Changing Minds: Exploring Brain-Computer Interface Experiences with High School Students

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Abstract
Relatively little research exists on the use of experiences with EEG devices to support brain-computer interface (BCI) education. In this paper, we draw on techniques from BCI, visual programming languages, and computer science education to design a web-based environment for BCI education. We conducted a study with 14 10th and 11th grade high school students to investigate the effects of EEG experiences on students' BCI self-efficacy. We also explored the usability of a hybrid block-flow based visual interface for students new to BCI. Our results suggest that experiences with EEG devices may increase high school students' BCI self-efficacy. Furthermore, our findings offer insights for engaging high school students in BCI.

Author Keywords
Brain-Computer Interface, Computers and Children, EEG, Neurofeedback, Scientific Outreach, Constructionism

CCS Concepts
•**Social and professional topics** → **Information systems education;** •**Human-centered computing** → *Interactive systems and tools;*

Introduction
Recently, brain-computer interface (BCI) advances have provided innovative input mediums for various applications.

BCI devices measure central nervous system (CNS) information that can be interpreted to represent different mental states from the user. A common type of signal is electroencephalography (EEG), a measure of electrical activity of the brain from the scalp, which can provide user states like drowsiness, attention, engagement, and more. BCI research often involves clinical applications such as prosthetic devices [30], brain-controlled wheelchairs [8] and virtual keyboards [5]. However, recent work have began to explore non-medical BCI applications. Examples of these include gaming [9], engagement monitoring [42], workload estimation [15] and education [1].

Existing software can leverage EEG data effectively for many purposes, but there is limited research on providing tools to assist novice programmers on the design and creation of such neurofeedback applications. A common purpose involves educational BCI implementations focused on the use of EEG data as an input for specific goals in an application. Example studies include educational and adaptive agents [45], contextual reading [25] and adaptive content reviews [43]; where the EEG data from users is a medium to understand their current mental state and adapt the application to their needs. Crawford et al. presents an example study where BCI development skills were explored [14]. This study observed that novice programmers can use block-based programming environments to ease their entry into the field. However, in this system, users have a limited ability to create custom filters for the neurophysiological data, which may limit their creativity.

This paper presents Neuroflow, a hybrid block-flow based visual programming environment for BCI education. This paper also discusses a study on the effects of EEG experiences on students' BCI self-efficacy. We observed 14 high school students experiencing the design and creation process of BCI applications via Neuroflow. Our evaluation results indicate that experiences with EEG devices can improve high school students' BCI self-efficacy and reveal insights on their potential engagement in BCI.

Related Works

HCI and EEG Technology

Due to EEG's ability to provide insights on covert users' states [48], a wealth of Human-Computer Interaction (HCI) EEG research has focused on ways to leverage EEG data to *evaluate* or *enrich* users' experiences.

EEG-based evaluation research in HCI has explored various promising applications. This work often explores the use of EEG information to supplement performance (i.e., task completion times), qualitative (i.e., interviews), and behavior measures [15]. In particular, recent HCI EEG research has been used to evaluate areas such as workload [22, 18, 24], face perception [31], icon design [11], audio notification [11], and haptic devices [20]. EEG-based research focused on *enriching* user experience is also prominent in previous HCI literature. Much of this work features investigations of adaptive experiences driven by passive measurements of brain activity [37, 3, 34, 23, 35, 42, 10].

Previous EEG education work in HCI has been used to both *evaluate* and *enrich* students' learning experiences. For example, Yuan et al. investigated the feasibility of using EEG to *evaluate* students' reading comprehension [47]. Szafir et al. presented a concept where attention levels measured by EEG data assisted teachers with *evaluating* which topics to review in a flipped learning scenario [44].

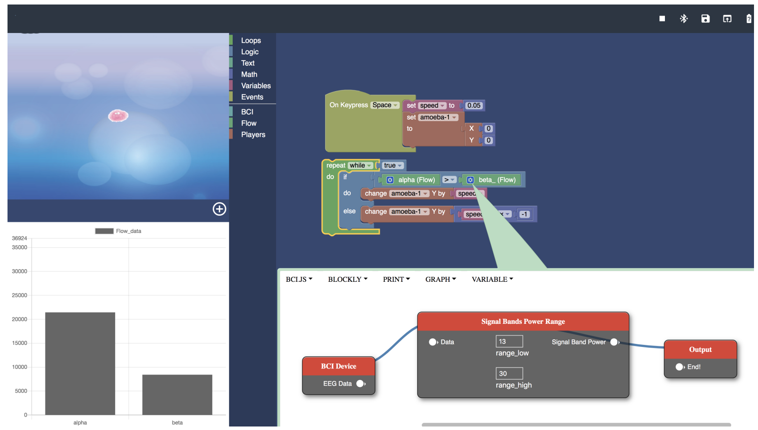

Figure 1: Neuroflow user interface.

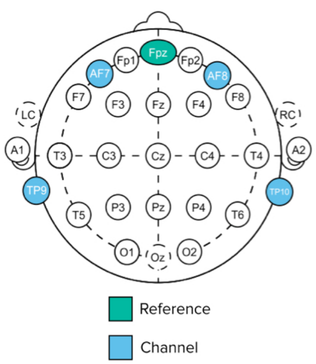

Figure 2: Muse Electrodes.

Previous HCI literature relevant to education that leverages EEG to *enrich* students' experiences often features adaptive systems. This approach differs from *evaluation* work in that the educational system dynamically changes in response to shifts in the student's cognitive state. This technique has been explored as a way to improve student outcomes such as engagement [26, 1, 42] and self-regulation [2, 3, 35].

Brain-Computer Interface Education

Additional EEG studies on ways to *evaluate* and *enrich* users' experiences are needed. However, the growing popularity of this novel technology often leads to misconceptions surrounding systems such as brain-computer interfaces [19]. In response to this issue, researchers have previously leveraged spatial augmented reality and tangible interaction to teach students about their brain activity in real time [19, 21]. However, software built to support BCI application development could still present barriers to users new to BCI technology.

This paper offers a new *novice-centric* BCI perspective focused on BCI education through the *construction* of BCI applications. The proposed *construction* perspective differs from previous *evaluation* and *enrichment* research in that the goal is to teach new audiences about how BCI applications are built. With this approach, students can learn how to construct EEG technology rather than being limited to its use. Our approach is guided by constructionism, an extension of the constructivist theory which views learning as a reconstruction rather than as a transmission of knowledge [32]. Furthermore, constructionism posits that learning takes place most reliably when the learner is engaged in a personally meaningful activity that makes the learning experience real and shareable [29]. While the existing body of constructionism work spans HCI, learning sciences, and

Figure 3: Student wearing Muse EEG device.

computing education [16], there is limited work specifically focused on BCI education.

The closest existing work to our approach offered a purely block-based programming approach to BCI education [14]. However, block-based interfaces may present challenges when trying to construct processes commonly used to construct a BCI pipeline (i.e., feature extraction, feature translation [46]). Previous researchers have leveraged a flow-based approach to address this issue [36, 12]. However, to our knowledge, no existing environment aims to ease both the creation of basic BCI application logic and signal filters within a single interface. This paper presents our observations after introducing 14 high school students to our hybrid block-flow based BCI development environment.

Neuroflow

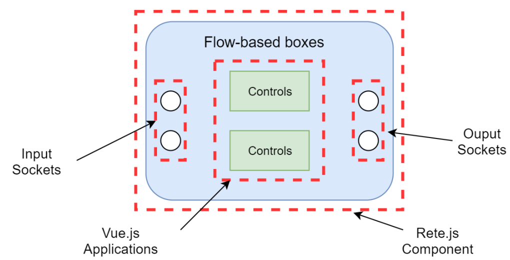

Figure 4: Structure of a component in the flow-based environment

Neuroflow is a front-end web application that provides a hybrid environment for programming BCI applications. Neuroflow uses a hybrid flow-block based environment that is guided by the design of previous tools such as Scratch [27] and OpenVibe [36]. NeuroFlow's block-based component builds on the concept of presenting traditional programming primitives as puzzle pieces. In contrast, Neuroflow's flow-based component is used to manage the flow of data from one processing node to another. By combining flow and block-based components, Neuroflow presents hybrid-block variables. These hybrid variable blocks are used to construct various frequency bands that have been associated with various affective states (e.g., Theta/Deep Meditation (4-8Hz), Alpha/Relaxation (8-13Hz), Beta/Attention (13-30Hz)). The hybrid functionality was achieved by leveraging features from the Blockly [17] and Rete.js [41] libraries. The application requires zero setup, making it accessible to novice programmers.

The application utilizes near real-time EEG data for interactivity by connecting with Muse EEG headsets (shown in Figure 3) using Web Bluetooth. As shown in Figure 2 in the Muse device features four channels (TP9, AF7, AF8, TP10) and on reference based on the international 10-20 electrode positioning system [33]. The Muse device performs at a sampling rate of 220Hz. Signal processing boxes are made available by abstracting JavaScript libraries such as BCI.js [40].

Users can initiate a connection with the device using the Bluetooth button featured in the top right corner of the web application (Figure 1). Users can also use buttons in this area to save and load their work via JSON files. Neuroflow provides users access to hybrid variables that can be constructed and manipulated in the block and flow-based environments. Users can create flow-blocks outfitted with a small button that presents a flow-based environment when clicked.

Neuroflow uses Rete.js to implement its flow-based components. Boxes inside these components have input sockets, output sockets, and controls (seen in Figure 4). Users design a dataflow by connecting input and output sockets. For example, in figure 1 Beta values are calculated by passing EEG data to the "Signal Band Power Range" box, entering the frequency band range in its "controls", and passing the result to output.

Processed data is output to the block-component when data reaches the "Output box". This allows users to perform signal processing in the flow-based environment and use that information to drive logic in block-based environments. When the program executes a flow-block, the latest value at "Output" box is passed to the Blockly environment.

NeuroSquare provides a WebGL based stage panel for creating characters and allows users to control them using block-based programming. It also provides a graphing window in the bottom left corner, where users can plot graphs by attaching variables to the "plot" block. For example, students can plot Alpha band power by passing the data through a "Signal Band Power Range" flow component, and returning the results to the block-based environment. Here, the "plot" block reads this calculated value and plots it on the graph panel. Along with performing basic data visualization, students can also use the processed EEG data to change the behavior of characters in the WebGL environment. This design allows students to construct basic neurofeedback applications rapidly.

Study Description

We worked with a local high school to investigate the developed tool's usability and influence on students' self-efficacy. A total of 14 participants (9 girls and 5 boys) took part in the experiment during a 1-day camp at the University of Alabama. The average age was 16.15 (SD=1.14) with a range from 14 to 18. Students' demographics were as follows: Asian (n=1); Caucasian (n=2); Black (n=10); and Pacific Islander (n=1). All subjects signed a consent form approved by the University of Alabama's Institutional Review Board (IRB).

Three lessons were designed to evaluate students' ability to construct neurofeedback applications. The design of each lesson was guided by previous visual programming resources that have been used by high school educators [28]. Lessons were modified to task students with creating programs that relied on neurophysiological blocks related to various user states. Students' were scaffolded through explicit instructions to assists them with getting started (e.g., "Create a beta band (13-30Hz) power flow-block."). As students progressed through the activities, tasks became more abstract in an effort to challenge students with creating their own custom neurofeedback programs (e.g., "Try creating a game that uses new custom EEG flow blocks.").

Procedures

The sessions began with students completing a pre-survey that captured demographic and BCI self-efficacy information. The BCI assessment featured a slightly modified version of Compeau and Higgins validated computer self-efficacy scale [13]. The modifications made the survey questions specific to BCI applications (seven-point Likert scale). Afterwards, facilitators provided a brief description of EEG frequency bands and the tool's features. Once the student preparation was complete, they were provided a handout with instructions to reference while building their neurofeedback programs. Students had 75 minutes to complete all three programs. Afterwards, students completed a post-survey on their BCI self-efficacy. Students also completed a System Usability Scale (SUS) survey which enabled us to gather insights regarding the system's usability [7].

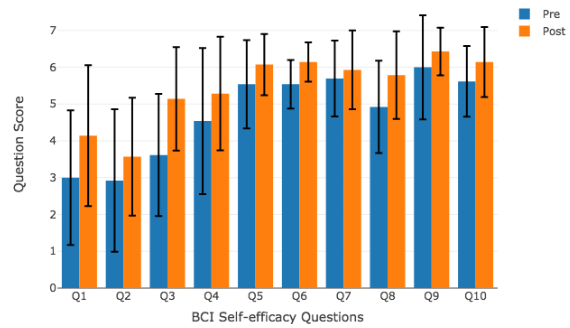

Figure 5: Self-efficacy scores

Results

To evaluate changes in students' BCI self-efficacy we surveyed students before and after they interacted with the hybrid block-flow based visual interface. Students reported numerically different scores before (M = 47.3, SD = 15.13) and after (M = 54.6, SD = 13.20). Furthermore, a paired t-test also showed that there was a significant difference between pre and post BCI self-efficacy score (t = -2.88, p = 0.012). Participants' also reported an average SUS score of 75.0 (SD= 19.43). Given insights from a previous study of over 2,000 students, scores greater than 70 are generally considered above average [4].

Limitations and Future Work

Despite our positive results, there is a chance that the signal quality of the consumer-grade EEG devices could hinder students from creating robust neurofeedback programs. Poor signal quality is mainly due to noisy data captured in our dynamic informal learning setting. While challenges related to accuracy may exist, these circumstances also present opportunities for students to develop new computational perspectives related to questioning neurophysiological technology [6].

Going forward, we plan to explore the feasibility of teaching students ways to build applications with functional near-infrared spectroscopy (fNIRS). This neurophysiological technology may be more resilient in a dynamic classroom environment [38]. In the future, we also will expand the study to evaluate if similar patterns emerge with a larger sample of students that have no previous experience with visual programming environments. Currently, Neuroflow only provides support for average band power calculations (see BCI.js [39] documentation for more details). Going forward, we plan to add additional support for EEG functionalities, such as ERP detection. Furthermore, additional studies are needed to understand further how our approach compares to other methods of BCI education (i.e. spatial augmented reality and tangible interaction)

During our conversations with participants, we observed that students sought to use the technology to assist friends and family members suffering from issues related to mental health. In the future, the approach discussed in this paper may be used to cultivate students' computational perspectives related to "creating for others" [6].

Conclusion

In this paper, we present Neuroflow, a web-based environment for brain-computer interface (BCI) education. Our experiment showed that experiences with Neuroflow may positively influence high school students' belief in their ability to create BCI applications. Furthermore, our quantitative assessment of NeuroFlow's usability suggests that students were able to build simple neurofeedback programs without many critical barriers.

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