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PAPER

EEG-Integrated Selective Attention Assessment Software Platform

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ABSTRACT

In this paper, we propose a software platform that enables respondents to complete different selective attention test variants, locally or remotely, while at the same time collecting their electroencephalogram measurements. The main goal is to provide an applied software solution for a platform in the domain of telepsychology to go beyond the current use of telecommunication tools in this field. The platform reconciles reliable and synchronized transfer of test data and measured electroencephalogram values in real time to create a test environment that does not disturb the respondent when completing the test and presents all the data to the (remote) examiner. The proposed platform comprises a data-source module and a data-collecting module, with the configuration of the electroencephalogram measuring device (its frequency and channels) being transferred before acquiring the measurements. This makes the communication between the modules independent in terms of the chosen headset. Even with providing only preliminary results, a pilot experiment was conducted to test the platform with both types of tests, utilizing an *Emotiv Insight* headset. This has yielded results that show specific variants added to customize baseline cases of the tests lead to higher response times and show higher cognitive load for respondents.

KEYWORDS

cognitive neuroscience, telepsychology, real-time communication, selective attention test, directional experiment, trail-making experiment, electroencephalogram measurements, wireless data transfer

1 INTRODUCTION

Telemedicine represents a tool for remote communication of medical information [1]. Three dimensions of telemedicine are functionality, application, and technology [2]. Among other components, functionality contains monitoring, which can be represented as forms of telemetry. The application describes multiple specialties, for example, tele dermatology, teleradiology, and telepsychiatry.

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The process of telepsychology refers to the use of telecommunication tools, mainly related to video conferencing and audio conferencing, but their use is limited only to psychotherapeutic or counseling work, not psychological services. Each application has a specific nature.

Telemedicine technology is described through three sets of variables: synchronicity, network design, and connectivity. Synchronicity, or timing, can be done in two ways—synchronous (real-time) or asynchronous (no real-time interaction), such as telemetry or remote sensing. Network design is referring to the configuration of data transfer through a virtual private network (VPN), the Internet itself, or using other third-party web software. Connectivity can be wired or wireless, depending on the bandwidth and speed needed to transfer information.

Systems for online experiments were created for modern research practice, which enabled the automatic and precise collection of psychological data from a large number of subjects [3], [4]. However, such online experiments were not applicable in the field of cognitive neuroscience, since this scientific field is focused on the study of the biological basis of mental processes (perception, consciousness, action, memory, decision-making, language, and selective attention). Mostly, cognitive neuroscience combines measurement of brain activity with a simultaneous performance of different tasks by human subjects [5].

Selective attention is a cognitive process of selecting relevant stimuli while simultaneously ignoring irrelevant ones and inhibiting responses to them. In this paper, two tests were implemented: the first one belongs to the domain of selective attention tests, and the second one to the domain of visual attention tests.

The first test, called the directional experiment, is used to examine the respondent when interpreting a conflict between the direction of the group of symbols and the symbol of interest. In the baseline case of the experiment, the symbol of interest is shown in the middle of the group. When the group is shown to the respondent, they are expected to notice the direction of the symbol of interest, not the group, and depending on the technique of conducting the experiment, the respondent needs to communicate the noticed direction.

The second variant tested in this paper is a Trail Making Test, which tests visual attention and is suitable for computer implementation [6]. When performing the test, the respondent is shown multiple objects on the screen that have a number on their surface. The task is to click on all objects, in ascending or descending order following their number values. After the object is clicked, it is removed from the screen.

The most common parameters that are registered are reaction time and accuracy in answering. A shorter reaction time and a higher number of correct answers are considered to be indicators of a higher ability of selective attention.

These types of experiments were chosen because they are performed interactively, asking the respondent to interact according to the given stimuli, as opposed to regular psychology tests, where an appropriate answer is chosen from the given options. This platform is a part of ongoing research, and it provides functional testing with a long-term goal of respondents learning how to improve their attention.

The goal of our study is the development of a software platform that provides examiners and researchers with the possibility to perform the selective attention test remotely. The platform is developed with telepsychology in mind as the application of telemedicine, with real-time communication and wireless data transfer.

In order for the modules of the platform to communicate through the computer network, transmission control protocol (TCP) is used. It is a part of the Transport Layer of the TCP/IP protocol set that guarantees a reliable data transmission from both endpoints. A guarantee of reliable data transfer is achieved by setting up the connection between the modules that are communicating through the computer network. An interface used to connect the application with the Transport Layer is called a socket. A socket can be described with its IP (Internet protocol) address and port number. Sockets are used as the communication endpoints between the two modules of our system.

The proposed platform contains a data-source module and a data-collecting module, with the data-source module being responsible for providing the respondent with the interface to perform the test. While the respondent performs the test, their EEG is measured. However, the respondent should be equipped with a headset that is used to acquire measurements and a person with the knowledge of setting it up.

Different types of users and their usage of the platform modules, the data-source and data-collecting module, are shown in Figure 1.

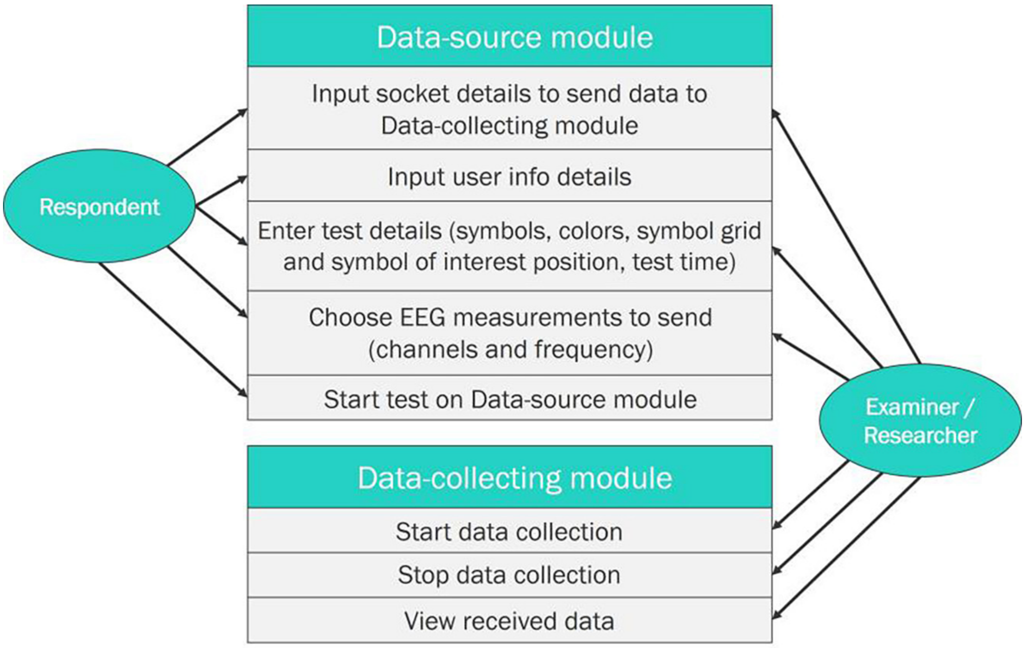


Fig. 1. Main functionalities of the platform modules and their availability to each intended type of user

1.1 Literature review

Visual attention is one of the topics of numerous scientific researches in the field of psychology but also in the field of neuroscience [7]. Here, it is broken down into spatial and feature attention. Spatial attention is a form of visual attention that involves directing attention to a location in space. On the other hand, feature attention is a form of visual attention directed to specific features of a stimulus, such as color, shape, or orientation. These forms of selective attention will be tested in our experiment.

An extensive presentation of telemedicine systems is given in [8]. First of all, the main focus of such systems is to monitor remotely located patients. Here, different specialties of telemedicine systems have been listed, but there was no mention of telepsychology systems. Another important factor when setting up a telemedicine system that was described here is the cost, if there are multiple devices needed to perform monitoring of patients, especially if there are multiple patients. Also, the standard is to keep patient data confidential but also to provide enough data to the experts so that they can propose proper care and treatment.

The propositions for applying network communication when developing telemedicine systems are described in [9]. Next to these propositions, the authors share important challenges and directions that should be taken when developing these systems. Among the network protocols that should be used for wireless communication, TCP is stated as providing diverse and cheap functionalities in order to transfer data efficiently, achieving high data flow but also a low error rate. Another important statement is that future solutions in telemedicine should support data security and privacy and also that the systems developed should combine different wireless networks in order to guarantee the quality of service. Our solution follows this proposition in terms of employing TCP and using wireless transfer.

Data visualization in visual analytics and the Internet of Things (IoT) should utilize multiline charts when comparing the same dataset in different time periods and including the cases when there are multiple data categories [10]. Besides that, the flexible visualization system should provide updates in real-time, since the measurements in IoT are dynamic. Visualization platforms that are listed in this paper follow a similar architecture, based on service oriented architecture (SOA), with four services:

1. Data Collection Service – is used to receive the data.
2. Data Visualization Service – is used to observe data intuitively.
3. Dynamic Dashboard Service – is used to provide an interface to organize and display various information.
4. Data Analytic Service – is used as a statistical analysis tool.

When talking about the significance of its application in healthcare, high dimensionality of data is a challenge to visualize properly and also to achieve performance in functionality, scalability, and response time. Next to that, the data gathered should be processed in order to get medical insight.

When processing data, one important challenge imposed in future IoT visualization systems is to clean and reduce data outliers without information loss. When approaching data visualization, it is important not to overwhelm the user with large datasets and try to condense them to fit the user's physical perception limits. Also, when visualizing data in real time, it is important to achieve optimal network bandwidth but also low latency. In our solution, the choice was to visualize more than the last 300 measurements in real-time.

The process of compression and removal of noise from the measured EEG signal values is enriched by applying the Savitzky-Golay filter (SGF) in order to process high-frequency digital signals and reconstruct the original EEG signal [11]. The goal with this was to measure all EEG signals, then clean them and send them as one bulk of data. With the quality of communication being the other important topic, real-time transmission of EEG data was something the authors emphasized as future research. Against sending the whole EEG data read from the *.csv, a decision was made in favor of performing real-time transmission.

Different approaches when performing wireless sending of EEG signals are listed and evaluated by [12]. The first comparison that was presented was that of sending an EEG signal image to a doctor's phone/computer as opposed to sending actual data, with the latter being superior for interpreting if the image itself is not high-resolution and cannot be enlarged to look at the details. Our solution follows a similar idea: while the data is being transferred, it is stored on the examiner's (remote) computer, while the visualization is available only while the real-time transmission is happening. One of the problems described is the quality of network communication is often the cause of failures when transmitting data. An even greater problem is a lack of a standardized format of gathering EEG signals with different hardware used to measure values. The authors recommend using a cloud-based framework to store measurements or an SQL database. Both of these solutions require additional support, whereas a simple *.csv file provides an easily readable table view of all received data.

An Android application for remote overview of patient condition is presented in [13]. It is developed as a dashboard that visualizes gathered data. Similarly to one option in our solution, the authors used data to simulate the actual Internet of Medical Things (IoMT) sensors in real time and provide the data flow in order to test the system. Depending on the type of data, it is visualized in a different type of chart (radar chart, heat map, and gauges).

Next to remote overview of patients, mobile phone applications can be a solution [14] for performing selective attention tests, providing its user with the option to perform two kinds of tests: one is a variant of the d2 test (finding a specific rendering of the letter “d” in an array of letters “d” and “p”), while the other is an image test (finding specific variants of an image in an array of similar images with different colors or orientations). To perform the tests, the users tap their screen to select one or more answers. When performing these tests, the respondent’s Concentration and Total Performance are calculated, with test parameters and results stored in three different text files in the local memory of the phone. Those results can later be shared using Amazon Web Services (AWS). In terms of interaction, when using our proposed solution, the respondent just has to press the direction of the symbol of interest on the keyboard, as opposed to pressing the actual symbol or more of them. In our solution, we gather more data about the respondent’s performance.

Another example of using a mobile phone application to perform a selective attention test [15] shows an array of three graphics of a flower with a facial expression. In each array, one of the graphics is different, and the user needs to find it. The test results (number of hits and misses), time intervals between answers of each question, total time to complete the test, and personal information of the respondent are stored locally in an SQL database. The target group for this platform was children of aged between six and twelve. Neither this nor [14] measure EEG activity but stores performance data similar to our solution.

Utilization of VR and a PC application in order to perform selective attention tests was presented in [16], similar to the solution presented by [14] with the goal of detecting letters “b” and “p” in the test. The test also contains visual, audio, and audiovisual distractors, with the visual distractor being shown on top of the letter grid, while the audio distractors are played to the respondent. Here, the reaction times are measured with different distractors being used in PCs and also in VR conditions. This test was conducted with six- and seven-year-old children.

One solution provides a possibility to conduct a test where the goal is to distinguish pictures with EEG measuring in parallel [17], a solution our study also follows, although we use symbols. Pictures could contain a male or a female face and could have an indoor or an outdoor background. Respondents pressed the keys that would indicate the gender and the background type, which would be stored along with EEG measurements in order to analyze the respondents’ visual attention. This test was performed on college students.

With the focus on selective attention and attention monitoring and training, a closed-loop neurofeedback (recording and analyzing of brain signals to provide feedback to the respondent) game named Adventures of Birds is introduced in [18]. This game is intended to help enhance the attention of young adults.

Each respondent was wearing an Emotiv BCI (Brain-Computer Interface) headset in order for their EEG to be measured while they played the game. Using neurofeedback, the attention levels of each respondent are shown on their computer screen with progress bars. The respondents also controlled the characters in the game with their attention. Authors got the best results of attention monitoring in terms of classification parameters accuracy, recall, and precision with the Improved Random Forest (IRF) algorithm.

Utilization of the Emotiv Insight headset in order to develop an EEG-based BCI TV remote was the main goal of [19]. Here, the authors have made use of Emotiv's Cortex API to acquire measurements from the headset on the computer in order to command a Raspberry Pi to act as a TV remote. In order to access the Raspberry Pi, a Bluetooth socket connection was used through Python code. When looking at the connection between the computer and the headset, the approach in this paper is the same, utilizing the Cortex API and the Emotiv Insight headset.

The Emotiv Epoc+ headset was used in [20] for measurements acquisition when evaluating construction workers. The Go-NoGo test is utilized here, with the respondents having to communicate when they see the letter "P" while being shown a series of letters "P" and "R" by pressing a button. During the test, the respondents were exposed to different types of construction site noise as distractors. The idea of the study was to find the features taken from EEG acquisition and to find attentional states while the respondents were exposed to construction site noise, as well as evaluating different machine learning models. The authors ultimately presented the idea of making a more cost-effective acquisition device that could capture values on just a couple of EEG channels in order to utilize them generally in construction companies and that could be worn under hard hats. In our study we follow a similar idea, not to use a large number of channels, and classify test results according to machine learning parameters, not just the values gathered from EEG measurements.

Challenges of EEG recording analysis by using various deep learning methods are shown in [21]. The findings in the paper suggest that feed-forward networks are easier to train compared to recurrent networks, which often suffer from issues that lead to not achieving learning progress. Similar behavior was not observed in feed-forward networks, reinforcing the argument for their use in EEG analysis. By incorporating attention mechanisms into recurrent deep neural networks, which improved performance across all datasets, attention can enhance the ability of models to focus on relevant parts of the input data, which the authors explained as crucial for EEG analysis. Performance is also an important factor when analyzing data from a larger number of EEG channels, which is often necessary in clinical settings, along with the need for high accuracy and efficient processing in automated systems. Next to that, the paper proposes window slicing—breaking down the EEG signals into smaller segments for analysis.

Approaching how to apply deep learning techniques in EEG data processing, [22] presents region-based pooling (RBP) as a new method designed for deep learning models that handle EEG data. It allows for effective processing of various EEG channels, which is crucial for improving model performance in real-world applications. The robustness and effectiveness of this approach in managing different channel configurations are validated, and it provides a straightforward solution for cross-dataset and cross-channel applications. Advancing the state of the art in EEG data analysis, the data used in this paper is an open-source dataset obtained from the Child Mind Institute. It consists of high-density EEG recordings from 129 electrodes, covering a diverse age range of five to 21 years, including both male and female subjects with various brain pathologies.

Some of the presented solutions provide a variety of charts to visualize measured data, as opposed to a single chart, giving different options for visual analysis and data interpretation. Sharing data through different Cloud systems is helpful. Even though the values that are calculated for these tests are considered expected, they can be further improved by calculating more statistics. Another advantage of some of these solutions is that the respondents can also affect the software with their attention, as opposed to just measuring EEG values. Some solutions go further in terms of utilizing Machine Learning algorithms, as opposed to just calculating classification parameters, but also generating EEG data when it is not complete, as a fail-safe mechanism. Some of the proposed solutions utilize different noise as input when calculating and interpreting results. VR headsets were chosen to present tests to the respondents [23].

Digital Educational Escape Games (DEEG) were combined with EEG acquisition in [24]. The authors recorded hippocampal theta waves that describe memory encoding or retrieval and low beta waves and alpha waves that we utilize in our solution as well. In their study, they utilize the Emotiv Insight headset with T7, T8, AF3, and AF4 channels to gather EEG measurements. The goal of gathering measurements was to capture neural markers for memory encoding/retrieval, perceived usefulness, and concentration. With three working groups, DEER condition, the task of group 2 was found to be the environment with a positive impact on memory encoding/retrieval, and the perception of activity's value might increase the mental activity of memory encoding/retrieval. They also underlined how integrating EEG analysis offers a richer view of the learning process by bridging neural measures with cognitive processes.

Distinguishing and treating students with attention deficit hyperactivity disorder (ADHD) using digital games with BCI was the goal presented in [25]. Similarly to our proposed solution, they designed a WiMind game that was based on the Stroop Test, and the values were gathered by a headset connected via Bluetooth. The respondents needed to identify the name of the color written on screen with two variants: when the color name matches the actual color or when it does not. Respondents with ADHD have shown less superiority in test performance, which came from inattention and anxiety when incorrectly answering, but after three phases of tests, their performance was improved.

1.2 Platform use case scenario

This platform can be used by researchers and examiners in order to perform the selective attention test with different setups in terms of test modifications, as well as by users who want to test themselves without professional analysis:

1. Step 1—The examiner/researcher inputs the port number on the data-collection module's user interface and starts the data-collection module to be able to receive data from the data source module.
2. Step 2—To be able to differentiate respondents' data on the data-collecting module side, when all of it is being received and stored, before taking the test, the respondent inputs his user data—identification number, age, and gender.
3. Step 3—The examiner/researcher or the respondent sets up the directional experiment test by choosing:
   a) Symbols that will be shown in the group (frog, turtle, bird, fish, or arrows)
   b) A set of colors for symbols (red, green, blue, dark yellow, orange, purple, pink, brown)

c) Group size (how many symbols are shown, with options for 3×3, 5×5, 7×7, and 9×9)
d) Group position/placement (the symbol group can be placed in a random position on the window each time, or the group symbol can be random, or the symbol of interest is placed in a different place in the group each time)
e) Time period over which the test is conducted (in seconds)
   – Examiner/researcher or the respondent sets up the Trail Making Experiment by choosing:
      a) Number of objects to be shown by inputting the minimum and maximum values, as well as the step between each value of the chosen interval
      b) If the objects should be tapped in ascending or descending order
      c) Time period over which the test is conducted (in seconds)

4. Step 4—For remote conducting of the test, data-collecting module socket details (IP address and port) input fields can be found by checking the "Online mode" checkbox in the Options menu of the data-source module. Both the examiner and respondent can then input the values in order to be able to send data remotely.
5. Step 5—Next to measuring EEG values by utilizing a headset, acquisition of EEG channel measurements can also be simulated, where the examiner or the respondent can choose a *.csv file from which the values will be taken.
6. Step 6—The respondent may then start the test and data transfer. The test itself is presented so that the respondent needs to communicate the direction of the symbol of interest by pressing the corresponding key (up, down, left, or right arrow key) on the keyboard, and the direction (in text form) is sent to the data-collecting module by adding it to EEG measurement data.
7. Step 7—The examiner/researcher looks at the received data in the form of a multi-line chart that shows both EEG values as a single line chart per channel, as well as the moments when the user sent the answer on the test as a vertical line over the chart.
8. Step 8—The examiner/researcher can look over the whole data received since it is stored on their computer.

This use case scenario is presented and compared with related papers in Table 1.

Table 1. Overview of the platform use case scenario

Step	Description	Comparison to Related Papers
1	The examiner starts the data-collecting module and chooses the port.	
2	The examiner sets up the test on the data-source module side and connects it to the data-collecting module. The respondent could also set up the test per the examiner's instructions or per personal preference in offline mode.	All either don't mention the transfer of data or store data locally (with the possibility of cloud transfer in [14]). Most of the literature examples are utilizing fixed types of stimuli (pictures or text). Modification of experiment time and how visual stimuli are rendered (different types mixed) was not covered. Distractors are utilized in [16] and [32].
3	Connecting an EEG headset to acquire measurements/Choosing an EEG *.csv file to simulate EEG measurements.	[17], [18], [19], [20], [21], [24], [25], [31], [32] and [34] utilize actual recording of EEG, with [31] generating artificial EEG to augment their classification. [22] uses an open-source dataset.

(Continued)

Table 1. Overview of the platform use case scenario *(Continued)*

Step	Description	Comparison to Related Papers
4	The respondent fills in their user data on the data-source module side in order for the data-collecting module to be able to create a folder to store experiment data.	All store user data.
5	The respondent starts and performs the experiment.	The experiment is performed by pressing the keys on the keyboard if the device used to capture responses is a PC/laptop or by utilizing a keyboard (the VR scene shown to the respondent in [17] also contains a keyboard).
6	The examiner/researcher can look at all the received data in multi-line chart form, along with the user answers.	[13] Visualize gathered data using basic charts; [12] propose sending actual data as opposed to an image showing all the signals so that it can be visualized more accurately.

Note: Each step is compared with its equivalent as described by the papers in the 'References'.

1.3 Author contributions

In terms of author contributions to the research, they are as follows:

- FDJ: research conceptualization, platform design, real-time EEG-task synchronization, experiment configuration and conducting, software for experiment data analysis, writing the original manuscript
- NP: research conceptualization, real-time EEG-task synchronization, experiment configuration and conducting, software for experiment data analysis, writing the original manuscript
- SB: research conceptualization, experiment definition, writing the original manuscript
- MB: validation, review, and editing of the manuscript
- DI: validation, review, and editing of the manuscript

2 MATERIALS AND METHODS

2.1 Data-source and data-collecting module

The solution is developed by utilizing Windows Presentation Foundation (WPF) and the design pattern Model View ViewModel (MVVM). To achieve chart visualization, the LiveCharts2 library was used, while working with *.csv files was provided by the CSVHelper library.

The data-source module provides this platform with the possibility to interpret test responses at the same time as the acquisition of EEG data is happening. The data-collection module provides the examiner with real-time visualization of the test progression, as well as the recording of all data on a remote computer (also in real-time), the main purpose of the module. The described system architecture is shown in Figure 2.

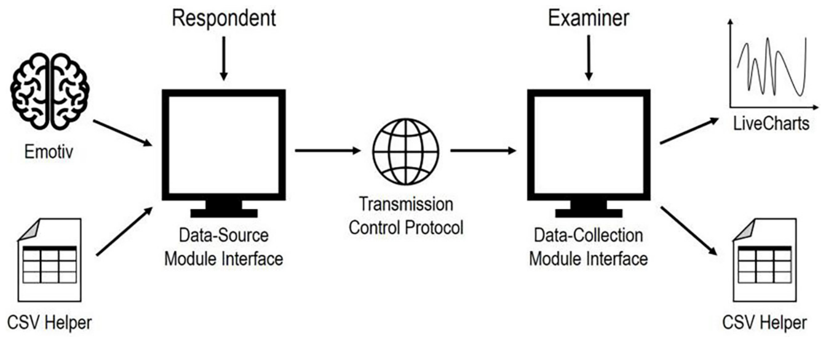


Fig. 2. Platform architecture—the utilized components of modules: Data-Source is acquiring data, and Data-Collection is receiving, interpreting, and storing values, with the data between them being transmitted using TCP for guaranteed data transfer, utilizing sockets on both ends

The graphical user interface of the data-source module allows its user to connect an EEG headset to get actual measurements or choose a *.csv file to be used to simulate EEG measurements being taken. The graphical user interface of the data-source module is shown in Figure 3.

a) **b)**

Fig. 3. Data-source module user interface: a) Initial view, with buttons to start the test, connect an EEG headset, load a *.csv file, and change test options, as well as fields to input user data b) All the parameters and options that can be specified to set up the test

The data-source module handles the conducting of the test. Here, same as in the base case of the elementary directional test, the symbol of interest is shown in the middle, and the base case group is a 3×3 matrix of symbols. When the group is shown to the respondent on the screen, they are expected to press the key on the keyboard that corresponds to the direction of the symbol of interest. When completing the test, the respondent's reaction time is measured, and the test itself can be set up in different ways depending on the goals of the examiner. All of the parameters cannot be dynamically changed while the test is performed, only by choosing their values in the User Interface of the data-source module. Test setup examples for the directional experiment are shown in Figure 4.

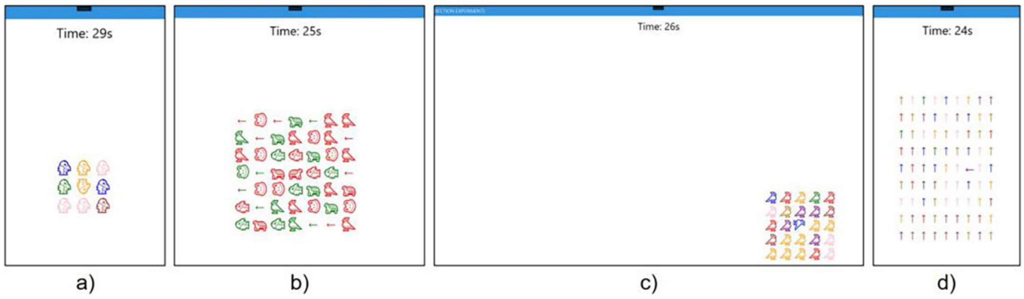


Fig. 4. User Interface of the directional experiment, with different setup examples: a) base case, 3×3 grid, all symbols, all colors; b) random group symbols, 7×7 grid, all symbols, limited colors (red and green); c) random placement of the grid on the screen, a 5×5 grid, and all symbols and all colors; d) random position of the symbol of interest, 9×9 grid, single symbol (arrow), all colors

The second, Trail Making experiment can be set up so that the numerical order of objects is either ascending (baseline case) or descending before starting the test when objects themselves are shown on screen. While the respondent is performing the experiment test, the time interval between clicking each object is monitored. If it is the actual object that is clicked, which object is it, and the coordinates of the point that's clicked as well as if it is the object in order. If a correct object in order is clicked, it will be removed from the screen.

This experiment's part of the data-source module is shown in Figure 5.

Fig. 5. User Interface of the Trail Making experiment data source: a) Initial view, with buttons to start the test and connect an EEG headset, as well as the fields to input user data and experiment options; b) Performing an actual experiment

The task of the data-collecting module is to process the data received from the data-source module and visualize it as EEG values in different channels and the moment in time that the respondent has chosen and communicated their answer on the current group in the test itself.

After it connects with the data-source module, the data-collecting module expects a message about the type of measurement for which the data is received, as well as the metadata about the user (ID, age, and gender).

After connecting with the data-source module, the initial message (called Data Transfer Setup Message) that is received contains the type of signal for which the measurements will be sent (in this case, EEG) separated by the "/" symbol from the channel labels for multichannel measurements and the aforementioned user's metadata, along with the sampling frequency of the device. In this case, after receiving this initial message, it is split to extract how many channels the data will be sent to but also which channels are being measured before the data-collecting module continues receiving multiple measured values from each connected data-source module (Test Response Data Message). The whole communication cycle between these modules is shown in Figure 6.

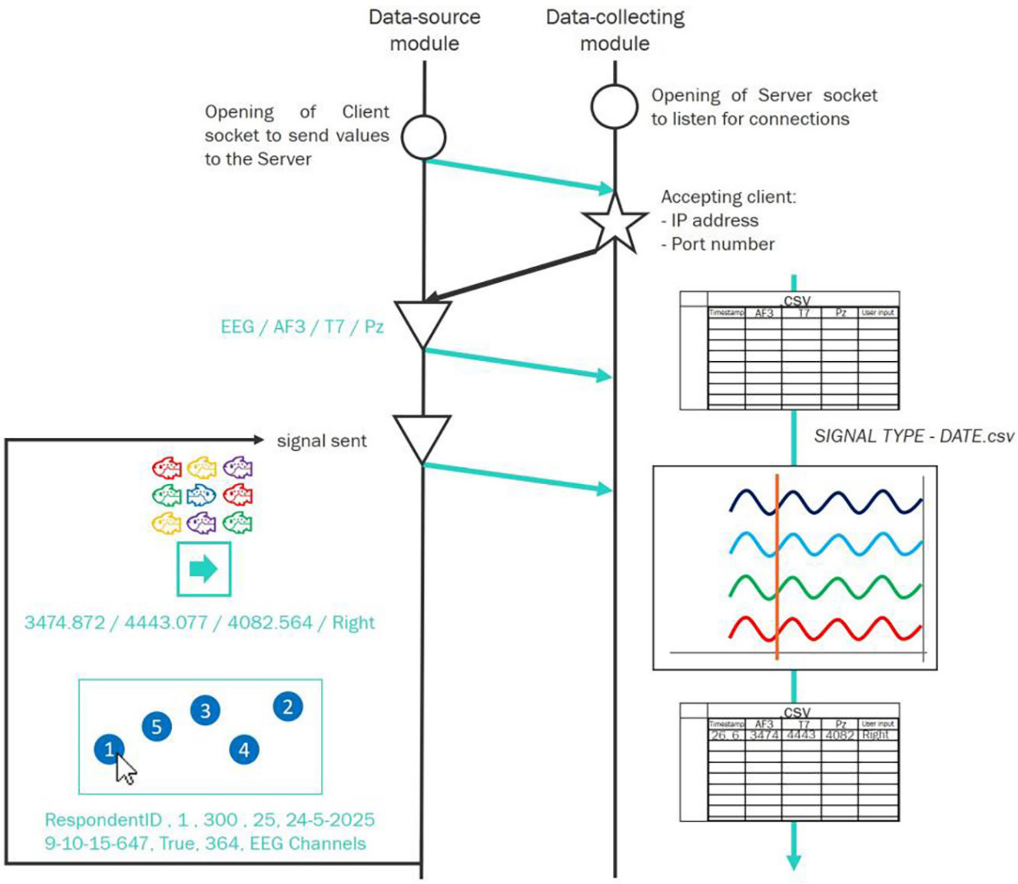


Fig. 6. Communication between data-source module and data-collecting module: After connecting with the data-collecting module, the first type of message that is sent is the EEG channels measured, represented by the second teal diagonal line, with the third teal diagonal line representing the actual messages that hold acquired values and answers

When collecting data, in order for it to be precise and interpreted correctly, it is gathered over time, with the time of performing the measurement being stored (Time Series Data). The Data-collecting module is utilizing visualization of the received values in the form of multi-line charts and writing the gathered data in a table form of *.csv files.

Values received are visualized on a line chart that shows the last 300 received values. Labels on the y-axis are calculated depending on the minimum and maximum values received (their amplitude), while on the x-axis the number of labels grows with each new received value and shows how many seconds have elapsed since the value was received. Depending on the number of channels, each line chart is translated up so that none of the charts are intersecting and so that amplitudes can be seen clearly.

If the data-source module happens to send multiple measurements in the same message, the data-collecting module will separate the values accordingly and update the chart with all of the values as they were supposed to be processed.

While performing the test, each time the respondent presses a key on the keyboard or clicks on the object marker, the message that is sent to the data-collecting module is expanded with the textual representation of the key pressed. It follows the same format and is separated by the "/" symbol.

The chart also shows a time point of receiving the data of the key pressed as a vertical line that moves along with the received values. Similarly to the visualized EEG values, after the time point that has a vertical line becomes the 300th value, the vertical line will be removed along with the received value points. When the test is complete on the data-source module side, the sending of EEG measurements from the connected headset or chosen *.csv file is stopped.

2.2 EEG value acquisition

When the EEG values are measured, our solution utilizes the Emotiv Cortex API, which, on the software side, acts as a link between the data-source module and EmotivBCI in order to acquire EEG values from the chosen headset.

Another important component of software working with EEG is how the acquired values are preprocessed. Here, we utilize the already integrated Emotiv preprocessing (doing a bandpass filtering of data between 0.5 and 43 Hz and the notch filter that removes the effects of 50 and 60 Hz signals).

Although there was no need to perform further preprocessing, we implemented a bandpass filter to be used in future research. It is performed by calculating an average value of data in a buffer (known as the DC component) and subtracting it from the data. That buffer should be filled each second, and then it is processed.

In terms of devices that can be used to measure the respondent's EEG, they should be portable and also should allow movement. The ones that fulfill these criteria are:

1. Emotiv Insight – provides measuring on up to 5 channels (AF3, AF4, T7, T8, Pz), with 128 samples taken per second per channel.
2. Emotiv Epoc + – provides measuring on up to 14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4), with 128 samples taken per second per channel.

This platform was implemented with the possibility to utilize both devices in mind, and even others, with the aforementioned Data Transfer Setup Message being sent from the Data-Source module, containing expected channel labels for multichannel measurements along with the user's metadata and sampling frequency of the headset that was used.

EEG signals were continuously recorded using the *Emotiv Insight* headset and saved as time-stamped CSV files. Participant responses and reaction times were recorded synchronously and aligned with the EEG data using shared timestamps.

For the Trail-Making Experiment, next to acquired EEG channel values, we keep track of cognitive performance metrics (attention, engagement, excitement, interest, relaxation, and stress), while for the Directional Experiment, we only take EEG channel values into account.

With the particular channels and frequency of each measurement being sent, we are fulfilling the standard 10–20 for measuring and recording EEG signals. In this way, we have achieved unambiguous transfer of data that both neurologists and psychologists use.

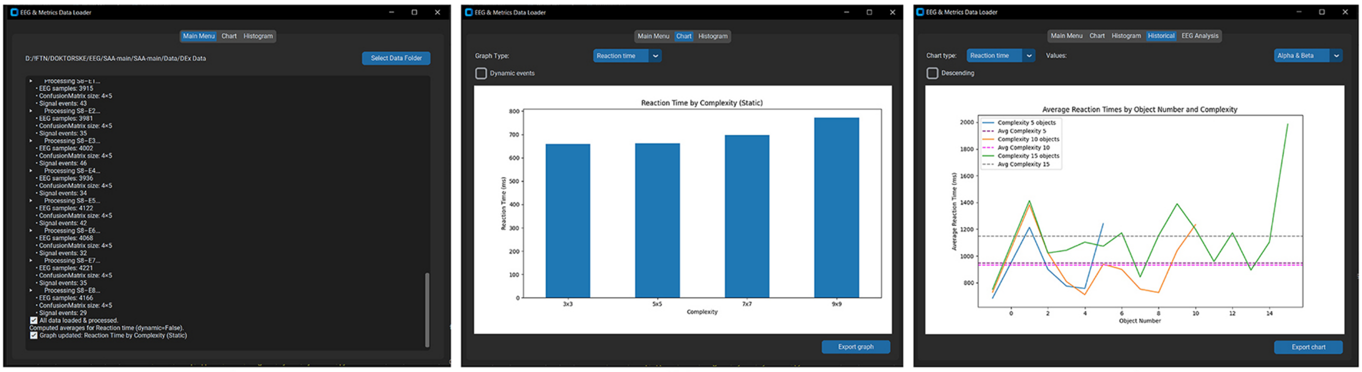
During each second, the 128 samples of values are sent to the data-collecting module that corresponds to the number of channels that were chosen to be measured. Measurement values are represented as floating point numbers (***float*** data type).

2.3 Result analysis and interpretation software

In order to interpret all experiment results and gathered EEG values, a separate Python application was developed to act as a tool to process all EEG signals and metrics data. It was developed also as a Graphical User Interface (GUI) application, using the Tkinter library. It also utilizes libraries pandas, matplotlib, and seaborn to interpret experiment data as DataFrames and then visualize those values as charts, but also visualize the Probability Density Function (PDF).

EEG, metrics, and signals files generated from the data-source and data-collecting module are read in order to form DataFrames and are joined according to Timestamp values in both. Overall average reaction times for both experiment types were calculated and visualized, as well as the Alpha and Beta spectrum of measured EEG (bar charts and a line chart). These values can be visualized for each possible experiment setup depending on the experiment. In order to properly show Alpha and Beta specters, the values from measured EEG had to be converted from micro-volts into decibels.

Next to that, we implemented chart visualization to show reaction times with the Alpha or Beta spectrum combined as a scatter chart visualizing the lead-up to each respondent's answer and enrich that chart with a PDF on the specific value segments. Again, this can be visualized for each experiment and all possible set-ups. Every application tab has an option to manipulate chart source data but also to export the charts as pictures. Parts of this application are shown in Figure 7.



a) b) c)

Fig. 7. User Interface of the Python experiment data processing tool: a) Initial view where the examiner can choose the files to process, and the overview of processed data is shown in textual form b) Plotting of overall average reaction times as a bar chart for the directional experiment. c) Plotting of overall average reaction times as a line chart for the trail making experiment

2.4 The pilot experiment data

The pilot experiment was conducted with a limited number of participants (four for the directional and five for the trail-making experiment), so the small sample size is enough to test the platform, but the results can be classified as preliminary, since the sample size limits the overall analysis of the findings.

All of the *.csv files used to simulate EEG values transfers do not contain any respondent's personal information, but also when recording received EEG values. The *.csv files are filled as described beforehand, with no user meta-data.

In terms of ethical approval, research that uses non-invasive methods and protects personal data of the respondents doesn't require specific ethical approval by the Code of Academic Integrity of the University of Novi Sad, which was taken into account when performing the pilot experiment.

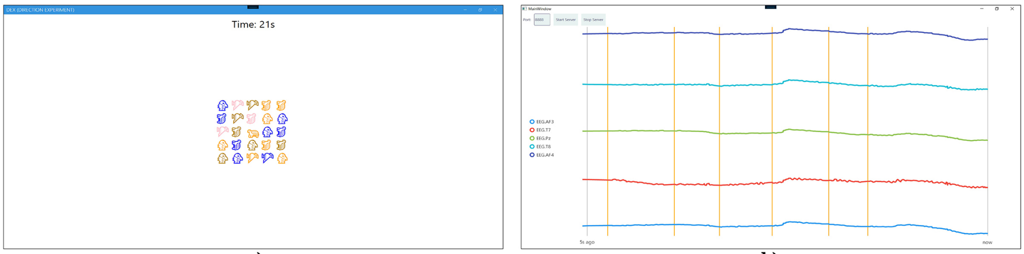
The role of the data-source module in the experiment is to be able to acquire values from the BCI headset or read any *.csv file that contains EEG values and extract channel names for the values stored. The values themselves are then read from the chosen *.csv file, depending on the number of channels that are stored in it.

To perform the test, the user meta-data that is requested is an identification number in order to differentiate respondents, as well as their age and gender. According to provided user meta-data, a folder is created on the local computer where the data-collecting module is running, and it is named by the following format: "TimestampOfTestStart – UserID-Age-Gender." This way the uniqueness of all data folder names is guaranteed. Each such folder would be the location where the data-collecting module will create *.csv files where the received values and the user's answers (keyboard inputs) while completing the test are appended.

Columns of the generated *.csv files contain timestamps of the moment when the measurements have been received. For multichannel measurements, columns that correspond to the specific measured channels and cognitive performance metrics are filled with corresponding values.

The reason to choose *.csv and *.json (for Trail Making experiment responses) formats to store data is that they are easy to comprehend for both the humans and the computer.

The two modules of the platform working together are shown in Figure 8.



a) b)

Fig. 8. Example of both modules working at the same time: a) Data-source module conducting the experiment (in this case, the directional experiment) b) Data-collecting module visualizing EEG measurements received from the data-source module, with vertical lines representing user inputs (answers)

3 RESULTS

3.1 The pilot experiment definition and setup

The directional experiment pilot test was performed with four respondents, while for the Trail Making experiment, the pilot test was performed with five respondents. As it was said in the previous section, the Emotiv Insight headset was used to gather measurements with five channels and 128 samples per second per channel.

That said, the number of channels used to acquire measurements can limit the precision when localizing neural activities and accuracy. Additionally, while the sampling rate used limits the analysis of rapid changes in neural activity, it is sufficient for investigating the frequency bands relevant to the present study (Alpha (8–13 Hz) and Beta (13–30 Hz) spectra). Future studies employing more channels when gathering EEG measurements with increased sampling rates could address these limitations.

The platform was tested in a wide-area network, after setting up the port forwarding on the computer that ran the data-collecting module in order to simulate the test performed with different computers, where the other acts as a data-collecting module. The data-source module is used to perform the test and sends the user inputs, as well as EEG measurements read from the connected headset.

In terms of communication technologies, we looked into using a mobile network as a source for internet access. Compared to Wi-Fi, 4G has latency up to 50 milliseconds, which is acceptable for real-time communication that is needed for transmission of the data set of this study. Using 3G may not be a good solution since the latency is much greater, going up to 500 milliseconds, which definitely would not be adequate for transmitting data with the high frequency of EEG measuring devices. That results either in loss of data or it being not accurate (not processed and annotated in real-time).

In terms of requirements to use this platform, a smart device running a Windows 10 or higher operating system, with at least 8GB of RAM, and a stable internet connection are recommended. If it is not already utilized, the computer that acts as a data-collecting module needs to set up port forwarding. If a user wants to perform this test with actual EEG data, they would need a headset that is used to record measurements.

In order to connect a headset, the user would need an Emotiv account and software needed to connect the headset to the computer. The communication between the headset and a computer is already implemented in our solution. As it was described before, by using the data-source module user interface, the user can set up the experiment by defining experiment parameters, as well as inputting the IP address and port of the examiner's application.

A directional experiment was conducted so that each respondent has done a test with all possible symbol group sizes: 3×3, 5×5, 7×7, and 9×9, when the symbol group is in the center of the screen, as well as when the symbol group is randomly positioned. The symbol group was shown with red, blue, and green colors, as well as all but the Frog symbol. The experiment resulted in 32 EEG recordings and also performance metrics and confusion matrices for each run of the experiment for all respondents. This test was conducted on a laptop computer with the Emotiv headset connected over Bluetooth and another computer receiving the data.

The Trail Making experiment was conducted so that each respondent has done a test with five, ten, and fifteen objects, in both ascending and descending order, two times. This experiment resulted in 60 EEG recordings as well as performance and respondent accuracy metrics. This test was conducted on a touch-screen tablet computer (13.3-inch display), where the respondents simply had to tap the objects in order, with the Emotiv headset connected over Bluetooth.

3.2 The pilot experiment results interpretative discussion

The data-collecting module-generated EEG measurements *.csv file for a 30-second experiment has more than 3000 rows of data. For that reason, the processed visualized results generated by the Python application are commented on. For each new task shown to the respondent during the experiment, EEG data were segmented into windows starting right after the previously given response and ending at the participant's next response included. In those windows, Alpha (8–12 Hz) and Beta (13–30 Hz) spectral values were calculated by averaging spectral power within their respective frequency ranges.

The synchronized acquisition of EEG and response data allowed direct association and alignment of band power features with task performance metrics, including reaction time and response accuracy.

The pilot experiment yielded the following results:

For the directional experiment, the longest average reaction time was recorded for the 9×9 symbol group, which was expected, as it was more complex than the baseline experiment (3×3) and provided the biggest cognitive load. Next to that, the dynamic positioning of the symbol group also yielded a gap in reaction times from when the symbol group was shown in the same place (static, which is also the baseline case). The chart that shows these response times is shown in Figure 9.

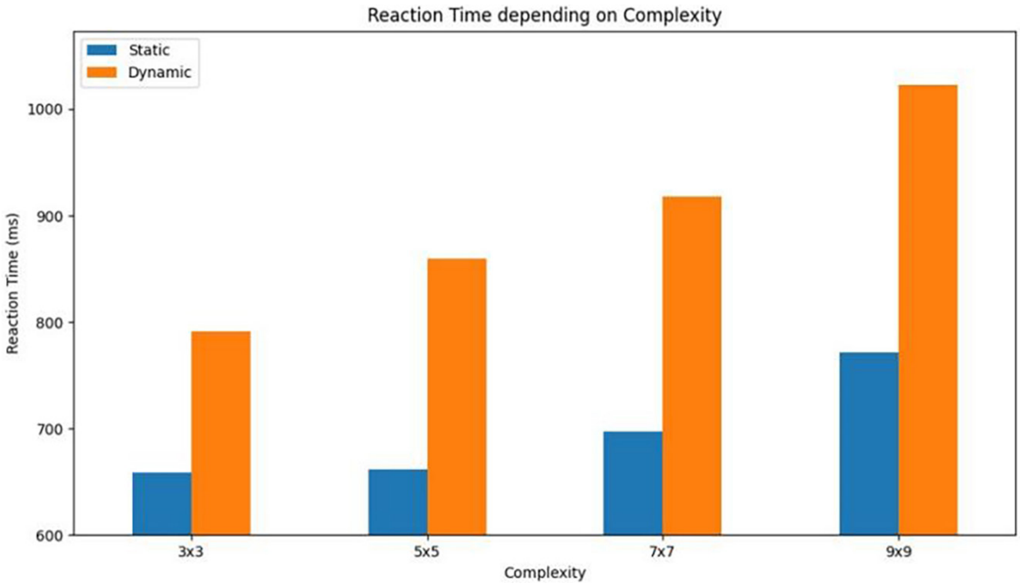
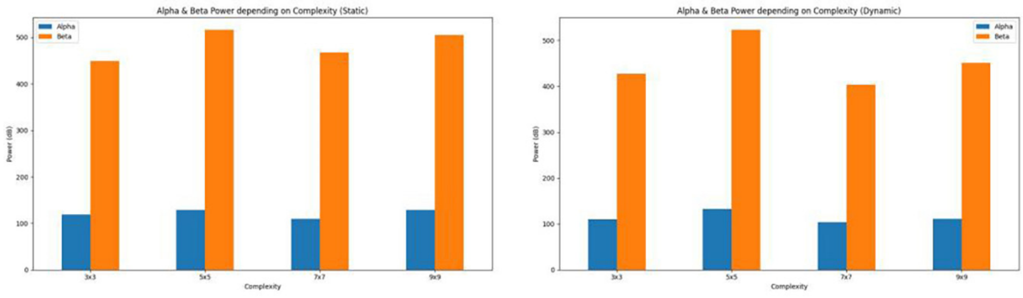


Fig. 9. Average reaction time depending on experiment complexity (symbol group size) chart

What is interesting and also confirmed by the results are the values of the Alpha and Beta spectrum of EEG, where Beta is at a much higher value. This is also expected because Beta is associated with active thinking, focus, and problem-solving, while Alpha spectrum values tend to decrease with increased mental effort or sensory processing. Since the experiment was conducted first with a static and then dynamic variant, the lower Beta values for 7×7 and 9×9 group sizes in the dynamic variant might be the result of them still showing up more or less near the center of the screen because of the group size and therefore being similar to the static variant, and, in turn, being something that the respondents have already experienced. These values, depending on the complexity of the experiment and the dynamics of group position, can be seen in the chart shown in Figure 10.



a) b)

Fig. 10. Alpha and Beta EEG spectrum values depending on experiment complexity (symbol group size) chart: a) static symbol group positioning, b) dynamic symbol group positioning

This can also be seen in PDF charts that show correlations between reaction times and Alpha and Beta spectra for the most complex 9×9 symbol group in Figure 11.

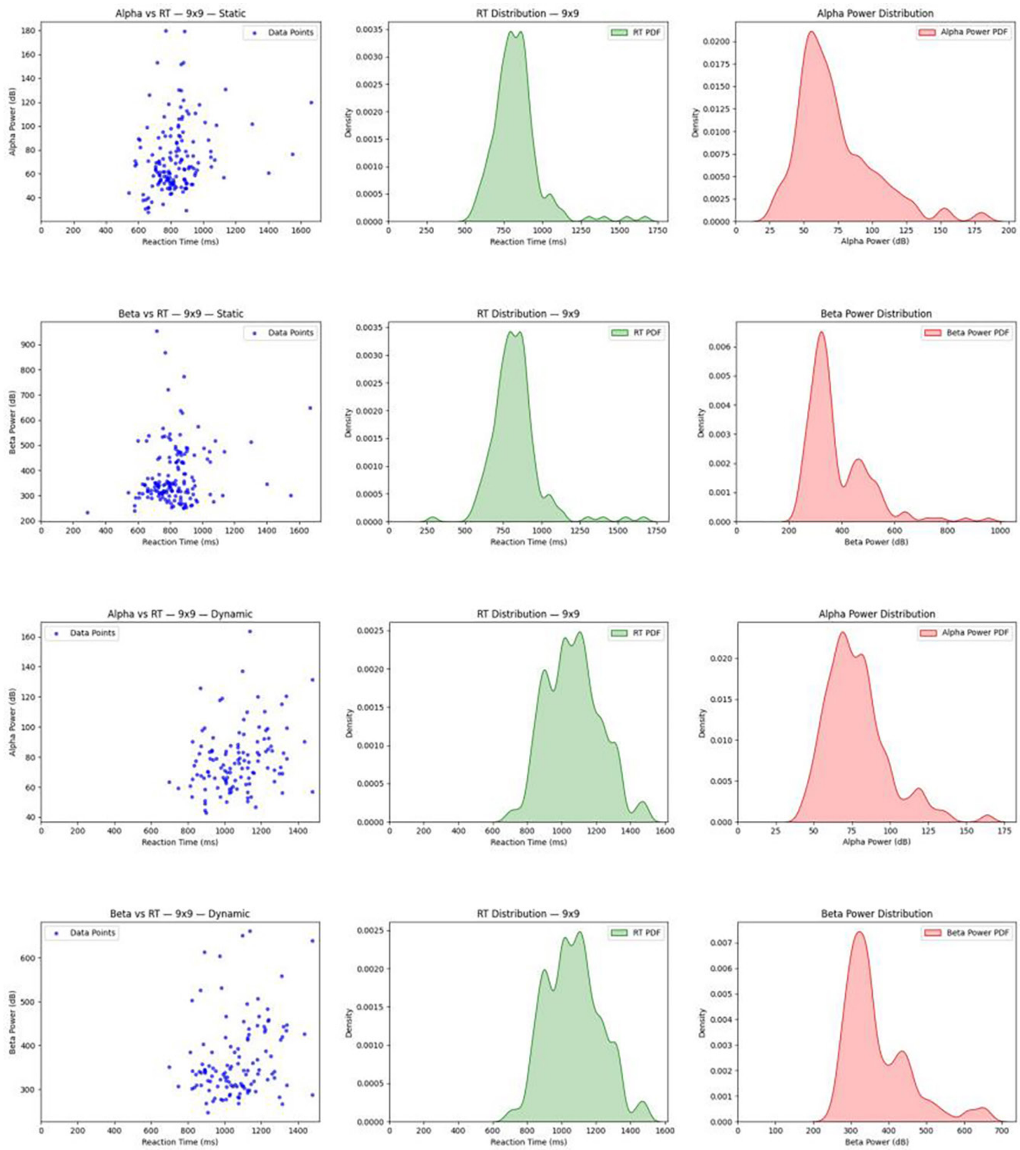


Fig. 11. PDF chart for all 9×9 symbol group experiments (static and dynamic positioning) that shows correlations between reaction times and Alpha and Beta EEG spectrum values

For the Trail making experiment, the average reaction times recorded for 5 and 10 objects are approximately the same, which can lead to the conclusion that they are equally demanding. When looking at 15 objects, cognitive load is greater, so for future research it would be interesting to check where the edge number of objects is for the experiment to become more demanding. The chart that shows these response times is shown in Figure 12.

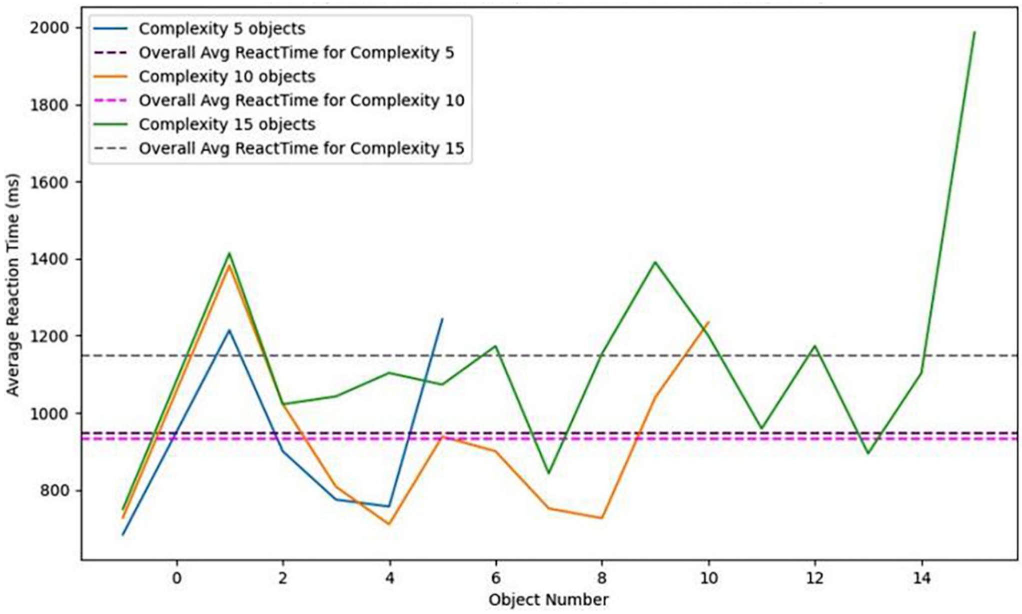
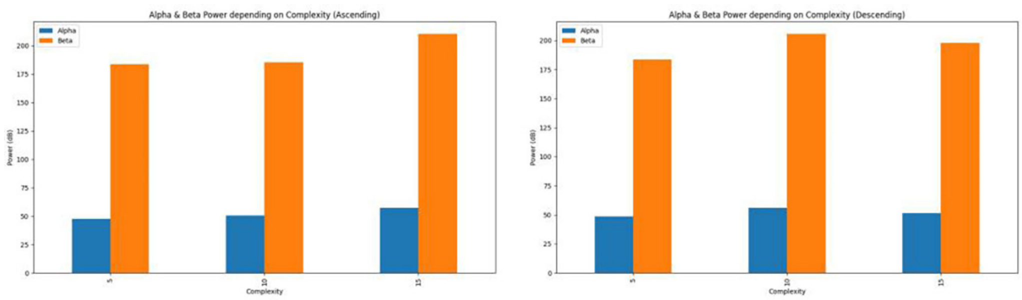


Fig. 12. Average reaction time depending on experiment complexity (symbol group size) chart, with the dashed lines showing average values as a benchmark

When clicking objects in descending order, the test is also showing higher engagement, which is a change from the baseline experiment (ascending order), especially with 10 and 15 objects. Although the gap is not that meaningful, the Beta spectrum values are higher for 10 and 15 objects while for ascending order, the Beta is more noticeable for 15 objects, while it is more uniform for 5 and 10 objects. Alpha and Beta spectrum values, depending on the complexity of the experiment in terms of the number of objects and of clicking object order, can be seen in the chart shown in Figure 13.



a) b)

Fig. 13. Alpha and Beta EEG spectrum values depending on the number of objects in the chart: a) ascending clicking order, b) descending clicking order

This can also be seen in PDF charts that show correlations between reaction times and Alpha and Beta spectra for the most complex 15 objects in Figure 14.

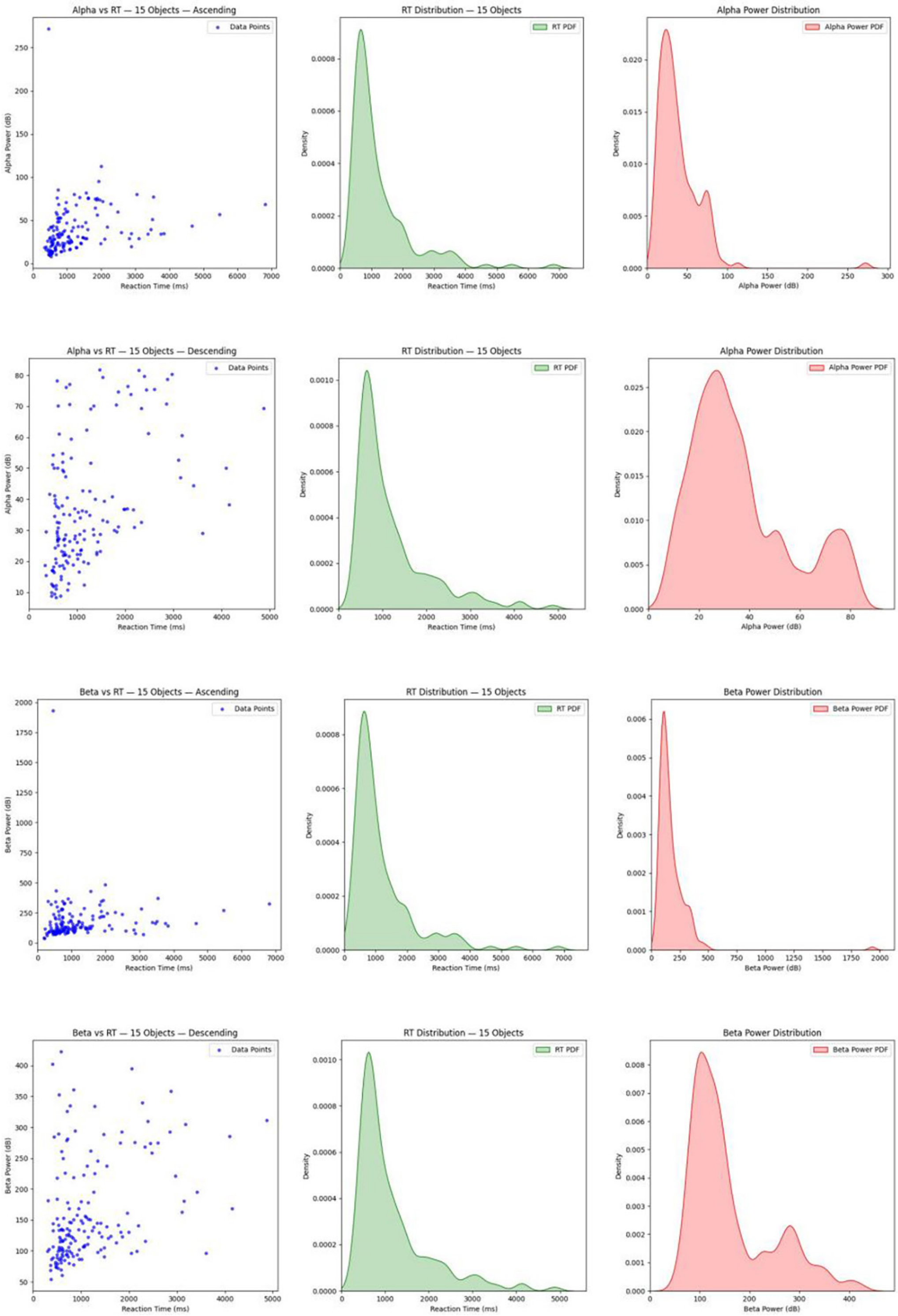


Fig. 14. PDF chart for all 15 objects experiments (ascending and descending order) that shows correlations between reaction times and Alpha and Beta EEG spectrum values

Spearman rank-order correlations were conducted to examine the relationship between reaction time and beta spectrum EEG values across both experiment results. For the Trail-Making Experiment, only those cases in the results that have shown considerable cognitive load were taken into account.

In the directional experiment when the symbol group is shown in the same place (static variant), correlations ranged from weak to strong ($\rho = -0.80$ to 0.80) but did not reach statistical significance (all $p \geq .20$). When the symbol group had dynamic positioning, a significant negative correlation was observed in the 3×3 symbol group task ($\rho = -1.00$, $p < .001$), indicating that higher beta power was associated with faster reaction times. This could be associated with the respondents learning from previous attempts with the static positioning. No other dynamic task variants showed significant associations.

For the Trail-Making Experiment, ascending (for 15) and descending (for 10 and 15) orders when providing answers exhibited moderate positive correlations that did not reach significance ($\rho = 0.30$–0.60, $p \geq .28$). Given the small sample size, these findings should just be considered exploratory. All values of Spearman rank-order correlations are shown in Table 2.

Table 2. Spearman rank-order correlations for specific experiment variants, according to reaction times and beta spectrum EEG values

Experiment (respondents)	Experiment Variant	Correlations
Directional, static (4)	3×3	$\rho = 0.400$, $p = 0.600$
	5×5	$\rho = -0.200$, $p = 0.800$
	7×7	$\rho = -0.800$, $p = 0.200$
	9×9	$\rho = 0.800$, $p = 0.200$
Directional, dynamic (4)	3×3	$\rho = -1.000$, $p = 0.000$
	5×5	$\rho = 0.400$, $p = 0.600$
	7×7	$\rho = 0.400$, $p = 0.600$
	9×9	$\rho = -0.400$, $p = 0.600$
Trail-Making, ascending (5)	15 objects	$\rho = 0.500$, $p = 0.391$
Trail-Making, descending (5)	10 objects	$\rho = 0.300$, $p = 0.624$
	15 objects	$\rho = 0.600$, $p = 0.285$

4 CONCLUSION AND FUTURE RESEARCH

The goal of this study was to provide a system that can successfully transfer user data (EEG signals and user inputs) and, after processing, structure and archive received data in singular folders containing *.csv files. Additionally, all received data is to be visualized in real time. The visualization helps in visual analysis of test results and provides a tool for examiners (psychologists) to provide opinions, plans, and training for respondents.

This platform finds its application in telepsychology through software development, with the possibility to transfer test results as well as the analysis of said test results, strengthened by the added Python solution for processing experiment results and visualizing them, which, along with presented functionalities of data-source and data-collection modules, forms a genuine software platform for performing psychological tests remotely.

In addition to registering the general success in the experiment, it is possible to measure the ability to select correct stimuli and inhibit responses to incorrect stimuli, as well as the existence of a certain cognitive strategy in responding.

It is possible to determine whether the respondent answers out of habit or by chance, or if they answer only when they are sure of their decision.

The objective of this platform is to examine cognitive phenomena, such as selective attention, reaction time, and cognitive load, present in a neurologically healthy population, without taking pathological conditions into account. These cognitive phenomena engage the frontal lobe (specifically the dorsal-lateral prefrontal cortex), parietal lobe, and temporal lobe regions [26], [27] of the brain. The experiments included in the proposed platform are used to reach specific responses, with the aim of achieving deeper understanding of the respondent's cognitive performance.

Although specific variants added to baseline cases of the experiment tests included in the platform lead to higher response times and show higher cognitive load, most conditions did not show statistically reliable associations between the beta spectrum of the EEG and reaction times. This suggests that beta oscillations may play a role in facilitating faster responses in low-complexity dynamic tasks but also provide preliminary support for a task-dependent relationship between the beta spectrum and response performance to motivate further investigation with a more adequately gathered number of samples.

The platform itself was not developed or validated with clinical diagnostic studies in mind. That said, it can serve as a technical foundation that could be refined and expanded for further research in neurological diagnostics. Its ability to collect behavioral and EEG data could support analyses in cognitive neuroscience, clinical research, psychiatry, and psychology, but due to the volume of our present research, that direction was not taken.

In terms of current EEG telemonitoring tools, Emotiv OpenBCI software can be used for data acquisition, but not for performing tests, just as a support tool to measure multiple signals and psychological variables. It can also provide real-time or near real-time measurement data transfer, by employing external solutions that need to be programmed, but they would also have to be expanded to gather test responses as well, which is what we proposed here.

Apart from application in scientific research in the field of psychology and cognitive neuroscience, this platform has great potential as a telepsychology tool that can enable fast and efficient psychological and neuropsychological assessment through synchronizing multiple experiments in real-time and applying computer network communication in the process, not just to transfer measurements but also user metadata and test responses. It is also possible to create different training plans depending on the development of individual abilities.

The development of systems that will be able to register and transmit human bio signals in real time, without delay or interruption, will enable great progress in the field of cognitive neuroscience but also enable understanding of the complex processes of the human mind and contribute to innovations in psychology, medicine, technology, and education.

With our further research, we will look at these goals:

1. Current data-collecting module solution is not able to visualize the results of multiple tests at the same time, so another advancement will be to not visualize every experiment but to notify the examiner when the experiments have begun and when they have concluded so that they can look at the results. Both modules will continue to function similarly, but the data-collecting module will visualize the complete EEG signal with user inputs and the calculated test results after the respondent completes the test.

2. Another advancement would be to provide the users with visual analytics of the state of the network connection between the modules by visualizing network diagnostic tool results (ping, trace route, jitter, and packet loss).
3. One important aspect of telepsychology and telemedicine in general is data privacy and security. In order to keep sensitive data obscured, an encryption layer can be added to the EEG and experiment data transfer, either by using the Secure Sockets Layer (SSL) security protocol or advanced encryption algorithms, where [28] proposes utilizing the Advanced Encryption Standard (AES) algorithm in order to enable secure transmission of multichannel EEG signals.
4. There is a possibility of integrating computed tomography (CT) and also magnetic resonance imaging (MRI). Both CT [29] and MRI [30] can be used as a validation tool in order to confirm that our system works adequately and give feedback that the results are valid, and we see the potential of it. But, in fact, those tools are not attainable for us, and their use, at this point, is out of reach in our study.
5. Expand our result processing and visualizing application with a detection of outliers to extract more accurate resulting signal values by utilizing functions of the numpy library.
6. Branch into different variants of psychological tests and add them as part of the platform, as well as, implement greater complexity for tests that are already part of the platform. This would, in turn, facilitate even greater cognitive engagement. One possibility is to include the Stroop test, similarly to what is described in [25].
7. In order to achieve greater versatility in technology needed to perform these tests, developing a mobile application similar to what was described in [35] can also be one direction of future research. This application would contain all of the described tests/experiments integrated and adapted according to the mobile interface and appropriate styles of interaction, while keeping the EEG headset connected and gathering values.

   Next to that, utilization of other EEG headsets could be introduced with extracting the channels that the headset uses to gather measurements, prior to receiving the measured values. Then, the Data-Collecting module can receive the information which channels to expect in the Data Transfer Setup Message.
8. Integration of machine learning models, where a temporal neural network will be used to further analyze the data by classifying the response correctness and respondent reaction time, depending on EEG measurements and estimated cognitive states. Next to that, we will be looking at experiment data interpretation in terms of Confusion Matrices and calculating model performance metrics: Accuracy, Precision, Recall and F1 score as described in [31–33].

5 CONFLICT OF INTEREST

The authors declare that there are no known competing financial interests or personal relationships that could have appeared to influence the publication of this paper.

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