Boggle: An SSVEP-Based BCI Web Browser

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Abstract. Brain-Computer Interfaces (BCIs) have led to significant enhancements in the lives of physically-restricted individuals. BCIs based on Steady State Visually Evoked Potentials (SSVEPs) are robust and rely on a neuronal response evoked when a person focuses attention onto a flickering visual stimulus. Our first study [5], which provided empirical insights on web technologies' applicability for SSVEP stimuli-generation, demonstrated that both Cascading Style Sheets (CSS) and Web Graphics Library (WebGL) can produce effective stimuli via square wave approximations, using Google Chrome and Mozilla Firefox. Building upon these findings, this work explores the feasibility of adopting these technologies to implement an SSVEP-driven web browser, supporting online and asynchronous BCI-based control. Informed by a systematic review of literature and a succession of user-centred studies, this paper discusses results produced throughout the development of Boggle - a novel SSVEP-based BCI web-browser. As for in-browser stimuli-generation, enhanced stimuli efficacy was observed when adopting a custom-developed CSS-based stimuli-generator on Chrome, particularly in high-load rendering conditions. In turn, this contributed to increased classification accuracy and Information Transfer Rates (ITRs), compared to other BCI-based browsers. When evaluated within an online, asynchronous BCI context, participants achieved a global mean classification accuracy and ITR of 90.98% and 29.58 Bits Per Minute (BPM) respectively. Moreover, various usability tests were adopted to gauge progress throughout the different iterations. Boggle is the first cross-platform, SSVEP-based BCI browser that is fully developed using web-native technologies, and which exploits approximation techniques for stimuli-generation. Feedback provided by domain experts further highlights Boggle's suitability as a primary assistive technology.

Keywords: Brain-Computer Interface (BCI) · Steady State Visually Evoked Potential (SSVEP) · SSVEP-based BCI web browser

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1 Introduction

World Wide Web (WWW) ubiquity has permitted instantaneous, global communication, greatly revolutionizing the ways in which humans interact with one another [8]. Notwithstanding this, millions of physically-restricted individuals face accessibility barriers, which hinder their ability to exploit a wide range of online services [32]. Assistive Technology (AT), such as that based on eye-tracking or brain control [4], can support web interaction for people with limited mobility, enabling their participation in employment, education and other sectors.

A Brain-Computer Interface (BCI) is a form of high-tech AT which operates independently of the body's standard output channels of the peripheral nerves and muscles [43]. BCIs often rely on electroencephalography (EEG), which offers a non-invasive approach to capture brain activity [5].

BCIs based on Steady State Visually Evoked Potentials (SSVEPs) are robust and necessitate negligible amounts of user training to operate. Humans produce SSVEPs in response to visual stimuli flickering at frequencies greater than 5 Hz [5]. During periods of SSVEP stimulation, scalp electrodes, positioned over the brain's occipital region, detect brain responses oscillating at the same frequency as the stimulus being attended to by the user [42]. BCI classification algorithms can identify which stimulus is being targeted and, based on this, trigger some corresponding action [5].

Within a BCI environment, stimuli stability and accuracy are key to robust SSVEP response generation. Literature shows that monitor-based stimulation is currently prevalent, with the adoption of technologies like C++, OpenGL and Psychtoolbox to reliably render visual flickers. Consequently, the applicability of web technologies for building highly flexible, accurate and portable SSVEP stimulation tools has been scarcely researched [5].

Although web browser interaction has been previously explored within the context of an SSVEP-based BCI [44,45], none of these attempts have focused on web-based stimuli-generation. In fact, solely a few initial works have considered in-browser stimuli, namely through the development of two online SSVEP spellers using Graphics Interchange Format (GIF) files [34] and Cascading Style Sheets (CSS) [33]. Rezazadeh et al. [31] have also succeeded at navigating a virtual home environment by means of browser-generated SSVEP stimuli.

Despite these studies' favourable outcomes, minimal empirical evidence exists on the feasibility of different web technologies and underlying browser engines for rendering effective in-browser SSVEP stimuli. Furthermore, stimuli approximation techniques, which permit enhanced user interaction efficiency, have not been investigated within a web environment [5].

Our previously published work [5] initially sought to address these two research gaps, by empirically evaluating web-based SSVEP stimuli's stability and accuracy, as well as their adequacy for BCI adoption.

This paper augments our first study [5], by building upon its findings to assess the viability of building a specialized, evidence-based, SSVEP-driven BCI web browser, via cross-platform and web-native technologies, for providing physically-restricted individuals with a reliable, alternative means of web access.

2 Research Background

BCIs facilitate interaction through the establishment of a direct communication pathway between a human's brain and a machine. BCIs can either function in synchronous or asynchronous modes, whereby interaction timings are fully controlled by the system or user respectively. When opting for synchronous approaches, brain activity is processed at predefined, regular intervals, and it is constantly assumed that the user wishes to trigger a specific BCI command. On the contrary, asynchronous systems provide a greater degree of independence to users, enabling them to proceed with system interactions at will [29].

The functioning of a synchronous or an asynchronous BCI can be summarized into four key, sequential phases, specifically: (a) signal capture, (b) feature extraction, (c) feature classification and (d) command execution. The procedure is initiated by the real-time processing of captured EEG signals, through which features are extracted to reliably classify the subject's intent. Based on this, an automatic control function is produced [5] and optionally, auditory or visual feedback is provided to the user. BCI performance is typically reported using a range of different metrics, with classification accuracy and Information Transfer Rate (ITR) (reported in Bits Per Minute (BPM)) being among some of the most widely adopted measures in literature [36].

SSVEP-based BCIs are this study's prime focus, given their minimal training times [11], high Signal-to-Noise Ratios (SNRs) [14], as well as their capacity to reach high ITRs [28]. Upon focusing visual attention onto an SSVEP stimulus, non-invasive scalp electrodes, located over the subject's visual cortex, record oscillations at the target stimulus' fundamental and harmonic/sub-harmonic frequency components [5]. SSVEP stimulation is typically presented using Liquid Crystal Displays (LCDs), although some efforts have also focused on visual stimuli-rendering via Light-Emitting Diode (LED) panels and Cathode-Ray Tubes (CRTs) [25].

Conventional constant-period techniques of stimuli-generation, as well as the relatively novel square wave approximation method are thoroughly discussed in our previous work [5], along with the benefits and limitations of each approach. The next section focuses on advancements in BCI-based web browsing, through which the current state of the art is also highlighted.

2.1 BCI-Based Web Browsing

WWW access is vital for individuals who live with some form of physical disability. Through the review of existing literature, several efforts aimed at providing an entirely BCI-based browsing experience were identified [2,3,21,26,27,40,44,45] (see Table 1). These systems depend on a range of input modalities, including Slow Cortical Potentials (SCPs), Sensorimotor Rhythms (SMRs) and P300 evoked potentials, and each have their own benefits and limitations.

Based on the conducted review, it is evident that the majority of BCI browsers lack support for core functionality [2,3,21,26,40,45], while some necessitate lengthy command detection times [21,27,44,45] or training periods [2,21], making them less than ideal for day-to-day use. Furthermore, some of the implemented tools have not been evaluated with actual users [40], or else have not reported any BCI performance evaluation results [2,3,26,45], which means that their viability is currently unknown.

Considering Mankoff et al. [26] and Mugler et al.'s [27] 'true web access' criteria for

Table 1. Table providing a brief overview of all BCI browsers identified through the review of literature [2,3,21,26,27,40,44,45], alongside their development dates and interaction paradigms.

BCI browser	Date	Paradigm(s)	Brief overview
Descartes	1999	SCPs	• Supports back navigation, link selection and typing; • The tool's major drawbacks are its limitations in the representation of different links, lengthy training/selection times, as well as restrictions in web pages that can be navigated to; • Descartes was tested by a single participant, who achieved a mean classification accuracy of 80%.
Mankoff et al.	2002	Neural signal modulation	• Supports history tracking, bookmarking, in-page element selections and back/forward navigation; • Web navigation is solely limited to a set of predefined web pages.
Nessi	2003	SCPs/SMRs	• Extends the Mozilla browser; • Supports typing, bookmarking, in-page element selections and interactions with a custom, in-built email interface; • Requires prior training for successful operation.
BrainBrowser	2003	Neural signal modulation	• Developed using JavaSwing; • Supports home/back navigation, page reloading, link selection and printing; • Not yet evaluated with actual users.
Yin et al.	2009	SSVEP	• Implemented using .Net C#; • Limited information is provided, yet it is understood that the browser supports page scrolling; • The browser has slow recognition speeds and lacks support for complex browser functionality.
Mugler et al.	2010	P300	• Supports typing, link selection, URL entry, page reloading, back/forward/home navigation, read mode, form element input and page scrolling; • Based on provided user feedback, web surfing via the P300 browser takes too long; • Healthy participants achieved satisfactory performance results, with a mean classification accuracy and ITR of 90% and 13.4 BPM respectively.
Bose et al.	2016	Attention level modulation	• Built as an Android-based tool; • Supports home/back/forward navigation and in-page element selections.
WeBB	2017	SSVEP	• Developed as an Eclipse plugin and uses constant-period designs for stimuli-generation; • Supports typing, scrolling, history traversal, link navigation, page previewing and bookmarking; • Command detection times for WeBB are lengthy and interaction with complex in-page elements is unsupported; • Globally, participants achieved a mean classification accuracy of 86.08%, while their ITRs fell between 3.39 BPM and 4.68 BPM.

low bandwidth input systems (refer to [26,27] for full web accessibility guidelines), it is worth noting that the SSVEP-based BCI browser, WeBB [27], may be considered as the most compliant, with the satisfaction of 80% of the proposed criteria. Despite WeBB's high accessibility ranking, the browser achieved low ITRs (3.39 BPM–4.68 BPM) in comparison to other studies, where the highest mean ITR reached 13.4 BPM [27]. Additionally, the browser's reliance on constant-period designs restricts stimuli frequency selection, and in certain screens, necessitates the use of multi-step selection techniques, which entail users to perform a greater number of steps to trigger the desired action.

Yin et al.'s [45] browser also operates via SSVEPs, however, is characterized by slow recognition speeds and a lack of support for complex browser functionality. Moreover, insufficient information is available on its performance and feature support.

3 Research Aims

This work's prime goal is to bring the WWW closer to individuals whose physical condition prevents them from gaining access via standard means of input.

Prompted by the various benefits of web-based SSVEP stimulation, in terms of portability, flexibility and cross-platform compatibility, the initial phase of our work [5] sought to deduce the viability of constant-period and square wave approximated in-browser SSVEP stimuli. To reach these objectives, standard web graphics and animation rendering technologies were considered, namely CSS and Web Graphics Library (WebGL), whose stimuli-rendering capacity was studied on Google Chrome and Mozilla Firefox, which are supported across major operating systems. Encouragingly, it was found that all studied browser-technology pairs can produce reliable and efficacious SSVEP stimulation via square wave approximations. These findings were evidenced by the consistent stability and accuracy of produced stimuli, as well as the minimal performance discrepancies noted between different stimuli-rendering scenarios [5].

Building upon our previous work's outcomes [5], this paper investigates the feasibility of adopting web technologies to build Boggle, a cross-platform, online and asynchronous SSVEP-based BCI web browser, and assesses its efficacy over a series of development and design stages (specifically **Stages 1–4**).

4 Methodology

Since the initial research phase demonstrated that multiple browser engines and web technologies are valid for stimuli-generation [5], the developed SSVEP stimuli approximation libraries (arising from [5]) were further studied under high-load rendering conditions, to re-confirm their applicability for rendering large quantities of concurrent on-screen stimuli (e.g. for the browser's keyboard menu) and to inform the choice of stimulation technologies for Boggle. Boggle's development was also based on a review process, which was conducted for features supported by most accessible web browsers, giving rise to a succession of iterative design cycles, as well as offline and online BCI experiments. Ultimately, feedback from domain experts was also gathered on the developed tool.

The methodological approach adopted for Boggle's multi-stage design process is further discussed in subsequent sections.

4.1 Stage 1 - Initial Prototype Design

Stage 1 of this study initiates Boggle's design process, and is targeted towards the development of an initial browser prototype, for which, design decisions are based on reviewed literature and empirical evidence, arising from both the first research phase [5], as well as high-load performance trials.

Specifically, a thorough review of literature was first conducted on existing accessible web browsers and alternative tools (such as browser-based accessibility plugins), operable through various alternative input modalities, including eye-trackers and BCIs. Information extracted through this review was collated in the form of a ranking table, listing widely-adopted browsing features in order of their adoption rates, to guide initial design decisions on Boggle's feature support.

Additionally, high-load stimulation trials were executed on a single machine to reconfirm the applicability of the developed CSS and WebGL approximation libraries [5] for rendering a large number of stimuli simultaneously on-screen, as was required for Boggle's keyboard screen. During experimental sessions, the stimulators were configured to run 40 concurrent on-screen stimuli, while maintaining horizontal and vertical inter-stimuli distances of 0.55 cm (see Fig. 1). A similar methodology to that applied in [5] was re-adopted such that, for each stimulus, tachometer readings were gathered over three separate test runs, for frequencies 8 Hz, 9.6 Hz, 10.8 Hz, 11.6 Hz, 12.8 Hz, 13 Hz, 14.4 Hz and 15.6 Hz. Frequencies for stimuli rendered via CSS and WebGL were recorded on both Chrome and Firefox, for a total of four minutes each. Considerations relating to each library's hardware resource consumption were also taken into account at this stage. These results, in turn, informed the choice of stimulation technologies for Boggle.

4.2 Stage 2 - Design Iterations

Stage 2 of this study iteratively improves upon the implemented browser prototype, in direct collaboration with potential users, following a User-Centred Design (UCD) methodology. A total of 7 participants were recruited for this phase of study (4 males, 3 females), none of whom had any prior experience with Boggle. This research stage's

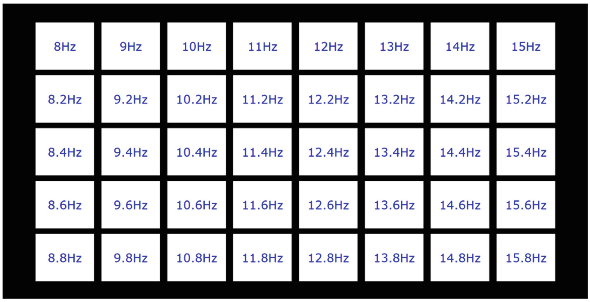

Fig. 1. The web-based approximation libraries' interface during the presentation of 40 concurrent on-screen stimuli, indicating the frequencies assigned to each stimulus.

iterative approach enabled the identification of usability issues within the browser, through a combination of methods, including usability metrics and feedback gathering techniques.

A within-subject study was designed, such that the same user group participated in usability testing sessions across different iterations, with the aim of minimizing subject-to-subject variability [37]. In total, two design rounds were conducted for Boggle, approximately four weeks apart, to 'wash out' learning effects from the previous run [37]. Each iteration involved the execution of a set of browsing tasks, which were executed via mouse clicks (performed on interface stimuli), without any form of guidance or feedback. Although Boggle is intended for BCI control, the use of mouse clicks ensured that this research stage's focus remained entirely on the browser's usability, without introducing the additional complexity of interfacing with a BCI. Usability insights, captured through the first iteration, led to the enhancement of certain browser components and features, whose impact was later evaluated as part of the second design round.

Throughout the first iteration, all 7 participants were assigned 11 browsing tasks, which were kept consistent between different subjects and also covered all of Boggle's supported functionality. These involved typing, scrolling, page reloading, back navigation, video playing, the use of read mode, link/input field/button selections, the triggering of Google searches (using an in-built menu), zooming in/out or resetting the page zoom levels, as well as visiting/adding and deleting bookmarks (individually or in bulk). As for the second design round, 6 participants (1 of the initial 7 participants was later unavailable) were given a total of 8 browsing tasks, which were focused on newly updated features within Boggle.

At each iteration, qualitative user feedback was collected through the think-aloud protocol and semi-structured discussions (held after the completion of each task or session), and later thematically analyzed. Gathered insights were either directly observed/noted during the session, or else extracted from transcripts of audio-visual clips recorded throughout the entire session. Additionally, each iteration involved the capture of a range of task-level metrics, namely the Single Ease Question (SEQ), completion rates, confidence ratings and error rates, which were applied for each executed task. With regards to study-level metrics, the System Usability Scale (SUS) was administered at the end of each browser evaluation session, to assess the entire system's usability. Overall, each iteration's usability testing sessions took around 1 to 1.5 h to complete.

4.3 Stage 3 - BCI Design Iteration

Following two iterative design rounds, **Stage 3** of this study aimed to evaluate Boggle within an online, asynchronous BCI context, and to deal with all intermediary steps necessary to reach this target. This research stage was split up into two parts, namely offline and online experiments, with the former laying the groundwork for online BCI sessions. Throughout both experiments, SSVEP detection was performed via the unsupervised, state-of-the-art Filter Bank Canonical Correlation Analysis (FBCCA) algorithm, which requires no prior training to operate, and is also capable of reaching high classification accuracies [6].

Web browsing activities within Boggle are facilitated through the browser's support for both non-control and intentional-control states [24]. Non-control states correspond to instances during which users are deliberately not focusing onto any SSVEP stimuli, for example while reading a web page, while intentional-control states refer to periods during which users are focusing onto SSVEP stimuli of interest, to trigger some browser function, such as the opening of a browser menu [24].

The EEG hardware setup, as well as the methods adopted for the conducted offline and online BCI experiments, are further discussed below.

EEG Data Acquisition. To capture brain signal data, participants were fitted with an electrode cap (g.GAMMACAP[1]) and 8 channels (PO3, PO4, PO7, PO8, POz, O1, O2, Oz), positioned over the brain's occipital and parietal regions, were used to record brain activity. Cz (ground electrode) and an ear lobe electrode clip were chosen as a means of referencing during EEG data collection. All electrodes were positioned in accordance with the International 10–20 electrode placement system.

Before attaching non-invasive g.SCARABEO (see footnote 1) electrodes to the corresponding g.GAMMACAP (see footnote 1) holder rings, conductive electrolyte gel was used to minimize impedance contact with the skin [39]. Electrodes were connected to the g.GAMMAbox (see footnote 1), which interfaces with the g.USBAMP (see footnote 1) amplifier, configured to run at a sampling rate of 256 Hz. Highpass and lowpass filters were applied at 0.5 Hz and 100 Hz respectively, while a 50 Hz notch filter was used to suppress power line interference.

Offline BCI Experiments. Offline BCI sessions involved EEG data collection with participants from **Stage 2** of this study, over a specific number of trials. During offline experiments, Boggle was run in a cue-based mode for complex (>10 stimuli) and non-complex (<10 stimuli) interfaces. Throughout these sessions (each one lasting roughly 1 to 2 h in duration), both intentional-control and non-control state EEG data was gathered from participants.

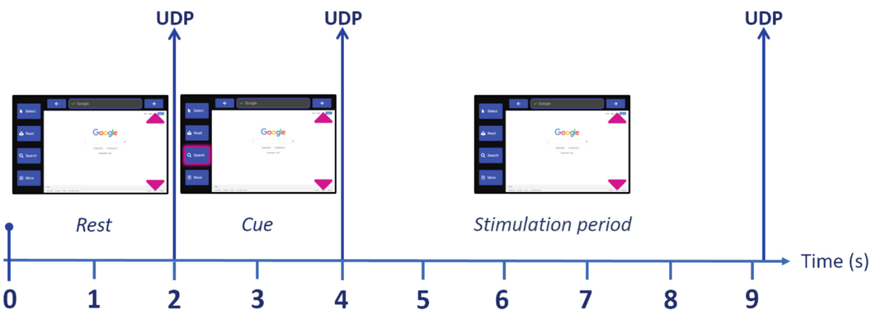

Fig. 2. Timing scheme for a single offline trial conducted within Boggle's home screen.

For intentional-control state EEG data collection, cues were shown in random order as a coloured stimulus border. A single stimulus trial (refer to Fig. 2) lasted 9.185 s

[1] Products developed by g.tec [13].

and for each participant, a maximum of 10 trials per stimulus were conducted. A trial commenced with a 2 s rest period, during which all SSVEP stimuli were inactive. In the next 2 s, a cue was shown around one randomly selected stimulus, to direct the subject's gaze to the target stimulus. At the fourth second, the cue was hidden and all on-screen SSVEP stimuli flickered simultaneously at unique frequencies, for a period of 5.185 s. A single run was completed once a single trial per stimulus within the interface was collected. Participants were also allowed several minutes of rest in-between two consecutive runs to minimize visual fatigue.

To facilitate EEG data segmentation, indicator values were transmitted from Boggle's client application to the implemented Simulink data processing module (via User Datagram Protocol (UDP) packets), at time points corresponding to the onset of cue presentation, start of SSVEP stimulation, end of each trial and completion of every run. All values transmitted via UDP were synchronized with captured EEG data and were stored in a separate file for further analysis.

Intentional-control state EEG data was initially collected for non-complex interfaces, namely Boggle's home screen, which consists of 8 stimuli. Data was collected from 5 participants over 10 runs, such that a total of 10 trials per stimulus were collected for each participant. Three stimuli conditions were considered, specifically (a) blue and magenta stimuli with non-flickering content[2], (b) blue and magenta stimuli with flickering content (see footnote 2) and (c) white stimuli with flickering content (see footnote 2), all of which were shown over a black background. Thus, a total of 2204.4 s' worth (9.185 s $\times$ 8 stimuli $\times$ 10 trials $\times$ 3 stimuli conditions) of EEG data was gathered for each participant. All subjects were exposed to the three different conditions in random sequence [37], so that the stimuli which yielded the highest classification performance and ITR could be adopted for subsequent data collection sessions, as well as online experiments.

A similar procedure was used to capture intentional-control state EEG data for complex interfaces, specifically for the keyboard menu, which contains 18 stimuli. A total of 4 participants were involved in data collection, with each session lasting approximately 1653.3 s (9.185 s $\times$ 18 stimuli $\times$ 10 trials) per participant. This time round, blue-magenta stimuli (with flickering contents) were used, based on the results obtained for non-complex interfaces, for the three studied stimuli characteristics (refer to Sect. 6.3 for the relative results).

Subjects' intentional-control state data for complex and non-complex screens, was segmented and processed offline by the FBCCA SSVEP detection algorithm. In this case, 5 sub-bands and 5 harmonics were considered, as suggested by Chen et al. [6], while a gaze shifting period of 1s and a visual latency of 0.135 s [9] were adopted. This initial analysis provided information on each participant's achievable BCI classification accuracy and ITR. A range of gaze window lengths were tested to identify a suitable time window for EEG capture, which is ideally as short as possible, without significant detriment to BCI performance.

Non-control state EEG data was also captured during the process of reading a web page within Boggle (with read mode enabled), to assess typical brain activity during idle

[2] Stimulus content refers to text/images contained within a stimulus, which could either be non-flickering or else flickering at the same rate as the stimulus' background.

browsing periods. This data was ultimately used to determine a reasonable classification threshold for FBCCA, which can discriminate between non-control and intentional-control states, thus satisfying this study's requirement for an asynchronous BCI.

Online BCI Experiments. The results of the offline study were subsequently used to assess Boggle's usability, when operated within an online, asynchronous BCI context. In this case, numeric identifiers were transmitted from Boggle's client application (via UDP packets) on every menu transition or stimulus state update, enabling the classifier to maintain an updated list of classifiable stimuli frequencies.

All 6 participants from Boggle's final design iteration (**Stage 2**) were involved in the BCI evaluation phase. Similar to offline sessions, EEG data was recorded over 8 channels, while the FBCCA algorithm was used with the previous parameter settings, for SSVEP detection and classification. Stimuli frequencies (6 Hz–14.5 Hz in 0.5 Hz steps) were common to all subjects, with the entire frequency range, or subsets of it, being reused across Boggle's various screens, depending on the required number of stimuli. Blue-magenta stimuli (with flickering contents) were also adopted, based on results achieved for offline analyses (see Sect. 6.3), conducted for non-complex interfaces, for the range of studied stimuli characteristics.

As opposed to the implemented offline system, the online BCI is constantly active and continually outputting a classification response every 4 s, corresponding to the specified gaze window length parameter (set based on offline evaluation results, discussed in Sect. 6.3). Users' EEG is continuously captured and processed in chunks of 1024 data points, that are either labelled as a particular stimulus frequency (intentional-control state) or a non-control state by the FBCCA classifier. The output label is sent to Boggle and, on its receipt, some corresponding action is executed and system feedback shown to the user, in the form of a coloured border around the selected stimulus.

For online experiments, participants carried out 5 web browsing tasks (chosen from the final design iteration for **Stage 2** of the study) through BCI control (see Fig. 3), with these tasks being read out once verbally, to ensure that users were confident with the task requirements.

Throughout online sessions, a range of usability/performance metrics, namely the Samn-Perelli Fatigue Scale (SPS), Raw Task Load Index (RTLX), Time on Task (TOT), completion rates, as well as classification accuracy and ITR measures, were adopted as task-level metrics. As for study-level metrics, the SUS was applied to holistically evaluate the entire BCI system's usability. Sources of data collection also included semi-structured post-study discussions, direct observations and audio-visual capture, which altogether, enabled a comprehensive understanding of Boggle's usability from different perspectives.

4.4 Stage 4 - Domain Expert Feedback

Boggle's design process was concluded with in-depth discussions on Boggle's usability, which were held with two senior occupational therapists (employed with a national agency), who often work with individuals from this study's target user group. A remote, semi-structured interview was set up, prior to which interviewees were also given a set

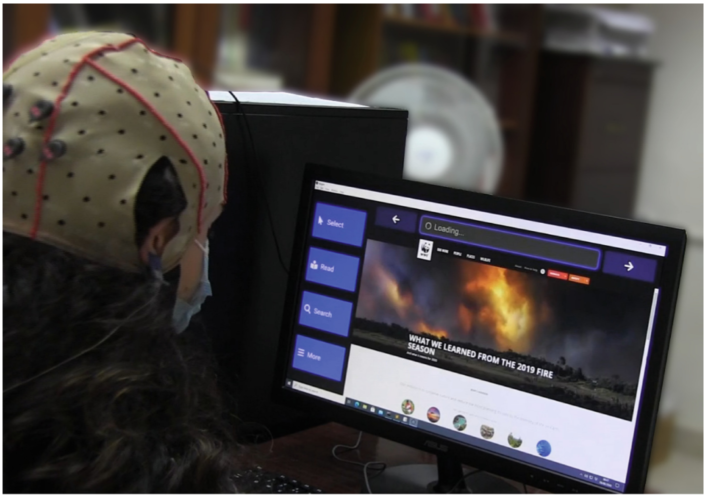

Fig. 3. User interacting with Boggle via asynchronous, BCI-based control.

of resources to familiarize themselves with Boggle. The resource pack included (a) a video of a participant interacting with Boggle via BCI, (b) detailed documentation on all features supported by Boggle and (c) screen capture of various browsing actions being executed via Boggle using mouse-clicks.

All captured interview details were transcribed based on audio-visual recordings and later thematically analyzed. In this way, present-day challenges in assisting motor-impaired individuals could be further understood, while gaining insight into Boggle's real-world applicability and possible enhancements that could address target users and carers' needs more accurately.

5 Boggle - Implementation Details

This section focuses on Boggle's final browser design (emerging from **Stage 3** of this study), which operates through various hardware and software tools (refer to Fig. 4), functioning in tandem with one another, to capture and process users' neuronal signals, and to convert them into browser commands or non-control state executions.

Boggle's operation (see Fig. 4) starts off with EEG acquisition (see Sect. 4.3 for EEG hardware setup) and is directly followed by signal processing, at which point a classification response is output by the FBCCA algorithm. The classification output is sent to the SSVEP hub (a Node.js server) via an HTTP POST request. In turn, the hub employs the publish/subscribe (pub/sub) communication model to publish classification labels, which are ultimately received by the Boggle engine (i.e. the client web browsing application) over a WebSocket connection. On the label's receipt, some corresponding action is triggered, resulting in User Interface (UI) updates, feedback provision and potentially, changes to Boggle's state (maintained via the state manager and an underlying SQLite database). Given the asynchronous nature of the adopted architecture, EEG classification may also lead to non-control state instructions.

5.1 Signal Processing Module

During online operation, Boggle's Simulink-based signal processing module processes EEG data in real-time, and handles incoming data from two main sources: (a) the amplifier's EEG signals and (b) numeric identifiers sent out by the Boggle engine (via UDP packets).

EEG data is received in batches of 256 data points per second and is held in a buffer until the data point count equals that required for a specified gaze length. For instance, in the case of this study, a 4 s gaze length was considered, thus, at most, 1024 data points (4 s $\times$ 256 data points) can be stored within the buffer. On collection of 1024 data points, the data block is released for further processing, only if the recorded menu scenario identifiers (received over UDP) are valid. These indicate the state of Boggle's UI to the signal processing module, such that classifications are solely performed between frequencies of interest, resulting in reduced error rates.

Additionally, a threshold-based approach [46] is adopted for non-control state detection within Boggle. The FBCCA algorithm's classification process involves the computation of correlation coefficients between SSVEP sub-band components and pregenerated sinusoidal reference signals, for all stimuli frequencies. Thus, a reference signal frequency having maximal correlation with multi-channel SSVEPs is deemed as the actual target stimulus frequency [6], only if its maximal correlation coefficient exceeds a predefined threshold. Otherwise, the signal is labelled as a non-control state and a classification label is output accordingly.

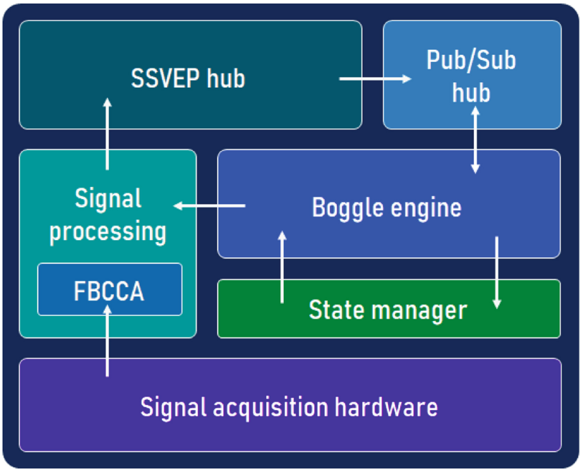

Fig. 4. Architectural overview of Boggle's online, asynchronous BCI framework.

5.2 Boggle Engine

The Boggle engine, which refers to the client web browsing application, was built using the Chromium-based Electron framework, which permits cross-platform desktop application development [10] via web-native technologies. The technologies chosen to implement the engine, as well as decisions on its feature support, were based on results arising from our first study [5] and **Stage 1** of this research (see Sect. 6.1).

The client application is responsible for (a) setting up a customized browsing experience, (b) transmitting numeric indicators to the signal processing module, (c) handling classification responses, (d) providing user feedback, as well as for (e) rendering Boggle's UI, using the initial research phase's [5] CSS stimuli approximation library, which was deemed as the most performant stimulator, based on the results of the conducted high-load performance trials (results for **Stage 1** of this study are available in Sect. 6.1).

Fig. 5. Screenshots from Boggle's interface showing the (1) home menu with basic navigation and reading controls, (2) an 18-target keyboard interface with auto-completion facilities, (3) on-page region selection control (to activate links/buttons/text fields in a particular region), (4) on-page link/button/text field selection control (numbered), (5) in-built Google search menu, as well as (6) page and bookmark management facilities.

Boggle's final interface design also includes several aspects, such as link selection functionality and bookmark management support, as outlined in Fig. 5.

6 Results

This section documents the findings of the high-load performance tests, as well as the results of a review process, which was conducted for features supported by various accessible web browsers and tools. Subsequent sections also highlight the usability results achieved for the iterative design process, as well as for Boggle's offline and online BCI experiments. Feedback provided by domain experts is also thoroughly discussed in upcoming sections.

6.1 Stage 1 - Initial Prototype Design

This section discusses the findings of the review, compiled for existing accessible web browsers/tools, as well as the outcomes of the high-load stimulation trials, conducted for the implemented web-based stimuli approximation libraries [5].

All identified web browsing functionality, arising from reviewed literature, was summarized in table form and ordered by popularity, based on each feature's adoption rate (computed as a percentage across all reviewed accessibility tools). It was noted that highly-ranked browsing functionality was common to both accessible browsers and alternative tools, hence **Stage 1** of this study focused on equipping Boggle with features that are widely supported by various accessible web browsers [1–3,20–23,26,27,30,40,41,44,45], as shown in Table 2.

In high-load stimulation conditions, an increased number of inaccuracies/instabilities were noted across all rendering scenarios, which were previously studied for the initial research phase [5]. Considering all stimuli-generation combinations [5], CSS and Chrome achieved the highest performance levels, with an overall mean bias of 0.0207 ($\sigma = 0.2708$) for all tested stimulation frequencies (refer to [5] for a definition of the 'bias'). On the other hand, the poorest performance was recorded for WebGL and Firefox, with an average bias of 0.0404 ($\sigma = 0.3963$) across all studied stimuli frequencies. With regards to hardware usage, all logged CPU, GPU and memory consumption values were in close proximity to one another, across all technology-browser setups.

Based on these outcomes, a performance advantage was noted for CSS and Chrome-based SSVEP stimuli as these showed the least inaccuracies and instabilities in high-load rendering scenarios. The adoption of Chromium (a core aspect of Google Chrome) and CSS was thus identified as the most plausible way forward, for the implementation of a highly performant and reliable SSVEP-based BCI browser. Altogether these results shaped Boggle's initial prototype design.

6.2 Stage 2 - Design Iterations

Quantitative/qualitative usability data, gathered over two design iterations, was crucial to the enhancement of Boggle's initial prototype design. This section goes over the

Table 2. Accessible web browsers' functionality listed in order of popularity. This table also indicates whether or not each browser feature is supported by Boggle's first design.

Browser feature	Adoption rate (%)	Supported by Boggle
Link navigation	85.71%	✔
Back/forward navigation	78.57%	✔
Scrolling	78.57%	✔
Home navigation	64.29%	✘
Page reload	64.29%	✔
Bookmarks	57.14%	✔
Web searches	50%	✔
Typing	42.86%	✔
Form elements	42.86%	✔
Menu navigation	35.71%	✔
Browsing history	28.57%	✘
Automatic scrolling	14.29%	✘
Multimedia content	14.29%	✔
Zoom in/out	14.29%	✔
Text selection	7.14%	✘
Tab management	7.14%	✘
Word prediction	7.14%	✔
Cut, copy and paste	0%	✘
Boggle's feature coverage (%)	—	**66.67%**

adopted evaluation strategies and the final usability results for Boggle's two-phase iterative design process.

A brief overview of results obtained for the final iteration's usability metrics, namely the SEQ, confidence ratings, task completion rates, error rates and the SUS is provided in Table 3. Task completion was measured based on the following Successful Completion Criteria (SCC): (a) users had to fully achieve task aims, (b) specified sub-tasks had to be followed to accomplish tasks and (c) no more than 3 erroneous selections could be performed during the task's execution.

As for task error rates, these were quantified using Eq. 1 [35], whereby participants' error counts were divided by the total number of browsing actions executed during the specific task. Resultant values were subsequently multiplied by 100 for conversion into percentage form. Additional error rectification steps were also considered as correct commands for all error rate computations.

$$ErrorRate = \left(\frac{ErrorCount}{TotalActions}\right) \times 100 \tag{1}$$

Table 3. Table portraying the 6 participants' global mean usability scores, benchmark values, and the least/most desirable scores for each metric applied during Boggle's final design iteration.

Usability measure	Participants' global mean score	Benchmark comparison score	Least desirable score	Most desirable score
SEQ	6.88	5.5 (based on research conducted by Sauro [16])	1	7
Error rate	1.82%	—	100%	0%
Completion rate	97.92%	78% (based on research conducted by Sauro [19])	0%	100%
Confidence	6.9	5.75 (based on research conducted by Sauro [18])	1	7
SUS	90.42	68 (based on research conducted by Sauro [17])	0	100

Statistical analyses were conducted using 95% Confidence Intervals (CIs), to estimate the uncertainty in participants' global mean usability scores [7]. Wherever possible, mean usability/performance measures were also compared against established benchmarks, either using the non-parametric Binomial test or its parametric alternative (the One Sample t-test). Furthermore, comparisons between participants' mean scores across design iterations were performed using the Paired Samples t-test (parametric) or Wilcoxon Signed-Rank test (non-parametric), to identify potential improvements in mean usability measures for the final iteration. An alpha level of .05 was also assumed for all statistical tests.

The final results of the iterative design process demonstrate Boggle's usability through the high task completion rates attained (95% CI [93.73%,100%]), in combination with the satisfactory SEQ (95% CI [6.78,6.97]) and confidence scores (95% CI [6.81,6.99]) given out by participants, for all browsing tasks executed via Boggle. Encouragingly, users also maintained low error rate levels throughout (95% CI [0.28%,3.37%]). Participants' SUS ratings (95% CI [81.89,98.95]) also complement these findings and evidence that, globally, the system was perceived as highly usable. Additionally, Binomial test/One Sample t-test results showed that, where applicable, participants' mean usability scores were all significantly higher ($p < .05$) than the specified benchmark values (see Table 3). A significant improvement ($p < .05$) in participants' mean SEQ scores was also noted for the final iteration, while discrepancies for confidence ratings (p = .08), completion rates (p = .655) and the SUS (p = .699) were found to be marginal, when using either the Wilcoxon Signed-Rank test or Paired Samples t-test as applicable.

Participants' feedback supplements these results, with the web browsing experience being described as "very positive" and most users perceiving the system as memorable [15]. Some participants also remarked on the effectiveness of newly implemented enhancements.

6.3 Stage 3 - BCI Design Iteration

This section highlights the evaluation techniques and results achieved for offline and online BCI studies, which were both conducted with potential target users, to gauge Boggle's usability in the context of brain control.

Offline BCI Experiments - Intentional-Control States. Offline BCI experiments started off with intentional-control state EEG data gathering for the browser's home interface (non-complex screen), with stimuli characteristics being set as described in Sect. 4.3. EEG data corresponding to SSVEP stimulation periods was segmented into 5.135 s time windows, which included an initial visual latency of 0.135 s. A total of 8 EEG stimulation segments (one segment per stimulus), for each of the 10 data collection runs, were passed to the FBCCA algorithm. Performance was measured through classification accuracy, via Eq. 2, and ITR, using both Eqs. 3 and 4.

$$ClassificationAccuracy = \left(\frac{CorrectClassifications}{TotalClassifications}\right) \times 100 \tag{2}$$

Eq. 3, introduced by Wolpaw et al. [36,43], provides an average measure of the quantity of bits transferred per selection (bits/trial) [38], where N refers to the total number of selection options available within the screen (in the home menu's case this is equal to 8), while p denotes the classification accuracy.

$$BitsPerTrial = \log_2 N + P \log_2 P + (1 - P) \log_2 \left(\frac{1 - P}{N - 1}\right) \tag{3}$$

$$ITR = BitsPerTrial \times \frac{60}{SelectionTime} \tag{4}$$

To convert ITR from bits/trial (result of Eq. 3) to BPM, Eq. 4 [38] is applied where *selection time* refers to the total classification time in seconds. For the purpose of offline experiments, selection time incorporates both periods of gaze focus (duration varied across tests, such that values between 0.5 s and 5 s were considered in 0.5 s increments) and gaze shifting (fixed at 1 s).

Across all gaze length parameters, participants' averaged performance scores indicate that the highest mean classification accuracies and ITRs were consistently obtained for blue-magenta stimuli with flickering contents. Given participants' overall higher performance, stimuli with these characteristics were deemed as the most effective SSVEP stimulation source out of all three studied options. Overall, the highest mean classification accuracies and ITRs amount to 97.75% and 40.51 BPM respectively, and correspond to data lengths of 5 and 2.5 s (see Table 4).

Table 4. Table depicting subjects' mean offline classification accuracies and ITRs, along with standard deviations, considering blue-magenta stimuli (with flickering content) across different gaze lengths, for the home menu (non-complex interface).

Data length (s)	Mean acc. (%)	Acc. std. dev. (%)	Mean ITR (BPM)	ITR std. dev. (BPM)
0.5	33.25	8.6	11.34	5.91
1	51	13.87	22.34	11.47
1.5	72	17.08	36.79	16.08
2	82.25	13.45	40.29	12.56
2.5	89.25	10.77	**40.51**	10.05
3	93	5.97	38.8	5.49
3.5	95.5	5.63	36.25	4.94
4	96.5	4.09	33.38	3.38
4.5	97	2.88	30.68	2.1
5	**97.75**	2.24	28.58	1.5

Since complex screens are likely to yield some level of performance degradation [12], attainable accuracy and ITR in such conditions were also investigated prior to selecting a gaze length parameter value. Thus, a similar analysis strategy to that described for non-complex interfaces was also employed for the complex keyboard screen, consisting of 18 stimuli. Based on the FBCCA algorithm's classification output, the highest mean accuracy and ITR for the keyboard menu amounted to 87.09% and 36.34 BPM respectively, corresponding to data lengths of 4.5 and 4 s (see Table 5), for blue-magenta stimuli with flickering contents. Based on these results, a 4 s gaze length was selected, which should permit for the maintenance of reasonable performance levels in complex screens, while giving a reasonable tradeoff between ITR and classification accuracy.

Offline BCI Experiments - Non-Control States. Given the asynchronous nature of this study's implemented BCI, offline studies also sought to determine a suitable subject-independent classification threshold, to discriminate between non-control and intentional-control states in a web browsing scenario.

The maximal correlation coefficients, recorded for different subjects for correctly classified intentional-control state trials, were occasionally as low as $\approx$0.8, going up to at most $\approx$1.6, whereas those of non-control states were found to range between $\approx$0.6 and $\approx$1. Based on this, a subject-independent correlation threshold of 0.85 was chosen for online BCI studies, which is expected to minimize false non-control state classifications and unnecessary delays during BCI-based interaction.

Table 5. Table depicting subjects' mean offline classification accuracies and ITRs, along with standard deviations, considering blue-magenta stimuli (with flickering content) across different gaze lengths, for the keyboard menu (complex interface).

Data length (s)	Mean acc. (%)	Acc. std. dev. (%)	Mean ITR (BPM)	ITR std. dev. (BPM)
0.5	4.86	0.83	0.23	0.13
1	6.39	0.96	0.68	0.52
1.5	19.86	9.12	6.01	4.63
2	46.53	20.43	22.87	15.77
2.5	65.42	19.89	33.89	16.39
3	72.5	21.35	35.74	16.05
3.5	79.17	16.81	36.29	12.74
4	84.58	11.72	**36.34**	8.85
4.5	**87.09**	10.64	34.63	7.65
5	86.94	9.32	31.53	6.02

It's worth noting that although classification threshold selection was required to satisfy this study's requirement for an asynchronous BCI, the system's effectiveness at discriminating between the two control states was not directly tested during subsequent online studies. Having said this, incorrect non-control state classifications still occurred throughout task executions, thus influencing the time taken to trigger a specific command and the achievable ITR.

Online BCI Experiments. This section discusses the adopted evaluation strategies and results obtained for online BCI experiments, which cover a range of standard usability/BCI performance metrics, and shed light onto insights gained through users' own feedback.

Table 6 depicts the various usability metrics applied throughout Boggle's BCI design iteration, including SPS, RTLX, SUS, task completion rates, as well as BCI classification accuracy and ITR measures. The global mean scores achieved by participants, the benchmark values considered for this study, as well as the least and most desirable usability score values, are shown alongside each metric.

Once more, task completion was measured by means of the three SCC defined for Boggle's iterative design study (Sect. 6.2). As for classification accuracy, Eq. 2 was applied, for which the *total classifications* and *correct classifications* values were specified based on actions executed across the different menus throughout a specific task. For the purpose of this analysis, and similar to the approach adopted in [34], any steps executed to rectify erroneous actions were considered as correct commands. Incorrect non-control state classifications were also excluded from accuracy measures, as these only result in classification delays [46], and were thus solely considered for ITR as discussed below.

ITRs were measured in BPM, using Eqs. 3 and 4 for individual browser menus, while for task executions across different menus, Eq. 5 (gives results in BPM) was used, where t_{tot} refers to the time taken to complete the entire task in seconds, N_m equals

Table 6. Table portraying the 6 participants' global mean usability scores, benchmark values, as well as the least/most desirable scores, for each metric applied during online BCI sessions.

Usability measure	Participants' global mean score	Benchmark comparison score(s)	Least desirable score	Most desirable score
SPS	3.1	—	7	1
RTLX	28.03	—	100	0
Completion rate	90%	78% (based on research conducted by Sauro [19])	0%	100%
SUS	77.08	68 (based on research conducted by Sauro [17])	0	100
Classification accuracy	90.98%	70% (based on criteria specified by Mugler et al. [27])	0%	100%
ITR	29.58 BPM	Equal to the maximum achievable ITR (ITR$_{max}$) per task: • **Task1**$_{ITR_{max}}$ = 33.703 BPM • **Task2**$_{ITR_{max}}$ = 31.005 BPM • **Task3**$_{ITR_{max}}$ = 37.359 BPM • **Task4**$_{ITR_{max}}$ = 36.784 BPM • **Task5**$_{ITR_{max}}$ = 43.610 BPM *Note:* ITR$_{max}$ was computed by using optimal values for Eq. 5, including for t_{tot}, which assumed a 4.25-s detection time per command (4 s gaze focus + 0.25 s feedback provision)	0 BPM	—

the total number of commands executed within menu *m*, B_m is the ITR in bits/trial for menu *m*, and *M* refers to the total number of menus used to accomplish the specified task goal.

$$ITR_{overall} = \frac{60}{t_{tot}} \sum_{m=1}^{M} N_m B_m \quad (5)$$

Although incorrect non-control state classifications did not result in any accuracy penalties, the average command detection time increased, leading to ITR drops.

For the most part, the adopted statistical evaluation technique was similar to that outlined in Sect. 6.2 (**Stage 2**). This involved the computation of 95% CIs, to approximate a range of plausible values for participants' true global mean usability results. Moreover, depending on the data distribution, the Binomial test or One Sample t-test were used to compare participants' mean usability scores against established benchmarks, permitting for a more accurate understanding of Boggle's true usability levels. Across all statistical test runs, an alpha level of $\alpha = .05$ was also assumed.

Boggle's usability is evidenced by participants' low SPS (95% CI [2.69,3.51]) and RTLX scores (95% CI [20.35,35.71]) throughout most task executions. Furthermore, high task completion rate scores (95% CI [78.61%,100%]) were achieved, with a global mean classification accuracy and ITR amounting to 90.98% (95% CI [86.52%,95.44%]) and 29.58 BPM (95% CI [27.05 BPM,32.11 BPM]) respectively. Considering all tasks executed by the different subjects, accuracies ranged between 61.29% and 100%, while ITRs fell between 11.589 BPM and 43.255 BPM. A total of 4 subjects had mean classification accuracies which were significantly higher ($p < .05$) than the benchmark score of 70% [27], yet each task's mean ITR was found to be remarkably lower ($p < .05$) than its corresponding ITR$_{max}$ value (see Table 6). Additionally, it was noted that for the majority of tasks executed via Boggle, the achieved ITRs surpassed 13.4 BPM [27], which corresponds to the highest mean ITR reported for any of the other reviewed BCI-based browsers.

Although 4 of the 5 assigned tasks resulted in mean completion rates which were higher than the benchmark score of 78% (refer to Table 6), the 6 subjects' individual mean completion rates did not differ significantly from this benchmark ($p > .05$). Obtained SUS scores (95% CI [68.24,85.93]) are also encouraging, with One Sample t-test results indicating that subjects' global mean SUS rating is significantly higher ($p < .05$) than the established benchmark (refer to Table 6). Overall, user feedback was also quite positive and reflects Boggle's usability, with some issues and areas of potential improvements being discussed.

6.4 Stage 4 - Domain Expert Feedback

As indicated earlier, Boggle was discussed with two domain experts (E1 and E2), who provided insightful feedback on Boggle's utility as an assistive BCI-based browser. Based on their experiences, E1 and E2 asserted that the web has the capacity to "open up the world" for motor-impaired individuals. E2 added that, to date, a sizeable portion of target users are excluded from Internet access, either because "no suitable access method is available to them" or because they are unable to handle the "increased complexity of web browsing".

As for the implemented BCI browser, the experts found the continuous stimuli flickering to be quite tedious, yet thought Boggle included all core functionality and also had a "very good response time". E1 particularly liked the browser's "simplification aspect", which makes it "ideal for individuals with limited cognitive abilities". All in all, both E1 and E2 believe that Boggle could positively impact target users' lives, giving them a sense of independence, which would ultimately translate to a "reduced reliance on caregivers".

7 Conclusion

Motivated by the pervasiveness of existing web accessibility barriers, especially those faced by individuals living with severe motor impairments, this work builds upon our initial study's findings [5], to investigate the applicability of web-native technologies for developing an SSVEP-driven BCI-based browser.

Stage 1 of this work re-confirmed the outcomes of our first study [5], and demonstrated web technologies' applicability for generating SSVEP stimuli, with a slight performance edge being observed for CSS and Chrome in high-load rendering conditions. Based on this, and a thorough review of literature to shortlist features necessary for building an accessible web browser, Boggle's initial prototype was designed and developed. Using this first design as a starting point, insights into the most adequate browser interaction patterns were primarily gained via usability metrics and participants' feedback throughout **Stage 2**, which involved a two-phased iterative UCD process. At this point, insights into interaction issues were gleaned, leading to further browser enhancements, which altogether shaped Boggle into a more usable tool. Results indicate that, when operated via asynchronous BCI-based control (**Stage 3**), in most cases, users found Boggle to be highly usable, as shown by the relatively high usability scores attained. All six subjects also maintained satisfactory online BCI performance, with mean accuracies and ITRs ranging between 84.93%–98.33% and 25.36 BPM–34.94 BPM respectively. Domain experts' feedback also complements these findings and demonstrates Boggle's potential for use by target users in a real-world context (**Stage 4**).

Overall, obtained results are very promising as they show that Boggle fared better than existing SSVEP-based BCI browsers, namely WeBB, whose maximum accuracy amounted to 90.7%, while the highest recorded ITR was as low as 4.68 BPM. Boggle's global mean ITR (29.58 BPM) also surpasses that of the reviewed BCI-based browsers, for which the highest reported mean ITR amounted to 13.4 BPM. In contrast to WeBB, Boggle is flexible and portable, since it is built using a web-native and cross-platform framework (Electron) that can be installed across major operating systems. Boggle also introduces other important advances over existing browsers, including its support for stimuli approximations, which permit enhanced user interaction efficiency, through the presentation of an increased number of SSVEP targets.

Based on these encouraging outcomes, one can conclude that Boggle, a cross-platform SSVEP-driven web browser, can serve as a suitable assistive technology for individuals with severe motor impairments, affording unrestricted web access through online and asynchronous BCI-based interaction.

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