach has a number of advantages. Brain activity provides a continuous source of data, that can be analyzed to go deeper and focus on the underlying brain mechanisms. Contemporary neuroscience achieved significant progress in measuring CAs through mental state assessment [16], which became possible thanks to the advances in the portable neuroimaging techniques such as electroencephalography (EEG) or functional near-infrared spectroscopy (fNIRS) [17], [18]. While mental state assessment is possible with just recording and analyzing brain activity, implementation of interactivity, feedback and adaptation to the system can widen its possibilities greatly. In neuroscience these terms are usually associated with brain-computer interface (BCI) — a computer-based system that acquires brain signals, analyzes them, and translates them into commands that are relayed to an output device to carry out a desired action [19]. Common area of use for BCI is medicine, where it is implemented to aid disabled users in regaining their communication [20] and motor abilities [21]. Nonetheless, innovative use of BCI technology can be found in other fields including education [22], [23], [24].

There are three types of BCI [19]: (i) active (commands are voluntarily induced by the user), (ii) reactive (commands are measured as a response to an external stimulus), and (iii) passive (commands are derived from spontaneous brain activity). It is believed that passive BCIs are the most suitable for the task of monitoring and assessing cognitive states. Indeed, in passive BCI the brain activity is not expressly or voluntarily modulated, but rather reflects aspects of the naturally present cognitive state of the user [25]. The feedback of such system is implicit, so it can be referred to as adaption, and since adaptation is based on brain activity, the system itself can be called neuroadaptive one [26]. Passive BCIs can be divided into categories according to the degree of their interactivity, i.e. how they respond to a user's input and form a feedback [27]. Two interesting categories here are systems with closed-loop and open-loop adaptation [28]. In closed-loop adaptive systems the behavior adapts to certain changes in the assessed state, which affects further input and future actions, while open-loop systems lack any direct coupling of the adaptation back to the input.

Despite many benefits BCI technology have its share of problems when it comes to implementation in education. Firstly, BCI usage is associated with brain activity recording which requires wearing a device with sensors. Modern EEG recording units can be fairly compact, which, however, comes at a cost of reduced number of recorded EEG channels and lower sampling rate. Obtaining clean EEG signal with high signal/noise ratio usually demands application of special conductive gel that only adds to the inconvenience of the study. There are some dry EEG electrode solutions [29], [30], but their implementation tends to result in the noisier signals. Secondly, BCI works in real-time and thus mental states can be adjusted only for a short time, which contradicts the main purpose of education — acquisition of skills. Any long-term effect requires extensive training and multiple BCI sessions [31], which amplifies earlier described issues. Summarizing all the above, BCIs are ill-suited for use in classrooms on a regular basis. However, general concept of neuroadaptive system (NAS) is still plausible. In this paper, we propose for the first time an approach to building an open-loop neuroadaptive system for enhancing student's cognitive abilities in learning, the general scheme of which is illustrated in Figure 1. Based on the results obtained in the cognitive neuroscience and the development of brain-computer interfaces, we can assume that neuroadaptation can be effectively implemented in the educational process as follows:

- experimental session is performed, during which a student's brain activity is recorded;
- brain activity is analyzed and used to assess certain CAs (offline);
- feedback is provided after the session in the form of recommendations aimed to adjust/enhance assessed CAs;
- student is supposed to follow given recommendations for a period of time, after that a new session is initiated, which signifies the start of the next loop.

Such a system is somewhat similar to open-loop passive BCI, except its performance is more distributed over time. We believe that this approach would achieve more robust performance, provided sound approach to assessing CAs and forming recommendations.

The described concept is in line with trends in education, which include individualization [32], [33], personalization [34], [35], [36] and the concept of lifelong learning [37].

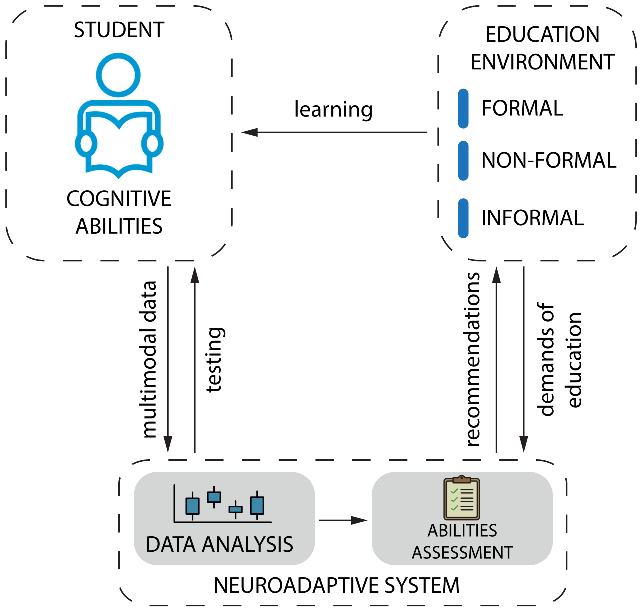


**FIGURE 1.** General scheme of the neuroadaptive approach.

In the context of lifelong learning, learning is not limited to the formal education at school, college or university. Non-formal learning outside of educational institutions, for example, in working groups or student clubs, as well as informal learning, which occurs naturally in everyday life, also becomes relevant. Individualization of formal education has limits at primary and higher education due to the preset educational program, thus non-formal and informal education provide more opportunities for personalization. Therefore, the recommendations of the neuroadaptive system based on the student's data can refer not only to formal but also to non-formal and informal learning, offering him different trajectories of choice of extracurricular activities.

In this paper we consider the creation of open-loop neuroadaptive system aimed to assess and enhance CAs of students through adjustments in non-formal/informal aspects of education. The contribution of our study was as follows.

- We proposed a general scheme of NAS;
- developed specific tests for assessing CAs and electronic environment to implement these tests;
- designed and carried out experimental EEG study for assessing CAs;
- introduced an approach for evaluating development level of CAs based on analysis of behavioral and neurophysiological characteristics;
- developed a system to provide recommendations for enhancing underdeveloped CAs.

## II. GENERAL SCHEME OF NEUROADAPTIVE SYSTEM

The general scheme of the proposed NAS is shown in Figure 2. The work of the NAS consists of several stages.

1) **Experimental session**. At this stage, the student is asked to perform a series of cognitive tests. At the same time, their multimodal data is recorded, including behavioral data and data on brain activity during the completion of tests. The multimodal data registration is carried out using two hardware blocks:
   a) Touch-screen device (tablet or laptop) with a specially designed electronic environment. It implements an interface for the student to complete cognitive tests. It also collects behavioral data on the accuracy and speed of task completion (in other words reaction time).
   b) EEG recording device. The device records the student's EEG signals during the completion of cognitive tests. The data is segmented and synchronized with the presentations and the student's responses on the touch-screen device.
2) **Data processing**. At this stage, the data is transferred to the cloud server. Here, with the help of specially developed software, biomarkers based on behavioral data and EEG signals are calculated to assess CAs.
3) **Formation of recommendations.** The software compares the calculated characteristics of CAs with the predetermined thresholds. As a result, the level of development for each individual CA is assessed. After that, a list of recommendations is formed, i.e. additional activities that can be used to adjust certain underdeveloped CAs.
4) **Verification of recommendations**. At this stage, the list of selected recommendations is analyzed by a teacher and/or a neuropsychologist, who forms a proposal for parents to include certain additional activities in the student's schedule.
5) **Implementation of recommendations**. The student follows the recommendations and, for a certain time, participates in the proposed additional activities. This is followed by a new study, a new assessment of the CAs' development levels and the next iteration in the work of the NAS.

The developed system was tested in the experimental study. At this stage the student performs a series of cognitive tests that are fundamentally unrelated to the student's educational tasks. However, the results of these tests are used to assess the development levels of CAs.

During the experimental study, the student is sitting in a comfortable chair with the touch-screen device on the table in front of them. In a specially designed electronic environment, the student performs a series of cognitive tests described below, and the answers are selected by pressing a finger on the touch screen. The study begins with familiarization with the task. The researcher explains the basics and they complete a couple of tasks together with the participant. Then the participant tries to complete several tasks by their own, the researcher assesses the student's understanding of the tasks and repeats their explanations if necessary. After that, the main part of the study begins — the student performs the tasks independently, while the researcher observes from the side.

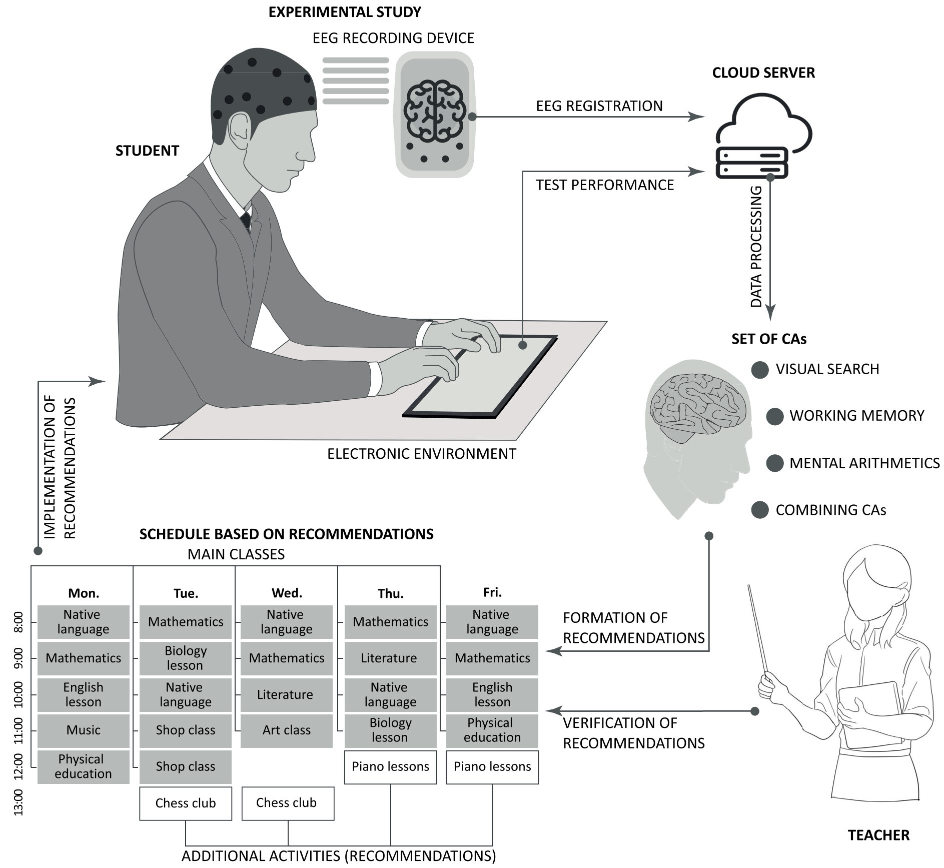


**FIGURE 2.** General scheme of the proposed NAS. The NAS involves five stages: (1) recording multimodal data including reaction time and accuracy of cognitive tasks solutions, as well as data on brain activity during cognitive tests. (2) Data are sent to the cloud where biomarkers based on behavioral data and EEG signals are calculated to assess CAs. (3) A recommendation system generates a set of recommendations for formal and/or informal learning. (4) The generated recommendations are verified by a teacher who forms a proposal to include additional activities in the student's schedule. (5) The student fulfils the recommendations, after which the next stage of cognitive development verification is possible.

## III. ASSESSMENT OF COGNITIVE ABILITIES

In psychology, executive functions (EFs), also known as cognitive control, are commonly used to assess basic cognitive processes such as attention control, cognitive inhibition, inhibitory control, working memory, and cognitive flexibility [38], [39], [40]. Number of studies reveal connections between EFs and academic performance, especially in primary education [40], [41]. There are reported methods for the assessment of individual EFs in children, both healthy and impaired [42], [43], as well as approaches for the development of certain EFs [44], [45]. We suggested that comprehensive analysis on EFs can be used to estimate CAs in the proposed NAS.

Psychological tests can be implemented to assess EFs, but neuroscientific methods make it possible to include estimates acquired through a direct study of brain activity, for example with EEG. In this study we proposed to assess EFs by analyzing behavioral and brain activity during certain cognitive tests. We introduced cognitive tests, which are closely related to various types of cognitive activity during learning (see Fig. 2) [4], [46], [47], namely:

- **Visual search** pertains to a person's ability to efficiently locate specific visual information amidst a complex array of stimuli. It plays a pivotal role in tasks that require visual attention, pattern recognition, and information retrieval.
- **Working memory** is integral to the temporary storage and manipulation of information during cognitive tasks. It influences a person's capacity to process and retain data, particularly in tasks that involve multitasking, problem-solving, and decision-making.
- **Mental arithmetics** focuses on a person's numerical processing abilities, including mental calculations, mathematical reasoning, and quantitative problem-solving. Proficiency in mental arithmetics is vital for a wide array of academic and practical tasks.
- **Ability to combine CAs** is crucial because almost any complex cognitive task can be decomposed into several CAs. Thus, the ability to solve such a complex task will be determined, in particular, by the efficiency of combining these CAs.

While these tests are not conventionally used to evaluate EFs, they are connected to EF skills, especially in the context of neuroeducation.

For example, visual search task is closely related to selective visual attention. According to the theory of visual attention, perception of visual scenes is considered in terms of competition among multiple representations — such as colors or objects [48]. Selective visual attention adds "bias" to this competition in favor of certain selected representations. According to Miller and Cohen's model [49], this selective attention mechanism is a special case of cognitive control, and thus the results of visual search test should correlate to the level of EFs' development.

Working memory is an important concept in EF theory as one of influential models is based on it. Baddeley's multicomponent model of working memory [50] is composed of a central executive system, that directs attention to relevant information and regulates three subsystems: the phonological loop that stores verbal information; the visuo-spatial sketchpad that stores visual and spatial information; and the episodic buffer that integrates short-term and long-term memory. The existing results show that working memory capacity correlates with some, but not all of EFs [51], so we suggest that working memory test is an adequate addition to our set of cognitive tests.

Mathematical proficiency is an important aspect of academical performance, and mental arithmetics (arithmetical calculations using only the human brain) has long been a component of mathematical education. There is ample evidence that EFs, namely working memory and attentional control, underly the mechanisms of mental arithmetics [52], [53], [54], hence this cognitive test matches the purpose of our study.

One of the important EFs is cognitive flexibility — mental ability of cognitive system to adjust its activity and content, switching between different task rules and corresponding behavioral responses [55]. In the context of our approach, we can consider some cognitive test comprised from combination of other, simpler, tests for evaluation of EFs/CAs. We believe that such test reflects the ability to combine several CAs and thus cognitive flexibility skill.

The completion of each cognitive test involves solving many tasks of the same type. The general schemes of the tasks are shown in Figure 3.

### A. VISUAL SEARCH ASSESSMENT TEST

One task example is shown in Figure 3a. At first, a cross appears on the screen to attract the participant's attention. The duration of the cross presentation varies from 0.75 to 1.25 seconds. The "floating" time of stimulus presentation is used to prevent the student from getting used to the task's timings [56]. Then the target number, which the participant needs to remember, is displayed on the screen for 1.5–2.0 seconds. Following this, a $5 \times 5$ table of numbers appears on the screen. The subject's task is to find and indicate the target number in the table. The table remains on the screen until the student provides an answer. In addition, the student has the opportunity to skip a particular task using the "skip" button, for example, if they were distracted and could not remember the target number. After the student's answer, a short pause of 1.5 seconds follows, and then the next task of this type begins.

This test uses two types of tables with two-digit numbers. Tables of the first type comprise numbers that contain at least one or both digits of the target number. For instance, if the target number is 24, a table of the first type might contain 25, 43, 44, 42, etc. In the tables of the second type, all the numbers do not include a single digit from the target number. For instance, for the same target number 24, a table of the second type might contain 50, 18, 39, 67, etc. This separation is introduced to test two visual search options: when the target object has similarities with other objects, and when it does not [57]. The test uses equal number of tables of the first and the second type, randomly mixed. There are 10 tasks for each type of table, resulting in a total of 20 tasks.

### B. WORKING MEMORY ASSESSMENT TEST

The design of the test is based on the widely used Sternberg paradigm [58]. One task example is shown in Figure 3b. At first, a cross is shown on the screen for 0.75–1.25 seconds. Then a set of numbers appears on the screen, which may contain 2 or 3 two-digit numbers. The set consists of two rows with fixed positions: three in the top row and four in the bottom. Two or three positions are randomly selected and filled with numbers, and the remaining positions are filled with "*". The set of numbers is demonstrated for 1.5–2.5 seconds, followed by a short pause of 2.0–4.0 seconds. After that, a cross appears again for 0.75–1.25 seconds, followed by a "trial" — a number is shown on the screen. The participant is required to determine whether the displayed number was earlier in the set by pressing "Yes" or "No" button, accordingly. The trial will remain on the screen until the student provides an answer. The answer is followed by a short pause of 1.5 seconds, after which the next task of this type begins.

The task's complexity is determined by the size of the set of numbers. This test uses an equal number of complexity "2" and complexity "3" tasks, mixed in random order. There are trials of two types: target (when the presented number is included in the set) and non-target (when the presented number is not included in the set). The test uses an equal number of target and non-target trials, randomly mixed. The test includes 2 complexity types and 2 trial types, with 5 tasks for each complexity and trial type, which results in a total of 20 tasks.

### C. MENTAL ARITHMETICS ASSESSMENT TEST

One task example is shown in Figure 3c. At first, a cross is shown on the screen for 0.75–1.25 seconds. Then a mathematical equality of the type $X-N = Y$ appears on

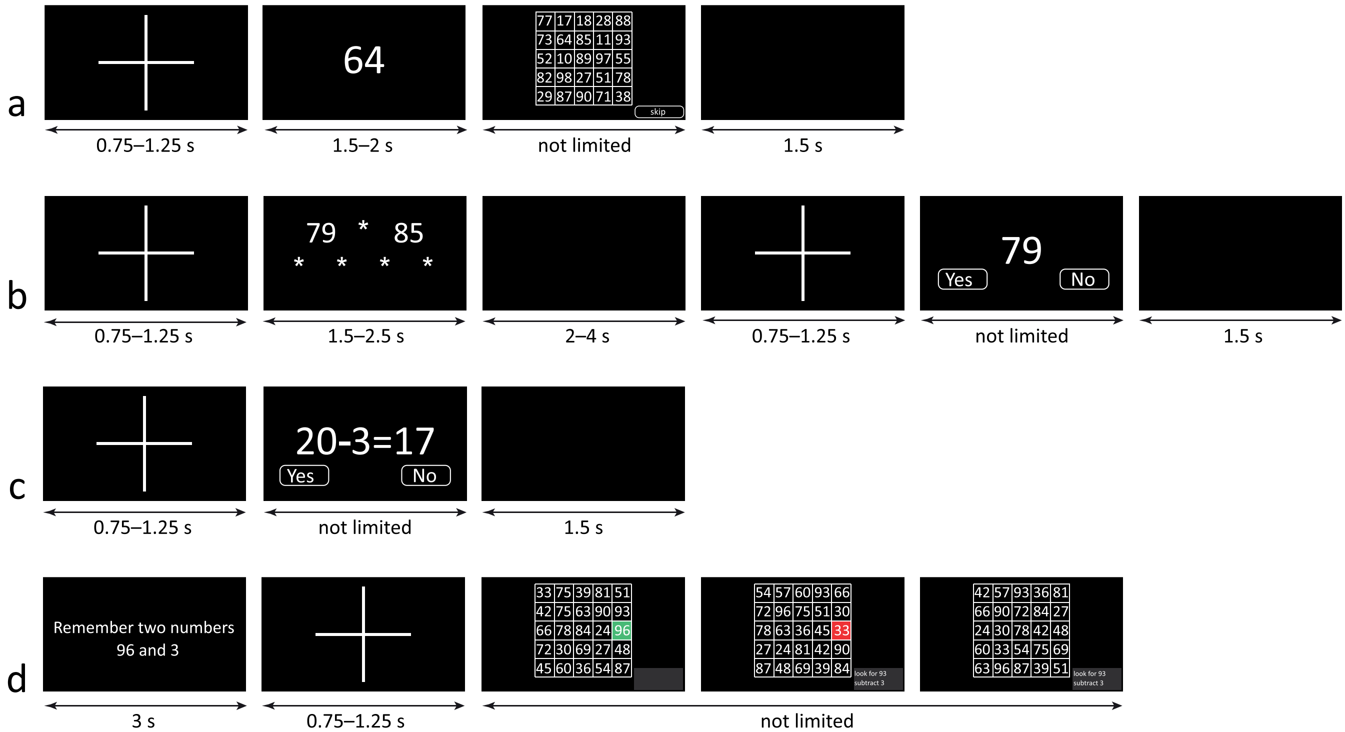


**FIGURE 3.** General schemes of tasks for assessing (a) visual search, (b) working memory, (c) mental arithmetics, (d) combination of CAs.

the screen, where $X$ and $Y$ are two-digit numbers and $N = 1, 2, 3$. The student's goal is to mentally calculate $X - N = Z$ and to compare their answer ($Z$) with the one shown on the screen ($Y$), i.e. to decide whether the given equality $X - N = Y$ is true. The student should press "Yes" button if the equality is correct and "No" button otherwise. The equality will remain displayed on the screen until the student provides a response. A short pause of 1.5 seconds follows the answer and then the next task of this type begins.

The task's complexity is determined by the value of $N$. An equal number of tasks of difficulty "1", "2" and "3" are used, mixed in a random order. There are 10 tasks for each difficulty level, resulting in a total of 30 tasks.

### *D. TEST TO ASSESS THE ABILITY TO COMBINE COGNITIVE ABILITIES*

It is based on the previously obtained results of assessing the effectiveness of children's performance in the Schulte table task. We demonstrated that the effectiveness of solving this test is determined not by one particular CA, but by their combination [59]. One task example is shown in Figure 3d. At first, two numbers are shown on the screen for 3 seconds for the student to memorize: $X_1$ and $N$, where $X_1$ is a two-digit number and $N = 1, 2, 3$. Then a cross is shown for 0.75–1.25 seconds, after which a $5 \times 5$ table of numbers appears. The student's goal is to:

1) find and indicate the first number in the table ($X_1$),

2) subtract the second number from the first number and find the result in the table ($X_2 = X_1 - N$),

3) subtract the second number from the result again and find a new number in the table ($X_3 = X_2 - N$), etc.

The table consists of $5 \times 5 = 25$ numbers, which form a sequence: $X_1, X_2 \ldots X_{25}$. The task is completed when the number $X_{25}$ is selected. To avoid unintentional memorization, the table is shuffled after each number selection [46].

During the task completion, a feedback system highlights the answers: correct ones in green and incorrect ones in red. In addition, if the answer is incorrect, a hint appears in the bottom right of the screen: the current $X_i$, that the participant needs to find, and $N$. The student can also access a hint by clicking on the same area of the screen, for example, in case of confusion.

The complexity of the task is determined by the value of $N$. In this case, the entire cognitive test is the performance of a single task with a certain complexity. Thus, formally, instead of one cognitive test, we get three tests with a different complexity: "1", "2" and "3".

The experimental study consists of three parts separated by breaks. In each part, six cognitive tests are randomly conducted, including visual search, working memory, mental arithmetics and three variants of tasks with a different complexity for combined CAs. A 120 second break occurs after completion of the last task in the part, followed by a 60 second recording of background activity. Total duration of the experimental session was about 50 minutes. When performing cognitive tests and recording background activity, the student is advised to avoid talking and to minimize motor activity that is not related to answering the tasks. During the break, the student can rest, but it is not recommended to get up from the table.

Before performing each cognitive test, instructions are displayed on the screen. Examples of instructions are shown in Figure 4. The instruction is provided to inform the student of the test type and to remind them the basic rules of the tasks. The instruction remains on the screen until the student clicks on the screen — after that, the instruction disappears and the tasks begin.

## IV. DATA ACQUISITION AND PREPROCESSING

In experimental study aimed at testing NAS, the LiveAmp electroencephalograph (Brain Products, Germany) is used to register EEG signals. This compact and wearable device permits unrestricted movement of the student during the study. We suggest, that using such system brings the study closer to natural environment of the school. Registration is performed for 64 EEG channels at a sampling rate of 500 Hz. The electrodes are placed into the sockets of a special cap in accordance with the international "10–10" arrangement scheme. Before installing the electrodes, a NuPrep abrasive gel is applied to the scalp, and a conductive SuperVisc gel is used during electrode placement to achieve low impedance ($<10$ kΩ) and high quality of EEG signals.

LiveAmp electroencephalograph is connected to the touch-screen device through the local Wi-Fi network and synchronized via the Lab Streaming Layer (LSL) system. LSL is a unified time series acquisition system that enables networking and synchronization of different types of research equipment to collect a variety of neurophysiological data. The choice of this system is due to its flexibility, high accuracy, open source code, cross-platform and ability to work within a wireless network. LSL helps to achieve precise synchronization between different modalities of the data, which is crucial for multimodal system. Electronic environment used on touch-screen device is developed with the goals of this study in mind. It is a cross-platform application capable of working on various types of devices such as laptops and tablets.

EEG data preprocessing is a two-step procedure.

First, Butterworth bandpass (1-100 Hz) and notch (50 Hz) filters are applied to the EEG signals. The lower cutoff frequency of 1 Hz is selected to filter out low frequency parasitic components, such as breathing artifacts and interference due to external mechanical action on the electrodes. The upper cutoff frequency of 100 Hz is used to eliminate high-frequency components, such as muscle activity [60]. The notch filter is used to suppress interference from the power grid.

Second, physiological artifacts whose frequency range interferes with the informative range of the EEG signal, are removed. Examples of such artifacts include eye movements and cardiac activity. At this step, a method based on Independent Components Analysis (ICA) is applied: 64-channel EEG data are decomposed into a set of independent components, components with artifacts are selected and removed, and then cleaned EEG signals are restored based on the remaining components [61], [62]. For preprocessing of EEG data, we use EEGLAB — set of MATLAB tools specifically designed for the analysis of electrophysiological signals, in particular EEG [63].

The study involved 60 students from Lyceum No. 23 in Kaliningrad, Russia and experimental school "New vision" in Moscow, Russia. The students were of two age categories: 9–10 years old (grades 3-4) and 11–12 years old (grade 5). There were 36 boys and 24 girls. 15 participants were excluded, since they could not complete all 3 parts of the experiment due to various personal reasons such as high fatigue and low involvement in the task.

The experimental study was conducted in the morning in a quiet room with sufficient natural light on the Lyceum premises. Before the experiment, the schoolchildren were advised to follow a healthy lifestyle for 48 hours, including an 8-hour night's rest, moderate physical activity and limited caffeine consumption. Before participating in the study, the student and their parents (legal guardians) were instructed of the general design, objectives and methods of the experiment. They were allowed to ask any related questions and received comprehensive answers. After that, the parents (legal guardians) filled out and signed the informed consent form. The experimental study was conducted in accordance with the Declaration of Helsinki. The study design was approved by the Ethics Committee of Immanuel Kant Baltic Federal University (Protocol No. 32 from 04.07.2022).

## V. LEVEL OF DEVELOPMENT FOR COGNITIVE ABILITIES

Several characteristics are used to assess the level of development for each CA. Some of the characteristics are behavioral, as they are based on the analysis of the student's behavior during the performance of cognitive tests. Two such characteristics were chosen: the correctness of the cognitive test $P$ and the average response time $\langle T\rangle$. The correctness $P$ shows the percentage of correct answers in the total number of tasks in the cognitive test. However, in our study, it is more convenient to use the inverse characteristic — the percentage of errors $C$, $C = 100\% - P$. The average response time $\langle T\rangle$ is calculated as the mean response time across all tasks in one cognitive test.

Other characteristics are neurophysiological, because they are calculated on the basis of neurophysiological data of the student. We have chosen two such characteristics that reflect features of attention and fatigue. These characteristics will be described in detail in the further sections of the paper.

An assessment is conducted individually for each characteristic of the CA. The level of a specific student's characteristic is determined by comparing the obtained value with the reference values. To obtain the reference values, an experimental study is carried out in advance on a group of students. For each characteristic, a distribution of values in the group is constructed, the quartiles of this distribution are calculated and the boundaries of the quartiles are taken as

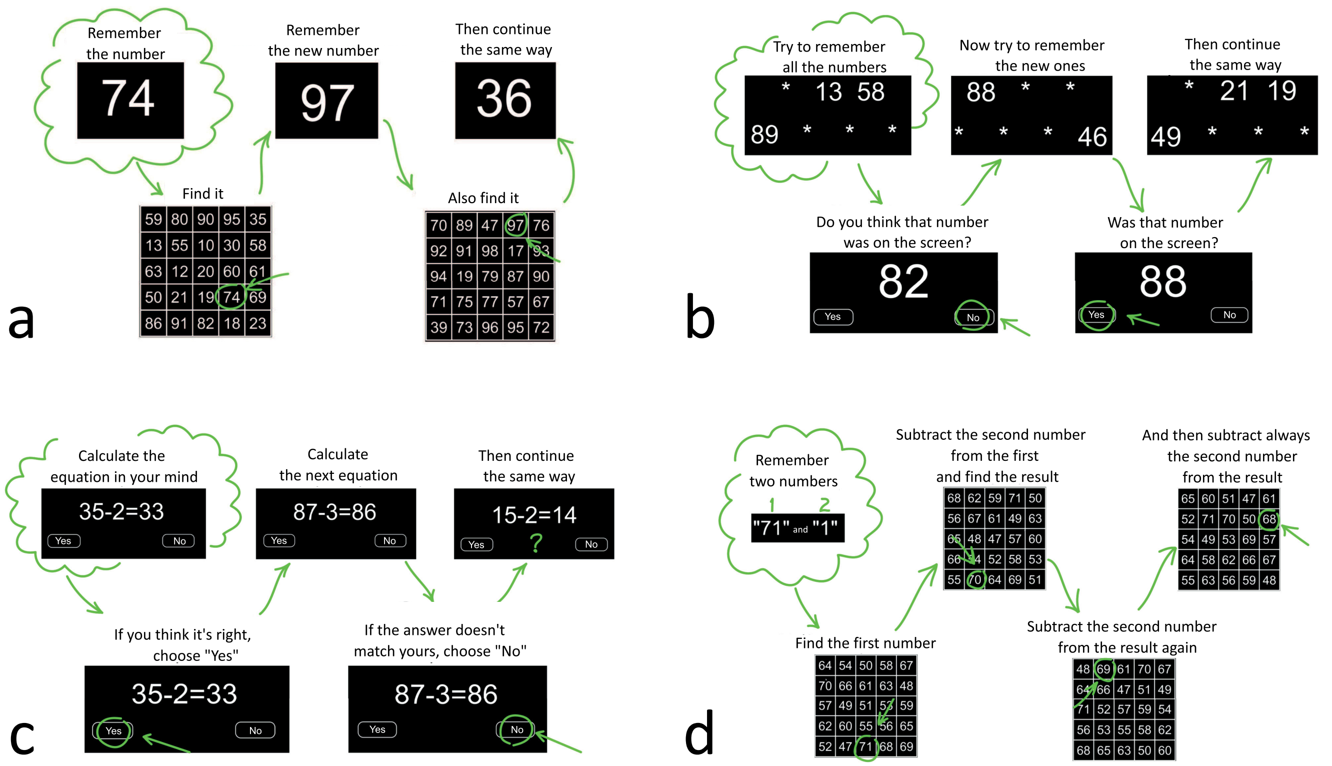


**FIGURE 4.** Instructions for tasks assessing (a) visual search, (b) working memory, (c) mental arithmetics, (d) combination of CAs.

the reference values. In the developed NAS, characteristics are assessed as follows: values in the second and the third quartiles are treated as norm, while values in the first quartile are below the norm and values in the fourth quartile are above the norm. Figure 5 illustrates the general scheme for assessing an individual characteristic of the CA.

To assess the overall level of CA's development, all its characteristics are considered together: if the level of two or more characteristics is above the norm, the CA requires additional development, i.e. it is necessary to form recommendations for its enhanced training.

## A. CHARACTERISTIC FOR ASSESSING ATTENTION

One of the important characteristics of individual is the capacity to stabilize the content of attention over time [64]. Here stability of attention, i.e. attentional control, indicates the ability of the student to maintain a certain level of attention during the performance of a cognitive task. Evaluation of attentional control is implemented here as a part of evaluation of EFs in general. However, previously we have proposed a reliable method for assessing the inverse characteristic — the instability of attention [65]. In this study, we decided to use the same method, the essence of which is described below.

1) The performance of one cognitive test is considered. The time frame for completing the test is determined from the moment the first task appears on the screen to the answer to the last task. Then the resulting time interval is divided into $n$ equal parts.
2) In each of the $n$ parts, EEG signal is considered, for which a time-frequency analysis is performed based on a continuous wavelet transform (CWT) with a Morlet mother wavelet [66], [67]. During the analysis, the wavelet spectrum of the EEG signal is calculated and then averaged over the frequency range of EEG alpha rhythm (8-14 Hz) and over time within each of the $n$ parts. As a result, the time-averaged power of EEG alpha rhythm $E$ is obtained.
3) For the obtained $n$ values of the alpha rhythm power, the variance $\sigma_E^2$ is calculated. The variance $\sigma_E^2$ is then normalized to the alpha rhythm power averaged over $n$ values $\langle E \rangle$:

$$\sigma_{Enorm}^2 = \sigma_E^2 / \langle E \rangle^2 \tag{1}$$

It is clear that the difference in the variance $\sigma_E^2$ in two students can be caused by a significant difference in the values of mean power of $\langle E \rangle$. Normalization is used to avoid this situation. The resulting normalized characteristic $\sigma_{Enorm}^2$ is used to evaluate the stability of attention — the higher is the value, the less stable is the attention.

To validate the proposed characteristic, an analysis was carried out to check for the presence of a correlation between this characteristic and behavioral data.

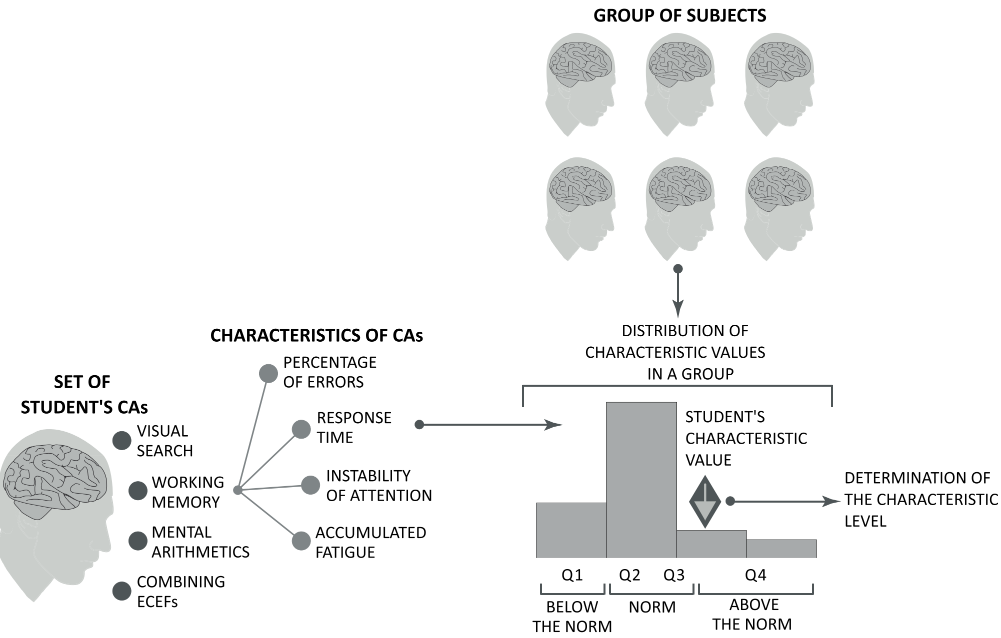


**FIGURE 5.** The scheme of assessment of an individual characteristic of the CA.

We believe that the response time $T$ is a measure of the performance in a single task. At the same time, the average response time $\langle T \rangle$ acts as a measure of the performance in the cognitive test as a whole. In this context, the variance of the response time $\sigma_T^2$ calculated for all tasks within a single cognitive test, can be considered as a stability of the performance in the test. However, the variance of $\sigma_T^2$ may depend on the average response time $\langle T \rangle$, so the difference in the variance for two students may be caused by the difference in the efficiency of the test performance rather then difference in the instability of attention. To resolve this issue, we have introduced a normalized variance of the response time $\sigma_{Tnorm}^2$, which is calculated as follows:

$$\sigma_{Tnorm}^2 = \sigma_T^2 / \langle T \rangle \tag{2}$$

In our opinion, this dimensionless characteristic better reflects the instability of attention and does not depend on the efficiency of the cognitive test performance.

Then a correlation analysis was carried out. The Spearman correlation was calculated [68] between the normalized variance of the alpha rhythm power $\sigma_{Enorm}^2$ in each of the 64 EEG channels and the normalized variance of the response time $\sigma_{Tnorm}^2$. Figure 6a shows a topogram of EEG channels for which the correlation was found to be significant ($p < 0.05$). It is clearly seen that the EEG channel with the highest correlation coefficient in the absolute value ($r \approx -0.6$) is F6, and the regression model $\sigma_{Enorm}^2(\sigma_{Tnorm}^2)$ was constructed for this specific channel (see Figure 6b). The obtained result justifies the use of the normalized variance of the alpha rhythm wavelet power $\sigma_{Enorm}^2$ in channel F6 as a characteristic for assessing the instability of attention.

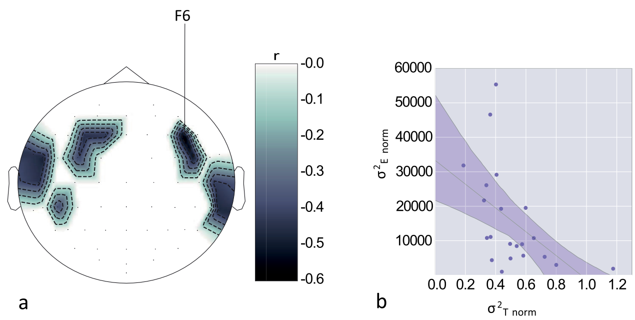


**FIGURE 6.** A topogram of EEG channels for which the correlation between the normalized variance of the alpha rhythm wavelet power $\sigma_{Enorm}^2$ and the normalized variance of the response time $\sigma_{Tnorm}^2$ was significant ($p < 0.05$) (a). A regression model constructed for channel F6 with the highest correlation coefficient ($r \approx -0.6$) (b).

## B. CHARACTERISTIC FOR ASSESSING FATIGUE

In cognitive test performance fatigue can be associated with fatigue of cognitive control [69], so fatigue evaluation can be beneficial for assessing EFs and CAs as a result. In this study, for the assessment of fatigue we used the characteristic proposed in the work by Johns et al. [70]. Characteristic $F$ is calculated as the ratio of the amplitude of blink $A$ to the peak closure velocity (PCV) of eye. In the original paper, these indicators were measured using a method based on the evaluation of infrared reflectance. However, it has been shown that the electrooculogram (EOG) signal is also suitable for accurate assessments [71]. As EOG was not recorded separately in our study, we applied methods to extract EOG from EEG signals using ICA. From a set of independent

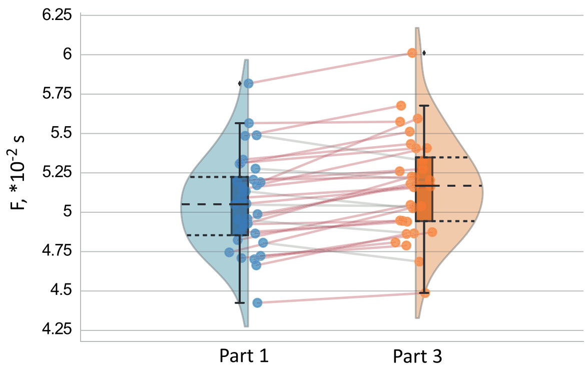


**FIGURE 7.** Change in characteristic $F$ between the start and the end of the experiment.

components, the ones that best correlate with the frontal EEG channels (Fp1, Fp2) are selected. Based on these components, the characteristics for fatigue assessment are calculated using a specialized BLINKER package on MATLAB [72].

In the original paper [70] it was shown that the value of the calculated characteristic $F$ negatively correlates with the subject's response time when performing cognitive tasks. The absolute values of the characteristic $F$ associated with states of low and high fatigue were also demonstrated. This study proposes the evaluation of "initial" fatigue level, which is measured at the beginning of the experiment before completing any tasks. This characteristic can be used to assess the reliability of the results obtained — if the subject's initial fatigue is high, the results of the study may be unreliable.

Analysis of the experimental data shows that characteristic $F$ significantly ($p < 0.005$) differs between part 1 and part 3 of the experiment, i.e. it increases from the beginning to the end of the experiment in the group of subjects (see Figure 7). This may be due to the accumulation of fatigue in the subjects during the course of the cognitive tests. In this context, we introduced the characteristic $\Delta F$, which is the difference between the values of $F$ at the end and at the beginning of the experiment. We believe that $\Delta F$ is a measure of the fatigue accumulated due to the performance of the tasks, which reflects the working load on the subject and can be used as a characteristic in assessing the CAs. Note that $\Delta F$ is calculated for the whole experiment in general and thus the obtained value $\Delta F$ is shared for all four cognitive tests.

## VI. EXAMPLE OF APPLICATION

The data obtained as a result of the pilot experiment was analyzed. To do this, all the characteristics for each individual CA were calculated for each subject. Characteristic value distributions of the subject group were constructed. To assess the norm, the reference values were calculated as the first and the third quartiles of the distribution. The distributions and reference values for each characteristic of various CAs are presented in Figure 8.

To demonstrate the work of the proposed NAS, the results of one subject were considered. The individual values of each characteristic of the subject are shown by "diamond" marks on the distributions in Figure 8.

From Figure 8 it is possible to draw conclusions about the level of development of all CAs in this subject. For visual search (Figure 8a), the values of all the characteristics are within the norm range, so this CA is well developed. For working memory (Figure 8b), the value of the "response time" characteristic is higher than normal, but the values of the other characteristics are within the normal range — we can assume that this CA is also well developed. For mental arithmetics and the combination of CAs (Figure 8c,d), the values of the characteristics "percentage of errors" and "response time" exceed the norm — this is enough to conclude that these CAs are not sufficiently developed.

## VII. DISCUSSION

In our system, the recommendations take the form of extracurricular activities, that consider the results of the CAs' assessment, student's personal preferences, as well as the capabilities of a particular school. We formed a database of recommendations based on meta-analysis of the scientific literature — we reviewed studies about the impact of certain types of activities (e.g. musics [73], sports [74], clubs of interest [75], etc.) on children's cognitive development. The database lies in the core of NAS, however, we do not describe the construction of such database here as it is a subject of another extensive study planned to be reported separately in the future. In this paper we discuss only the basic principles of this database and NAS development. In the database, the tag system is implemented: each potential recommendation (type of activity) has a number of tags, that reflect developed CA(s) as well as areas of interest, availability, time demands, etc. Hence, the selection of a particular recommendation is dependent on a comprehensive assessment of its characteristics in order to best match the student's needs and preferences. The proposed system conceived as a tool for decision support, so while recommendations are offered automatically, they can be adjusted by teacher/psychologist, for example, considering student's previous negative or positive experiences with extracurricular activities.

The NAS for schoolchildren has been tested at Lyceum No. 23 in Kaliningrad and has shown its high efficiency in identifying the features of the individual development of the CAs of schoolchildren. 54 schoolchildren aged 9–12 years took part in the experiment, and we used their data to determine the reference values of the development of each of the CA. Currently, a prototype of the NAS has been prepared, which is able to measure and process behavioral characteristics and EEG signals of the subjects in order to assess the individual development of CAs and to offer recommendations for their improvement.

Research on connections between cognitive development and educational success can be quite diverse as it includes studies on the influence of nervous system features [76], [77], impairments [78], [79], age [80], etc. A special place in this research is given to executive functions and cognitive

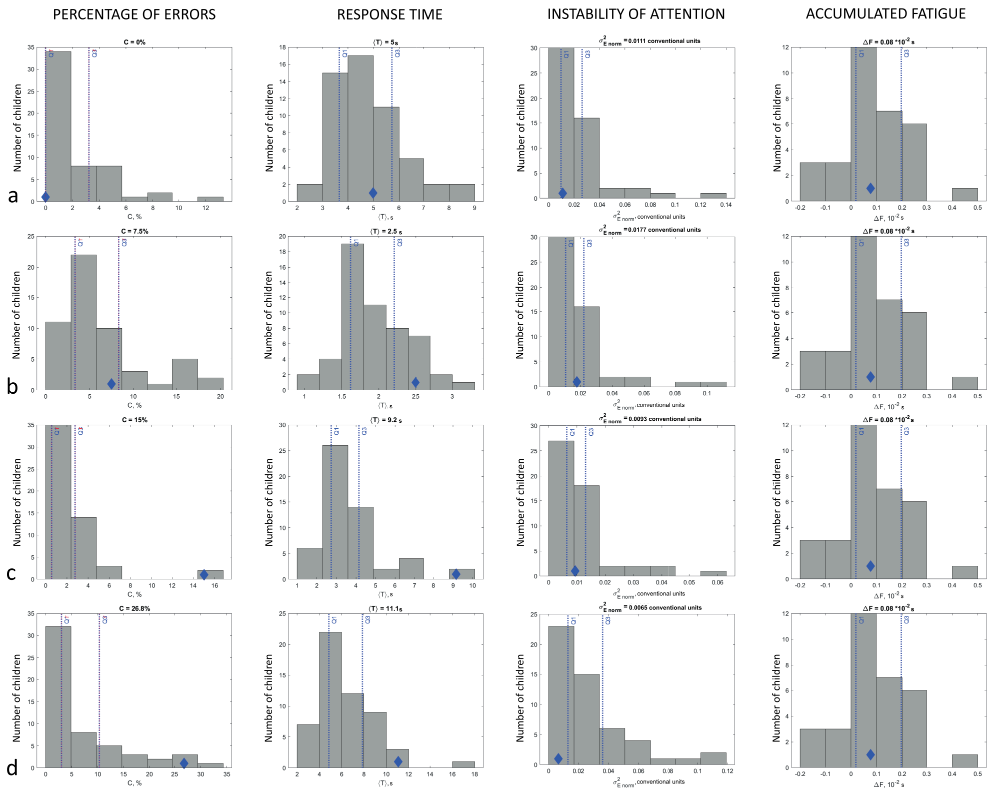


**FIGURE 8. Results of the analysis of CAs' characteristics in the group of subjects: distributions of values in the group (histograms) and reference values of the norm Q1 and Q3 (vertical dotted lines) for CA visual search (a), working memory (b), mental arithmetics (c), combination of CAs (d). Individual values for one of the subjects are shown on the distributions by "diamond" marks.**

abilities, especially attention [81] and working memory [82]. However, in majority of these studies CAs are considered separately, mostly due to the difficulties in identification and separation of multiple CAs [83]. Thus, in our work we proposed a novel approach to evaluate individual CAs and their combination, which provides opportunity to investigate the contribution of each of CAs and possible interactions between them.

Another issue in this field is related to the technical aspect of the studies. By now a substantial success is achieved in the sphere of neuroimaging techniques, which includes reliable and accessible means of portable neuroimaging [17]. However, the scope and methodological approach in such studies can be spotty. Researchers usually tend to focus on one topic such as reading performance [84], [85], influence of presentation patterns [86], [87], human-computer interaction [88], game-based learning [89]. Studied cognitive aspects are also limited per work: most commonly it is attention [90], [91] or motivation [89], [92]. There is also inconsistency in analyzed types of data — it is usually the results of psychological tests or some derivatives from neuroimaging data and rarely combination of both [83]. Distinctive feature of our approach is the combination of behavioral and EEG data used to assess multiple aspects of cognitive development, which ensures more general coverage of the studied area.

Decision support aspect of our proposed system is also very important. There were some attempts in development of various decision support systems for education, including artificial intelligence-based ones [93], [94], yet we couldn't find a direct analog to our system that would consider subject's features of cognitive development as well as personal preferences.

## VIII. LIMITATIONS AND FUTURE STUDIES

Limitations of our study are shared with many other works in this field. Firstly, it is an ambiguity of obtained results that is mainly tied to the somewhat ambiguous nature of neurophysiological studies. Tests designed to assess cognitive abilities are all based on literature search and our own studies, however, their precision in reflecting targeted cognitive functions requires further validation and research. Additionally, number of characteristics used to assess cognitive abilities in this study is limited. Connection between brain activity and level of cognitive abilities is still under study, and implementation of additional EEG-based characteristics may add to precision of assessing cognitive abilities.

Another open-ended question is about influence of age and environment. Our pilot study included schoolchildren in the age of 9–12, yet we expect the age to be an important parameter in our system affecting, for instance, complexity of cognitive tasks and reference values during assessment of cognitive abilities. Thus, we are planning to reiterate experimental study for other age groups to expand existing database and correct parameters in our system. Additionally, an important direction of future research is to study effects of the system's implication over time, since lasting enhancement of cognitive abilities is the very purpose of such system. It would be very interesting to evaluate cumulative effect of multiple successive loops of cognitive assessment and enhancement and compare it to natural cognitive development of students. It is a challenging task, but we are planning further experimental studies.

Last but not least, there are legal and ethical questions [95]. These commonly emerge in studies that involve underage students or changes to established educational system. We believe that extensive consulting with teachers and psychologists will eliminate any barriers for the system's implication.

## IX. CONCLUSION

In this paper we proposed an open-loop neuroadaptive system aimed to assess and enhance cognitive abilities of students. The system is based on the assessment of CAs in learning process with the help of executive functions theory. The technical part of the neuroadaptive system is aimed at measuring the student's both behavioral characteristics and brain activity estimated by EEG during the performance of specially developed cognitive tests. The system includes a portable EEG recording system and a tablet PC for presenting tests and recording the student's reaction to these tasks, as well as cloud-based software for analyzing the obtained experimental data and calculating biomarkers of cognitive abilities. We developed a set of specific cognitive tasks for testing CAs and implemented it in the form of an electronic testing environment. While the subject performs these tasks, we collect both behavioral and neurophysiological data to extract specific biomarkers related to corresponding CAs. We use these biomarkers to estimate the level of development of each CA and to propose recommendations aimed at advancing underdeveloped CAs.

We believe that such system is suitable to be used in educational institutes, as it has few key features.

Firstly, it is modular approach. Our proposed NAS uses two hardware blocks to record multimodal data:

1) touch-screen device used to perform cognitive tests and gather behavioral data;
2) EEG recording device used exclusively to gather neurophysiological data.

The EEG device is certainly the more demanding of the two, since in addition to higher costs it requires special conditions and trained personnel. This creates a potential barrier for the system's application in institutes that cannot afford EEG device. In this paper and our previous studies [47], we theorized that cognitive abilities can be assessed with combination of behavioral and neurophysiological characteristics, however, in a pinch even a fraction of this set will suffice. In this context, to assess cognitive abilities, we can use behavioral data only — this provides more rough but still reasonable estimation. Thus, we can propose a variant of the system that is just a tablet with electronic environment. This variant would have lower confidence of estimation for cognitive abilities but also much lower costs, so it could be implemented in most educational institutes.

Secondly, it is implementation of recommendations. The system provides recommendations in the form of extracurricular activities, i.e. non-formal or informal learning. This is an important advantage, since formal education is commonly bounded by the preset educational program and is ill-suited for individualization.

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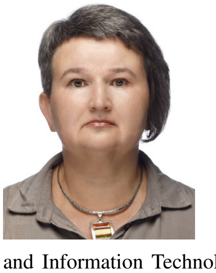

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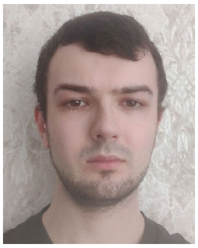

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