# BOARD #110: WIP: A Reconfigurable Testbed for Assessing Cognitive Workload in N-back and Multi-Object Tracking Tasks

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Yug Patel is an undergraduate student in Computer Science at the Missouri University of Science and Technology (MST). Yug has conducted research in both the Department of Computer Science and in the Department of Biology at MST, exploring the intersection of these fields through interdisciplinary projects. As a previous NSF-REU intern, Yug has gained valuable research experience and a deeper understanding of the applications of computer science in biological research. This paper presents Yug's work on a novel reconfigurable testbed for cognitive workload assessment and management, which demonstrates a comprehensive and customizable platform for evaluating cognitive workload and physiological responses under controlled experimental conditions.

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# WIP: A Reconfigurable Testbed for Assessing Cognitive Workload in $N$-back and Multiple Object Tracking Tasks [*]

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## ABSTRACT

Cognitive workload assessment and management are critical in managing work efficiency in high-stress environments and long-duration tasks, such as critical infrastructure operations, first-responder responses, healthcare, military, and transportation. A major challenge in developing cognitive assessment algorithms lies in designing an experimental testbed that integrates diverse systems like brain-computer interfaces, physiological sensors, and task-specific hardware for synchronized multi-modal data collection. This paper presents a novel reconfigurable testbed for assessing cognitive workload using Letter $N$-back, Flanker $N$-back, and multiple object tracking (MOT) tasks. The testbed features customizable parameters such as trial length, difficulty level, and task complexity, allowing simulation of various stress levels. The integration of Neuroelectrics EEG headsets and Bluetooth-enabled physiological sensors ensures real-time multimodal data acquisition. In addition, the modular design supports future expansion for new tasks and devices, fostering advancements in cognitive neuroscience and human performance research.

## INTRODUCTION

Workers experience *cognitive workload*, i.e. the amount and type of mental effort required to perform any given task, which often dictates their performance of the task, particularly in high-stakes environments. Therefore, assessment and management of cognitive workload are vital to improving operational efficiency, health outcomes and safety, particularly in individuals working at computers[1]. Traditionally, cognitive workload has been assessed using unimodal data sources[2] such as subjective surveys, behavioral metrics, heart rate and EEG signals. These unimodal data sources typically lack the necessary features to perform a wholesome assessment of cognitive

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workload[3]. For example, subjective surveys can contain misinformation, EEG signals suffer from poor spatial resolution, and behavioral approaches are sometimes inaccurate. Therefore, there is a need to design a reconfigurable cognitive assessment testbed that integrates data from multi-modal sources[4]. However, this involves many challenges: (i) multi-modal data sources have disparate sampling rates, which need to be synchronized using simple markers, (ii) a reconfigurable testbed demand a modular design to support diverse cognitive workload studies as well as diverse physiological sensors, and (iii) the testbed should be user-friendly in terms of experiment setup and data storage so as to make it accessible to researchers beyond computer science.

The main contributions of this paper are summarized as follows. This paper presents the first-of-its-kind reconfigurable cognitive workload testbed, which generates a web dashboard that can be interfaced with multimodal physiological sensors to engage participants in a user-defined experiment. The testbed currently supports a repertoire of three different types of cognitive tasks, namely *Letter N-back*[5], *Flanker N-back*[6] and *multiple object tracking* (MOT)[7] tasks in order to investigate the impact of cognitive workload on participant's working memory, response inhibition, attentional capacity and spatial awareness. In order to interface with multi-modal physiological sensors, the testbed is equipped with two communication protocols, namely *Lab Streaming Layer (LSL)*[8] for supporting time-synchronized data streams (e.g. EEG headsets) and *Generic Attribute Profile (GATT)* protocol[9] to connect with Bluetooth Low Energy (BLE) devices such as smart watches. Currently, the testbed has been successfully interfaced with Enobio 20 EEG headset and Polar Verity Sense wristband. Depending on the designer's need, the generated web dashboard will automatically record markers within the web dashboard, as well as record markers in multi-modal sensor data streams, all in a synchronous manner. Moreover, the modular architecture of the proposed testbed ensures the generation of a custom web dashboard according to the experiment parameters (e.g. task length, difficulty level, and stimulus type) chosen by the designer to develop a wide range of experiments. Finally, the testbed offers a user-friendly interface to support researchers with diverse technical backgrounds. For example, in both $N$*-back* tasks, experiment designers can adjust the parameter $N$ to modulate the load on the working memory, while the MOT task is customized to support varying number of objects to track, their colors, and movement patterns. Thus, the proposed reconfigurable multi-modal cognitive workload assessment testbed contributes to major scientific advancements in the areas of cognitive neuroscience, psychology, human factors engineering, and related disciplines.

The overarching goal of designing this testbed is to collect physiological data to continuously detect cognitive overload and/or underload[10] in diverse tasks[11,12,13], and how this inference can be utilized to develop neurofeedback to improve task productivity. Furthermore, we anticipate that the testbed will also greatly help improve our understanding of how cognitive load and stress impacts the functionality of human brain[14]. This can lead to significant scientific advancements in real-time applications with stressful environments in defense[15], healthcare[16], transportation[17] and education[18] sectors.

## TESTBED DESIGN

Figure 1 depicts the testbed's modular design, which comprises of *experiment design interface*, *web dashboard* generated based on the designer's parameters, two types of sensor interfaces to support diverse physiological sensors, data storage, and various task/survey containers to enable

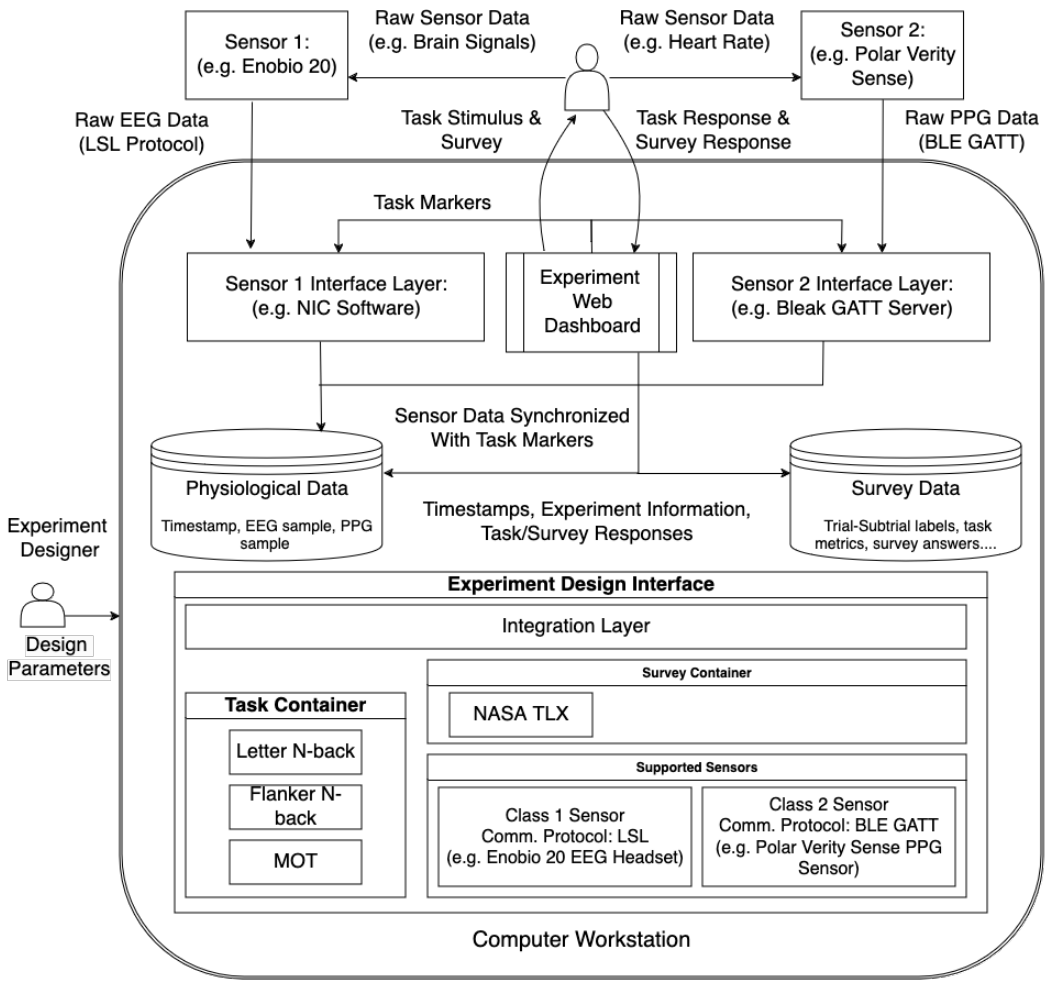
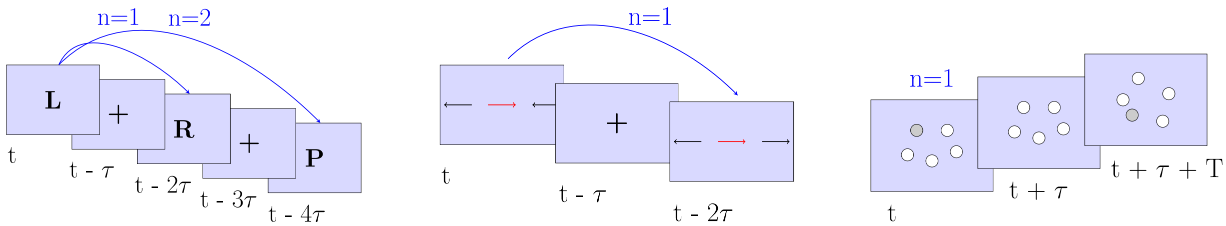



Figure 1: Testbed Design

flexible design of experiments.

**Sensor Interfaces:** The proposed testbed supports two classes of sensors depending on how they communicate data to the participant workstation. Class-1 sensors are those that communicate data using the *Lab Streaming Layer* (LSL) protocol, which provides a standardized mechanism for transmitting time-synchronized data streams, ensuring reliable communication between the sensor and the testbed[8]. LSL also supports automatic discovery of data streams and handles high sampling rates, making it ideal to detect any faulty sensor electrodes. While most EEG headsets utilize the LSL protocol to communicate data to the workstation, the proposed testbed is specifically tested using an Neuroelectrics Enobio 20 EEG headset, which utilizes LSL protocol within the Neuroelectrics Instrument Controller (NIC) software to manage high-resolution time-series data acquisition and real-time monitoring. Class-2 sensors are those that utilize Bluetooth Low-Energy (BLE) communication protocol called *Generic Attribute Profile* (GATT) to share data to the participant workstation. Most smart watches equipped with multiple sensors typically share data using the GATT protocol over Bluetooth channels. GATT operates on a client-server model, where the PPG device serves as the server, exposing its data and functionality, and the testbed acts as the client. Data is organized into services and characteristics, each identified by a unique UUID, enabling efficient, low-power data transfer crucial for real-time physiological monitoring[19]. Specifically, the




(a) Letter $N$-back (b) Flanker $N$-back (c) Moving Object Tracking

Figure 2: Repertoire of Supported Tasks

testbed utilizes a lightweight and efficient interface built using the BLEAK python library. This testbed was validated using the Polar Verity Sense, a smart wrist/arm band that monitors optical heart rate using photoplethysmography (PPG) sensors, which utilizes the GATT protocol within its BLE communication interface. Technically, both class-1 and class-2 sensor interfaces available in the testbed are also expected to support other sensors, such as galvanic skin response (GSR), functional near-infrared spectroscopy (fNIRS) and eye-tracking devices. This potential to expand the testbed to other physiological sensors will be explored in the future. Thus, the proposed testbed supports multimodal physiological data collection, which is crucial for a robust and reliable cognitive workload assessment.

**Web Dashboard:** The web dashboard is a web application that automatically generated using HTML, CSS, and JavaScript, in which an experiment is presented to a human participant to assess the cognitive workload. This browser-based interface provides an intuitive and interactive dashboard for researchers to configure experiments without the need for any extensive programming knowledge. As the participant performs the prescribed task during the experiment, the web dashboard automatically records all the participant actions using timestamps and markers to distinguish different events. Researchers who design experiments are provided with a design interface, which allows customization of task parameters, such as trial duration, difficulty levels, and stimulus types. For example, researchers can select the number of objects to track in the multiple object tracking task, adjust the value of '$N$' in the letter $N$-back task, or define the duration and intervals for stimuli in the Flanker $N$-back task.

**Synchronization with Task Markers:** One of the major contributions of the proposed testbed is the automatic synchronization of task events with the time-series data generated by the interfaced sensors. This is achieved by synchronizing the timestamps within the task markers generated by the web dashboard with the timestamps present within the sensor data streams. For example, in the context of EEG signals generated by the Enobio 20 EEG headset, the MatNIC MATLAB library was utilized to send markers to the NIC software with precise timestamps.

**Experiment Design Interface:**

- *Task Container:* A task container is a collection of all the cognitive tasks that are supported by the proposed testbed. Currently, the task container supports three cognitive tasks listed below:
  - *Letter $N$-back:* This task assesses working memory by requiring participants to determine whether the current stimulus matches the one presented $N$ steps earlier, as depicted in figure 2a. Participants are shown a sequence of letters (e.g., Z, X, C, V, B), with the option to customize the set of letters displayed. The difficulty level is adjustable by modifying the value

of $N$ (e.g., 1-back, 2-back, 3-back). Researchers can also configure the duration for which each letter is displayed and the inter-stimulus interval.

– *Flanker $N$-back:* This task combines response inhibition and working memory by presenting a sequence of left-right arrows, as depicted in figure 2b. Participants must identify whether the middle arrow matches the one presented $N$ steps earlier while ignoring distracting flanking arrows. This task introduces cognitive load by increasing the difficulty of filtering out incongruent stimuli. Customizable parameters include the number of trials, stimulus duration, number of flanking arrows, and the interval between trials.

– *Multiple Object Tracking:* This task measures attentional capacity and spatial awareness by requiring participants to track multiple moving objects among distractors. As depicted in figure 2c, the target objects present within the region-of-interest (RoI) are highlighted at the start of the experiment trial. After a prescribed delay, the target objects are de-highlighted, and all the objects move randomly within the RoI . At the end of the trial, the objects stop moving, and the participants are expected to identify the target objects by clicking on them. Experiments can be customized by changing various parameters such as the number of targets, their initial colors, and the underlying randomness that dictates the motion of objects.

- *Survey Container:* The survey container is designed to host diverse surveys to collect participant opinions regarding their mentak workload experience. Currently, the survey container contains one standard questionnaire called *NASA Task Load Index (TLX)*[20], which collects participant opinons about their perceived workload on six cognitive dimensions, namely mental demand, physical demand, temporal demand, performance, effort, and frustration. A 5-level Likert scale (with 5 sub-levels within each level) is used to collect opinions on each of these six dimensions, as shown in figure 3. From the perspective of interface design, participants click and drag on the green square across the scale to indicate their levels in each of the six categories. These surveys record the differences in individual perceptions regarding the cognitive workload, which enables the study of the relation between perceived workload and the corresponding sensor data.

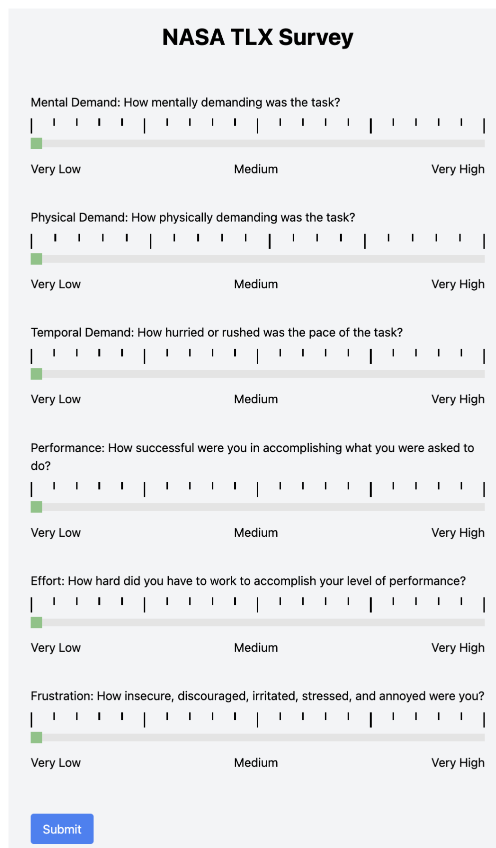



Figure 3: NASA TLX Survey

- *Supported Sensors:* As presented earlier, two different classes of sensors defined based on the supported communication protocols are included in the supported sensor container. This container contains all the necessary code and dependencies needed to support the LSL and BLE GATT communication protocols. For example, this repository contains the code built using MatNIC MATLAB library to seamless connect with NIC software so that EEG markers are precisely aligned with task markers.

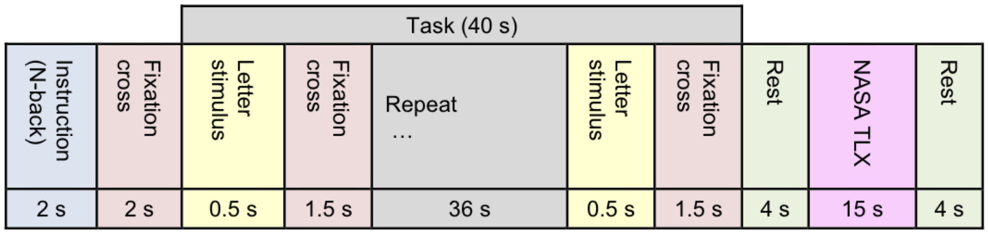



Figure 4: Pilot $N$-back experiment designed using the proposed testbed

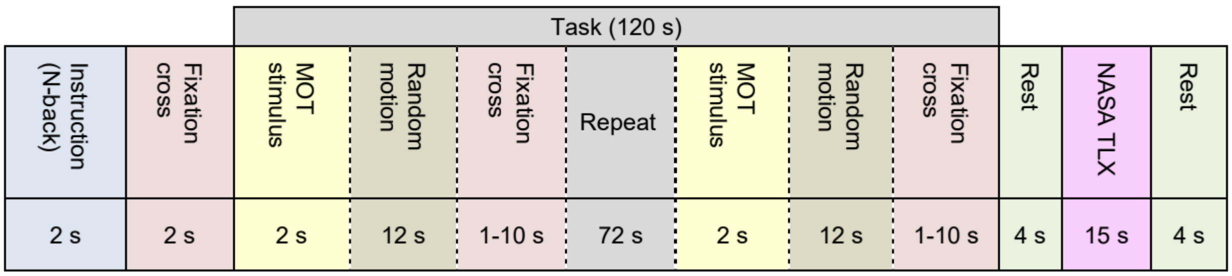



Figure 5: Pilot MOT experiment designed using the proposed testbed

- *Integration Layer:* Based on the experiment design parameters submitted by the researcher, the integration layer designs the experiment based on the supported tasks in the task container, the surveys present within the survey container and the sensors supported by the testbed. The output of the integration layer is the generated web dashboard which is ready to be interfaced with the prescribed sensors in the experiment design.

**Data and Supported Filetypes:** All collected data, including EEG signals, PPG readings, and task performance markers, are stored in standardized formats such as CSV or JSON, ensuring compatibility with popular data analysis tools and facilitating post-experiment processing. Task performance data, NASA TLX survey results, and physiological measurements were stored in separate files for each trial and run. The physiological data files from EEG and PPG sensors include synchronized task markers. These markers were additionally logged in a dedicated text file with precise timestamps to ensure accurate data synchronization across all modalities. Specifically, EEG data from the Enobio 20 headset, initially stored in .easy format by the NIC software, is converted to a .csv file using the NEPy Python library[21]. This conversion enhances accessibility and allows researchers to perform detailed analysis using common data processing workflows. This distributed file structure was implemented to ensure robust data management and enable efficient post-processing, with the capability to consolidate all data into a database for comprehensive analysis.

## CASE STUDY: GENERATED PILOT EXPERIMENTS AND DATA COLLECTION PLAN

The testbed has been validated by generating three pilot experiments. These pilot experiments are designed using parameters depicted in figures 4 and 5 for both $N$-back tasks and MOT task respectively. Each of these pilot experiments comprises of $R$ runs, where each run contains $T$ trials and each trial has $S$ sub-trials. The participant performs any given task once in every sub-trial. In the case of both $N$-back pilot experiments, we chose $R = 3$, $T = 9$ and $S = 20$. Furthermore, the value of $N$ is also varied randomly between 1 and 3 (i.e. $N = 1$ for low workload, $N = 2$ for medium workload, and $N = 3$ for high workload) across trials to alleviate boredom. In the case of MOT pilot experiment, we chose $R = 3$, $T = 5$ and $S = 5$. As depicted in figures 6 and 7, the web dashboard records the participant's response for the stimulus presented in each sub-trial along with a label that deems if it is correct, physiological data with synchronized task markers and participant responses in the NASA TLX survey, all in their respective CSV files.

In both $N$-back pilot experiments, an indicator screen is displayed to the participant where the run-ID is disclosed along with a clickable start button. Once the participant clicks the start button, each trial begins with the instruction screen, where the web dashboard provides a short list of instructions for the participants for 2 seconds. After that, a blank screen with a + symbol at the center (a.k.a. fixation cross) is shown for two seconds to let the participant compose themselves for the experiment. After that, a sequence of 20 sub-trials are repeated wherein a stimulus (e.g. a letter in letter $N$-back task, and a sequence of 5 arrows in Flanker $N$-back task) is shown for 500 milliseconds, followed by a fixation cross screen for 1.5 seconds. At the end of each trial, a rest period of 4 seconds starts before a new trial is repeated until all the $T$ trials are completed. The only difference between the two $N$-back tasks is the single letter in Letter $N$-back is replaced by a set of 5 random left-right arrows in the Flanker $N$-back task.

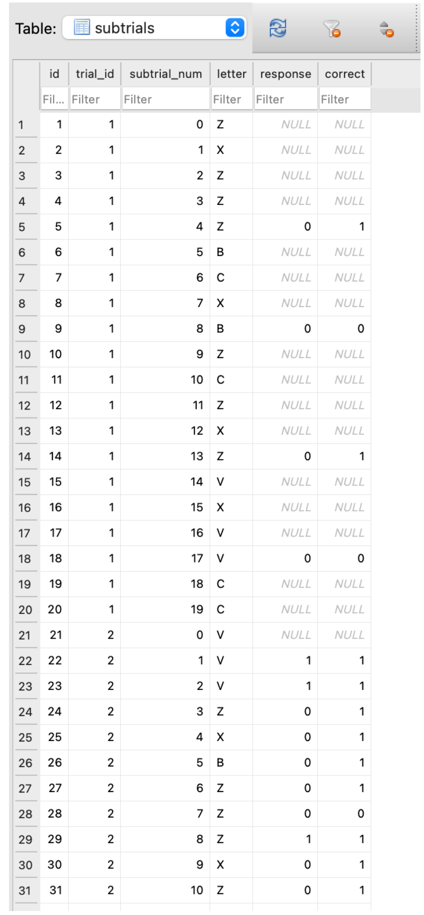
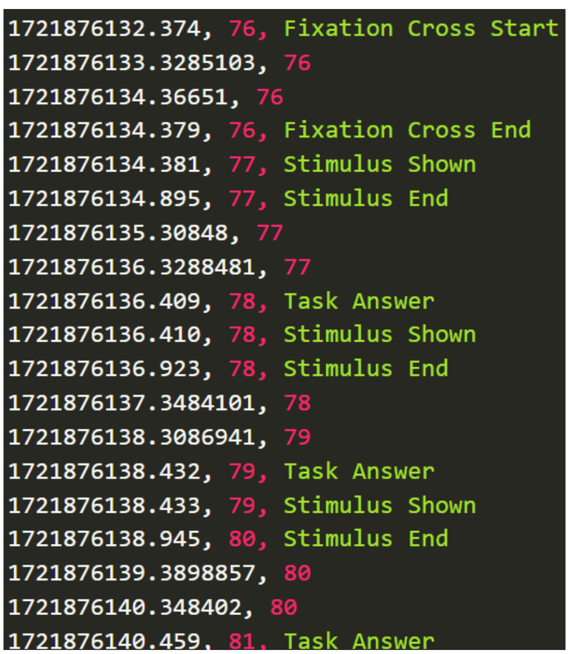


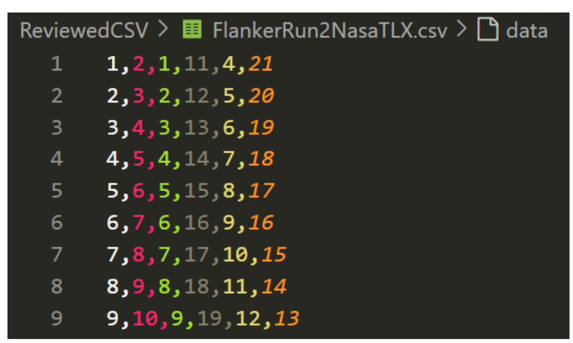
Table: subtrials

| | id | trial_id | subtrial_num | letter | response | correct |
|---|---|---|---|---|---|---|
| | Fil... | Filter | Filter | Filter | Filter | Filter |
| 1 | 1 | 1 | 0 | Z | NULL | NULL |
| 2 | 2 | 1 | 1 | X | NULL | NULL |
| 3 | 3 | 1 | 2 | Z | NULL | NULL |
| 4 | 4 | 1 | 3 | Z | NULL | NULL |
| 5 | 5 | 1 | 4 | Z | 0 | 1 |
| 6 | 6 | 1 | 5 | B | NULL | NULL |
| 7 | 7 | 1 | 6 | C | NULL | NULL |
| 8 | 8 | 1 | 7 | X | NULL | NULL |
| 9 | 9 | 1 | 8 | B | 0 | 0 |
| 10 | 10 | 1 | 9 | Z | NULL | NULL |
| 11 | 11 | 1 | 10 | C | NULL | NULL |
| 12 | 12 | 1 | 11 | Z | NULL | NULL |
| 13 | 13 | 1 | 12 | X | NULL | NULL |
| 14 | 14 | 1 | 13 | Z | 0 | 1 |
| 15 | 15 | 1 | 14 | V | NULL | NULL |
| 16 | 16 | 1 | 15 | X | NULL | NULL |
| 17 | 17 | 1 | 16 | V | NULL | NULL |
| 18 | 18 | 1 | 17 | V | 0 | 0 |
| 19 | 19 | 1 | 18 | C | NULL | NULL |
| 20 | 20 | 1 | 19 | C | NULL | NULL |
| 21 | 21 | 2 | 0 | V | NULL | NULL |
| 22 | 22 | 2 | 1 | V | 1 | 1 |
| 23 | 23 | 2 | 2 | V | 1 | 1 |
| 24 | 24 | 2 | 3 | Z | 0 | 1 |
| 25 | 25 | 2 | 4 | X | 0 | 1 |
| 26 | 26 | 2 | 5 | B | 0 | 1 |
| 27 | 27 | 2 | 6 | Z | 0 | 1 |
| 28 | 28 | 2 | 7 | Z | 0 | 0 |
| 29 | 29 | 2 | 8 | Z | 1 | 1 |
| 30 | 30 | 2 | 9 | X | 0 | 1 |
| 31 | 31 | 2 | 10 | Z | 0 | 1 |

Figure 7: CSV file with participant's stimulus and responses


```
1721876132.374, 76, Fixation Cross Start
1721876133.3285103, 76
1721876134.36651, 76
1721876134.379, 76, Fixation Cross End
1721876134.381, 77, Stimulus Shown
1721876134.895, 77, Stimulus End
1721876135.30848, 77
1721876136.3288481, 77
1721876136.409, 78, Task Answer
1721876136.410, 78, Stimulus Shown
1721876136.923, 78, Stimulus End
1721876137.3484101, 78
1721876138.3086941, 79
1721876138.432, 79, Task Answer
1721876138.433, 79, Stimulus Shown
1721876138.945, 80, Stimulus End
1721876139.3898857, 80
1721876140.348402, 80
1721876140.459, 81, Task Answer
```

(a) CSV file with heartrate and task markers


ReviewedCSV > FlankerRun2NasaTLX.csv > data
```
1,2,1,11,4,21
2,3,2,12,5,20
3,4,3,13,6,19
4,5,4,14,7,18
5,6,5,15,8,17
6,7,6,16,9,16
7,8,7,17,10,15
8,9,8,18,11,14
9,10,9,19,12,13
```

(b) CSV file with NASA TLX survey responses

Figure 6: Data files stored from a partial trial run of the pilot experiment

The MOT task pilot experiment follows a slightly different design due to its unique tracking requirements, as shown in figure 5. Each trial begins with an instruction screen and fixation cross similar to the $N$-back tasks. After that, in each sub-trial, 10 circles are presented on the screen in the RoI for 2 seconds with $C$ target circles highlighted in black. In our pilot experiment, we chose $C = 2$ for low workload, $C = 4$ for medium workload, and $C = 6$ for high workload task. Then, the target circles are de-highlighted and all the circles follow Brownian motion and move randomly in the RoI for the next 12 seconds. After the movement phase ends, participants are given a maximum of 10 seconds to identify the $C$ target circles by clicking on them. Participant responses are recorded along with their correctness labels in real time. At the end of each trial, participants complete a NASA TLX survey for 15 seconds, followed by a 4-second rest period before the next trial begins.

## DISCUSSION AND FUTURE EXTENSIONS

The proposed reconfigurable testbed addresses key limitations of existing platforms by providing *flexibility* to design tasks with varying parameters and diverse sensors, *automatic synchronization* of the web dashboard with sensor data, and *user-friendly interface* so that a wide range of researchers (even with limited programming expertise) can adopt this testbed. Furthermore, the open-source nature and modular design of the proposed testbed allows anyone to add new features (e.g. tasks, sensors) to design new experimental paradigms in the future. This adaptability makes the testbed a valuable resource to neuroscience researchers. The pilot experiments designed with this testbed exhibited some minor concerns in terms of reliable data acquisition due to occasional Bluetooth connectivity disruptions. Additionally, during heavy tasks involving overwhelming I/O operations, a small amount of latency is observed in marker read/write steps.

Future work will focus on collecting data using the described experiments to develop novel multimodal neural network models to predict cognitive workload optimizing and integrating additional cognitive tasks and expanding sensor compatibility. Additionally, adding remote access functionality would allow researchers to monitor experiments and collect data from geographically dispersed participants, making the testbed viable for large-scale collaborative studies. To ensure a robust system, incorporating strong encryption protocols for data security would further enhance the testbed's suitability for online applications. The testbed's adaptability will be advantageous for cognitive neuroscience research with diverse applications in education, defense, healthcare, and transportation.

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