2021 ASEE ANNUAL CONFERENCE
Virtual Meeting | July 26–29, 2021 | Pacific Daylight Time
Paper ID #34114

Design of a Low Cost EEG Headset for Educational Research

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A LOW-COST, EASY-TO-USE EEG HEADSET FOR EDUCATION RESEARCH

Abstract – Electroencephalography signals are used widely in medical and pedagogical research because they quantitatively and non-invasively reflect brain activity. However, commercially available EEG devices are often either prohibitively expensive, or do not offer the correct capabilities such as enough electrodes. This work-in-progress study aims to address this gap through the design of a low-cost, easy-to-use, and effective EEG headset for engineering educational research studies.

The current study includes a relatively small sample size (N=6); however, it does identify some preliminary trends. For example, although most participants found the authors' current design to be more comfortable than commercially available designs, the design also had a much larger range of reported comfort levels. Additionally, no distinct conclusion could be drawn from the signal quality comparison between the current design and the commercial device due to limited sample size and large variation among collected data. This exploratory study provides a framework for future studies when more data could be collected. There is potential for such a device to provide insight into learner behavior in the remote learning environment due to its lower cost, light weight, and small size.

I. INTRODUCTION

Electroencephalograms (EEGs) present a non-invasive way of collecting data with high temporal resolution that provides meaningful real-time data on student brain activity during learning activities. Building on this work, this paper provides a potential candidate currently in development that could be used not only in EEG studies, but also for demonstrations in courses or other educational purposes.

One of the ways that EEGs have been used in educational studies is in the assessment of students' attention. The results of these experiments could be used to provide feedback to instructors during remote learning activities, or to test the efficacy of new teaching methods. EEG signals can be divided into 5 frequency domains: delta (0.5 – 4Hz), theta (4 – 8Hz), alpha (8 – 14Hz), beta (14 – 30Hz), and gamma waves (> 30Hz). Ko et al. [1], Talalay et al. [2] and Rihs et al. [3] were able to demonstrate that measurable changes in brain wave patterns occur during periods of attention. Ko showed that during sustained attention tasks, participants experienced changes in the power of multiple brain wave frequencies in various areas of the brain, including delta, theta, and beta waves in the occipital and temporal regions [1]. Talalay found that functional links across the brain in the alpha band were present in both voluntary and involuntary anticipatory attention [2], while Rihs demonstrated that increased alpha wave activity may be involved in inhibition during selective attention processes [3]. All three studies show that attention results in brain-wide changes in brainwave activities.

Additionally, Chen et al. developed an attention aware system using machine learning to categorize EEG signals as 'high-attention' or 'low-attention' [4]. Their algorithm was able to identify attention levels with an accuracy of up to 89.52% using a NeuroSky MindWave headset [4], which has one electrode in the Fp1 position [5]. As acknowledged in their paper, the limited number of electrodes used may have lowered the accuracy of their algorithm [4]. Due to the findings of Ko, Talalay, and Rihs, as well as relative success of Chen's attention aware system, it is possible that an algorithm that uses data from more positions in the 10-20 system [6] could categorize attention even more accurately, and thus be deployed in many educational contexts.

Another way EEGs have been used is to track brain synchrony in classroom settings, which has been linked to engagement and social dynamics [7], [8]. Dikker et al. used EEGs to measure brain-to-brain synchrony, correlating it to a variety of factors such as teaching styles, individual differences, and social dynamics, all of which could mediate attention in students [7]. Poulsen et al. further demonstrated that synchrony measurements could be done with commercial grade equipment, specifically one based on the 14-channel Emotiv EPOC headset [8]. This gives more motivation to the development and use of low-cost, commercial grade EEG headsets for scientific studies in education.

Other educational studies using EEGs include correlations between EEG signals and the flow state [9], and understanding how mobile learning applications change brain activity [10]. Drawing some conclusions from the literature review, a low-cost, easy-to-use, commercial grade EEG with more electrodes could be beneficial to education research studies to assess student physiological signals related to attention, classroom engagement, and other markers of successful teaching. The EEG headset presented in this paper seeks to fill this gap.

The EEG was designed as a mixture of custom designed 3D printed parts as well as off-the-shelf components. The performance of this headset was measured through four general criteria: manufacturability, usability, versatility, and data quality. Each prototype was tested, first on a part-by-part basis, then holistically, using measurement processes associated with each criterion, such as Likert scale questionnaires for comfort, and time elapsed for assembly.

II. Design Requirements

The EEG headset in this paper was developed as an alternative to the off-the-shelf EEG used in a study run by one of the authors [11]. As such, it was designed to address the study's specific needs: an affordable EEG headset that not only provided reliable data to better understand factors affecting student performance, but also facilitated easy transport, did not interfere with students' learning, and could be used remotely to continue data collection during the COVID-19 pandemic. Final design requirements included cost, comfort, manufacturability, usability, versatility, and signal quality.

Cost was defined by the cost of production per EEG headset, which should be less than the average price of a similar commercial model, while manufacturability was mostly centered around design for 3D printing, procurement of materials, and the difficulty of production. To collect as much data as possible, it would be ideal to use multiple EEGs at the same time. Thus, in order to produce a large number of EEG headsets while staying under budget, low costs and easy manufacturability were required. Additionally, the design had to be comfortable so that participants were not disturbed by the headset during data collection; therefore, comfort data was collected using participant responses on a ten-point Likert scale.

Usability consisted of how easy a headset was to transport, store, and operate, while versatility was evaluated by the variety of people and configurations a single design could fit. These requirements address specific concerns that came up during the previous study, including transportation, adjusting the electrodes used, and remote data collection. For example, the off-the-shelf headset used before was a rigid, helmet-like device that came in three sizes. It was difficult transporting the devices around due to their volume, weight, and sizing constraints. However, it offered a large variety of potential electrode configurations, something that the EEG headset developed seeks to preserve. Additionally, due to the difficulties of remote data collection, the headset must be simple enough for an inexperienced participant to operate with remote guidance.

Signal quality was another key metric for evaluating the effectiveness of an EEG headset. EEG signals are noise-prone due to physiological and non-physiological artifacts. A good headset design should minimize these artifacts. Metrics for signal quality assessment evaluated the data in both the time domain and frequency domain. EEG signals are divided into 5 frequency domains: delta wave (0.5 – 4Hz), theta wave (4 – 8Hz), alpha wave (8 – 14Hz), beta wave (14 – 30Hz), and gamma wave (> 30Hz) [1]. Among these frequencies, the power for alpha, beta, and theta waves are often used to analyze cognitive activities in a classroom setting [1], [12], and they will be used to differentiate signal qualities between designs.

The method used in Radüntz's study was employed to evaluate the signal quality of each EEG device [13]. The five metrics were proportion of noise, signal to noise ratio, parietal alpha power difference between easy and demanding tasks, frontal theta power difference between easy and demanding tasks, and parietal alpha power difference between eyes open and eyes closed baseline activities. Easy and demanding tasks were classified by the relative cognitive difficulties. The 0-back test has been selected for as the 'easier' task because it involves less cognitive power. The test is a simple procedure where the participant is prompted to press the keyboard within a short reaction time when a specific stimulus appears on the computer screen. On the other hand, the stop-signal task is used as the 'harder' task as it requires more cognitive demand with multiple stimuli and inhibition. The stop-signal task requires the participant press different keys on the keyboard for different stimuli. In addition, the participant should avoid pressing any keys when a stop-signal occurs. Therefore, the stop-signal task is used as a more cognitively demanding task than the 0-back task. Similar experimental setup had been employed in Radüntz's study [13].

No extra safety requirements were considered due to the usage of commercial electronics components in the prototype and the focus of the study on mechanical design. See Appendix A for a full, product design request-for-proposal-style list of metrics, constraints, and criteria.

III. Current Design

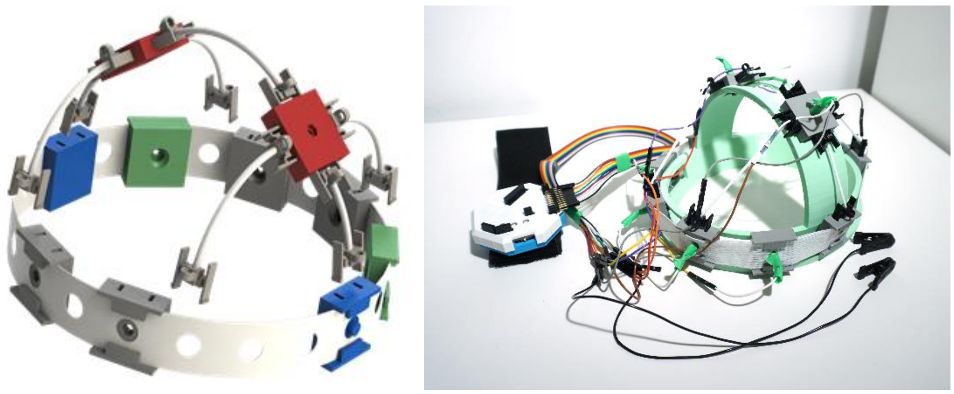

Fig. 1. Left: CAD model of EEG Prototype. Right: EEG Prototype resting on a green holder.

The current electroencephalogram prototype (EP) is a set of modular electrode holders clipped to a main band that rests along the circumference of the head, while other electrodes resting on top of the head are attached using smaller elastics with snap hooks. This is shown in the color-coded CAD model above. The circuit board (PCB), which is not shown, is attached to the user's upper arm by a Velcro strap and connected to the rest of the headset via jumper wires. Dry electrodes were used instead of wet electrodes since they provided more convenience in set-up and clean up without much loss in performance [14].

The main feature of this design are the elastics, which are affordable, off-the-shelf, and very lightweight. Due to their flexibility, the EP takes up much less space in storage compared with many commercially available devices by folding in upon itself, and molds itself to a variety of head shapes and sizes. The elastics also allow much more accurate electrode placement, as the relative positions of the electrodes do not change when the elastics stretch and contract. A combination of small, round elastics and larger, flat ones were chosen due to the utility of their differing spring constants: the large elastics are tight enough to secure the headset to the head without sacrificing too much comfort, while the small round elastics stretch much more easily to aid in the versatility of the design.

The clips and the modular electrode holders also offer utility at low costs. The clips are used to attach modules that are not located on the main band, while also preventing the wires from tangling. The electrode holders perform a variety of functions in addition to holding electrodes, such as redistributing the pressure of the elastic and providing grooves for the clips to attach to. These parts were all 3D printed in PLA using a Prusa i3 MK3S.

Overall, the entire prototype costs approximately $569.49 USD including all electronic components, with a goal of future development work to bring the price down to less than $250 USD. For a full list of off-the-shelf parts used in the construction of this prototype, see Appendix B.

IV. Testing Procedure

The engineering design approach was employed for the design and verification of the EP. This study has been approved by the Human Research Ethics Board at the University of Toronto. Participants have reviewed and signed consent form which outlined the procedure, conditions, and confidentiality of the study. All participation is voluntary, and participants could withdraw from the experiment at any point.

First, participants were asked to follow typed instructions to set up the headset by themselves, without any prior exposure. Their set-up time was recorded, and their comfort level was measured using a Likert scale from 1 to 10, where 1 was defined as “absolutely unbearable, I cannot wear the headset for any longer” and 10 was defined as “I could wear this all day”.

Participants were then asked to complete eight tasks: two eyes open baselines, two eyes closed baselines, two 0-back tasks, and two stop-signal tasks. The 0-back tasks consisted of letters that would flash across the screen. If the letter was an ‘M’, participants pressed the corresponding character on their keyboard; otherwise, they were to do nothing. The stop-signal tasks were much more challenging tasks that required participants to discern between left and right arrows. If the arrow pointed left, the participant was to press ‘B’, and if the arrow pointed right, the participant was to press ‘N’. However, there was a ‘stop signal’: when a red circle flashed, the participant was to do nothing. The 0-back and stop-signal tasks were coded and compiled using PsyToolkit [15], [16]. The default tests were modified to suit the needs of the current study, with changes made to delay time and number of trials. After each task, comfort was measured again.

The same procedure was completed on the EP and a commercially available EEG, the OpenBCI Mark IV. This commercial EEG was selected since it was similar to the proposed EP: it uses dry electrodes, is easy to set up, and has a low price range in comparison to other devices with a similar number of channels. The EEG time series data was collected using the OpenBCI GUI interface [17] and analyzed using a MATLAB add-on, EEGLAB [18].

Data preprocessing, band-power extraction, artifact identification and removal are implemented by the EEGLAB toolbox [18]. The data is band-pass filtered from 1 to 40 Hz, with the first and last 30 seconds of data removed.

V. Testing Results

Due to the restrictions of COVID-19, only limited sets of data have been currently obtained (N=6). The two EEG designs are evaluated against the design requirements.

For comfort, most participants (n=5) reported a preference for the EP over the commercial headset, while one participant reported the opposite. This creates an interesting trend, where with the exception of that participant's data, the comfort level of the EP starts at a relatively higher comfort value and decays more slowly. However, more participants are required to determine whether the extent to which the comfort is polarized.

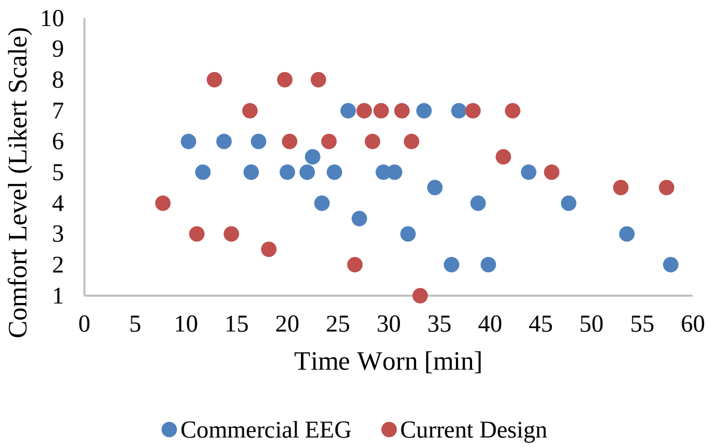

Fig. 2. Comfort level of the OpenBCI headset vs. Prototype. Each individual data point is one instance of when a participant was asked to rate their comfort.

The average set-up time for the prototype was 5 minutes and 10 seconds, while the average set-up time for the OpenBCI headset was 4 minutes. However, there were large variations for both, causing their standard deviations to be over 2 minutes. Further data is needed to find trends, although currently, it appears that set-up time is heavily dependent on the individuals.

TABLE I
COMMERCIAL DEVICE VS. EP SIGNAL QUALITY

Measure of Signal Quality	Commercial Device	EP
Proportion of noise (%)	44.1 ± 19.7	43.1 ± 11.8
Signal to noise ratio (dB)	2.6 ± 6.5	2.7 ± 9.3
Parietal alpha band power difference between easy and demanding tasks (uV^2): easy – demanding	0.8 ± 1.6	4.1 ± 6.0
Frontal theta band power difference between easy and demanding tasks (uV^2): demanding – easy	18.9 ± 34.1	-0.6 ± 15.8
Parietal alpha band power difference between eyes closed and eyes open (uV^2): demanding – easy	10.0 ± 13.2	15.3 ± 15.5

Data is average ± one standard deviation (N=6). Raw data with individual participants is presented in Appendix C.

The results in Table 1 illustrate the proportion of noise, signal to noise ratio, parietal alpha power, and frontal theta power across 6 participant datasets. Due to the limited sample size of 6, it is difficult to identify any trends or significant difference between the data collected using two devices. The proportion of noise and signal to noise ratio (SNR) between the commercial and EP headsets display similar ranges: the commercial headset has a proportion of noise of 44.1% ± 19.7% and a corresponding SNR of 2.6 dB whereas the EP has a proportion of noise of 43.1% ± 11.8% and a corresponding SNR of 2.7 dB. In terms of parietal alpha power difference between the easy (0 back test) and demanding (stop signal test) tasks, the data obtained by the EP shows a larger difference of 4.1 uV^2 compared with 0.8 uV^2 from the commercial headset. On the other hand, the data obtained from the commercial headset shows a larger frontal theta power difference than the EP. A larger difference in frontal theta power means a clear distinction between the easy and more demanding tasks, which indicates better signal quality according to Appendix A, Table C. Lastly, the EP and commercial headset result in similar levels of parietal alpha band power differences between eyes open and eyes closed tasks, with 10.0 uV^2 difference in the commercial headset's data and 15.3 uV^2 difference for the EP data.

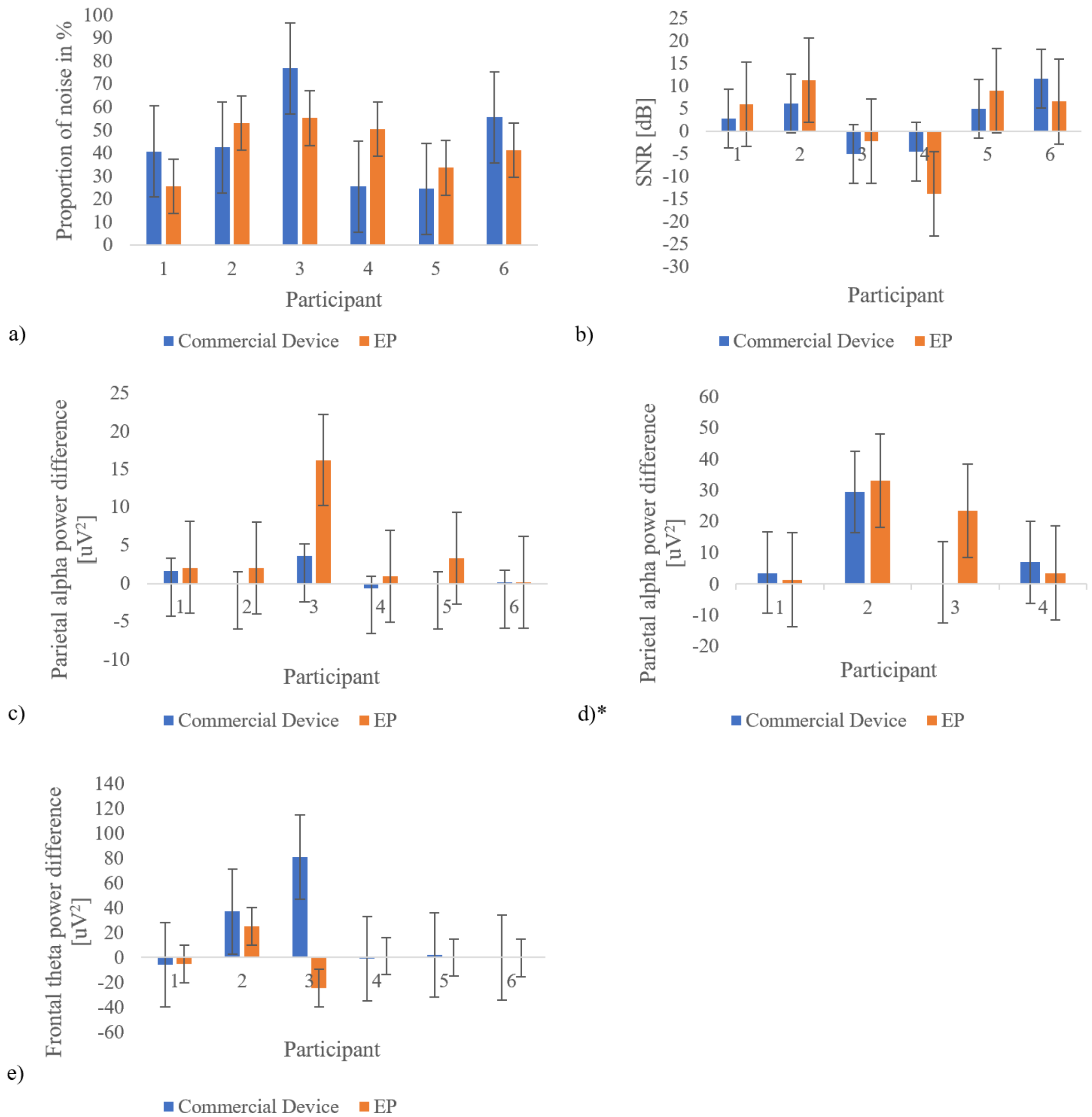

Fig. 3. Commercial Headset vs. EP: a) Proportion of noise; b) SNR; c) Parietal alpha power difference (easy vs demanding tasks); d) Parietal alpha power difference (eyes open vs eyes closed baselines)*; e) Frontal theta power difference (easy vs demanding tasks)

* With the development of experimental technique, the parietal alpha band power of eyes closed and eyes open were not collected for two initial participants. Therefore, only four sets of data were available for this signal quality feature.

VI. Discussion

A. Advantages of the design

From the data that was gathered, it was found that participants show a slight preference of the EP over the commercial headset but take slightly longer to set it up. Additionally, there is no distinct difference between the signal quality of the commercial device and the EP. However, the EP offers a variety of unique features. The inexpensive and readily available elastics offer easy, accurate, and modular positioning of electrodes and clip-on design, and 3D-printable parts reduce the cost of manufacturing and increases versatility. Using dry electrodes instead of wet electrodes significantly decreases both set-up and clean up time, and the low Young's modulus of the elastics ensures a fit of more head shapes. These features increase the manufacturability, cost-effectiveness, usability, and versatility of the design, which may increase viability in educational research and take-home experiments.

B. Limitations

The remote experimental setting introduces various challenges for the accuracy of the data collection process. Since the researchers were not physically present when the participants were using the EEG headset, it is hard to determine if there are obvious data collection artifacts such as misplaced reference node, electrode positions, and incorrect usage of the data collection software. The team tried to mitigate these challenges by asking the participant to share their screens during data collection so that the researchers could identify any obvious issues.

Additionally, this remote setting has also made it difficult to gather data from many participants using multiple commercial devices. As a part of the University of Toronto's response to the pandemic, remote learning was guaranteed so most students never need to be on campus. Thus, the Research Ethics Board required the devices to be delivered to the residences of the participants through contactless drop-off and pick-up. This reduced the pool of applicable participants, as well as the amount of time required to gather data per participant and per device.

It should be noted that the group of data is relatively spread out as reflected by the large standard deviation among participants. This could be a result of the data collection processes as well as data analysis techniques. As the sample size is relatively small ($N = 6$), not enough information is present to effectively eliminate outliers.

In addition, some trends displayed in previous studies [13] such as the increase in frontal theta power when comparing more demanding tasks with easier tasks are not well shown by the six datasets. For instance, the average frontal theta power difference between easy and demanding tasks produced by the prototype is -0.64 uV^2, contradicting the theory that the frontal theta power should be larger when the participant is conducting a more demanding task.

C. Use in Education and Educational Research

Commercial EEGs have already been used in a variety of different correlational studies on topics in education such as attention, teaching methods, and student synchrony [1] - [4], [7] - [11]. The EP was primarily designed to act as a way to collect physiological data for this type of research. Once complete, the EP can be deployed in an educational research context in a variety of ways, including providing real-time feedback on student attention, collecting data during tests of new teaching strategies, and studying the effects of remote learning environments. Additionally, both the relative inexpensiveness of the EP and its versatility allow it to be used as demonstration or labs in biomedical engineering, neuroscience, physiology, and other similar courses [19], [20].

VII. CONCLUSION & NEXT STEPS

The EP performs well in terms of comfort, cost-effectiveness, and versatility, although conclusions are yet to be drawn from the data quality requirement due to a limited sample size. The prototype may be suited for educational research studies such as the evaluation of student attention in online lecture settings, as well as for teaching purposes such as in demonstrations or labs, since it is easy to use and inexpensive in an educational setting.

Due to the COVID-19 pandemic, the sample size and the number of devices in this study are greatly limited as the data collection process is prolonged, and equipment is generally not directly accessible to participants. Future work aims to increase the sample size, compare the EP with more commercially available EEG headsets, and improve the data quality evaluation process to compare the current design in a more accurate and holistic manner. The researchers also plan to redesign the control board such that it retains similar functionality to our current off-the-shelf PCB, for a much lower cost. As more data is collected, the designed EEG headset will be used in future educational research such as classifying the attention levels of students [11].

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Appendix A

Design Requirements for a low-cost, easy-to-use EEG for education research

A. Cost

The EEG should be able to be produced at a relatively cheap price

Metrics	Constraints	Criteria
Cost of production, divided by the number of units produced	Must be less than the average price of a similar EEG (commercial, 8+ channel), approx $850 USD [21] - [22]	Lower is better

B. Usability

The EEG sets should be easy to transport from location to location

Metrics	Constraints	Criteria
Weight of one set, in grams	Must be less than or equal to commercially available EEGs with a similar number of channels	Lower is better
Stackability (YES/NO)	Should be yes	Yes is better
Volume of storage taken up by one set, in cm^3		Lower is better
Can it be shipped by mail? (YES/NO)		Yes is better

The EEG sets should take little effort to set up

Metrics	Constraints	Criteria
Time to set up by a user without setup experience, in minutes (with instructions)	Should be less than or equal to commercially available EEGs with a similar number of channels	Lower is better
Time to set up by a user with experience, in minutes	Should be less than or equal to commercially available EEGs with a similar number of channels, approx 3-5 min [22]	Lower is better

C. Signal Quality

The electrodes should be able to get the best signal possible

Metrics	Constraints	Criteria
Proportion of artifacts: the length of data identified as artifacts divided by the entire length of the data [%]		Lower is better
Signal to noise ratio: calculated using the formula, where s_i is the band-pass filtered signal and x_i is the signal after ASR (Artifact Subspace Reconstruction), which is provided by EEGLAB* [dB] $SNR = 10 \cdot \log_{10} \frac{\sum_{(i=1)}^{N} x_i^2}{\sum_{(i=1)}^{N} (s_i - x_i)^2}$		Higher is better
Berger effect: the decrease in parietal alpha band power for eyes open compared with eyes closed. [uV^2]	Parietal alpha band power should be larger for eyes closed.	Bigger difference is better.
Decrease in parietal alpha band power for demanding tasks compared with easy task† [uV^2]	Demanding tasks should produce lower parietal alpha band power compared to easy tasks.	Bigger difference is better.
Increase in frontal theta band power for demanding tasks compared with easy tasks† [uV^2]	Demanding tasks should produce higher parietal frontal theta band power compared to easy tasks.	Bigger difference is better.

* Parameters are tuned for the ASR algorithm in EEGLAB to have a *Burst Criterion* of 10 and *Window Criterion* of 3 for optimal artifact removal and reconstruction [13]

† In the experiment, the 0-back task is the easy task, while the stop signal task is the demanding task.

D. Versatility

The EEG should be able to fit on most heads

Metrics	Constraints	Criteria
Can it fit on a head (YES/NO)	Must be able to fit on all heads between 1st and 99th percentiles (see below)	More is better
Circumference of EEG, in cm [23]	Must be able to encompass 51.34 cm to 60.65 cm	The larger the range, the better
Breadth of EEG, in cm [23]	Must be able to encompass 13.33 cm to 16.52 cm	The larger the range, the better
Length of EEG, in cm [23]	Must be able to encompass 17.23 cm to 21.34 cm	The larger the range, the better
Length of the EEG 'headband', in cm (Bitragion Coronal Arc) [23]	Must be able to encompass 30.78 cm to 38.48 cm	The larger the range, the better

The EEG should be able to support a variety of electrode configurations from the 10-20 system

Metrics	Constraints	Criteria
The number of electrode points the EEG encompasses	Must have the ones required for current study (Fp1, 2; C3, 4; P5, 6; O1, 2)	More is better

E. Manufacturability

The EEG should be easily built, and should have easily replaceable parts

Metrics	Constraints	Criteria
The number of parts that need to be assembled [24]		Lower is better
The number of 'self-assembling' parts [24]		Higher is better
Is the work location easily viewed and accessed? (YES/NO) [25]	Should be Yes	Applies more for parts that must be replaced regularly/fail easily
Are tools required? (YES/NO) [26]	Should be No	If Yes, the more common/ simple to use the tool is, the better

Should also follow sections 5.8 and 5.9 of MIL-STD-1472G [27]

The EEG should be designed around 3D printability

Metrics	Constraints	Criteria
Print time, in minutes	Must be less than 24 hours	Less is better
Wall thickness, in mm [28]	Must be greater than 0.8 mm	Larger is better
Overhang angle, in degrees [28]	Must be less than 45 degrees	Lower is better
Embossed/engraved detail dimensions, in mm [28]	Must be larger than 0.6 mm wide and 0.2 mm high/deep	Larger is better
Horizontal bridge length, in mm [28]	Must be less than 10 mm	Less is better
Hole diameter, in mm [28]	Must be greater than 2 mm	Larger is better
Connecting clearance, in mm [28]	Must be greater than 0.5 mm	Larger is better
Minimum feature size, in mm [28]	Must be greater than 2 mm	Larger is better
Pin diameter, in mm [28]	Must be greater than 3 mm	Larger is better
Misprint tolerance, in % [28]	Must be greater than 0.5%	Larger is better
Post-processing time required per device, in minutes		Less is better

Design should also consider the anisotropic nature of FDM printing [29]

Design should attempt to lessen the impact of the various considerations in this article [29]

F. Comfort

Participants should be comfortable with wearing the EEG for extended periods of time

Metrics	Constraints	Criteria
Subjective rating of participant, on a Likhert scale from 1 to 10, measured during preparation, during the experiment, and after the experiment	Should be at least 5	Higher is better

Method taken from [14]

APPENDIX B
BILL OF MATERIALS PER EEG HEADSET

Part	Source	Amount/EEG	Cost/EEG* (USD)
OpenBCI Cyton Board†	OpenBCI	1	$499.99
TDE-210 electrodes	Florida Research Instruments	6	$3.67
TDE-201 electrodes	Florida Research Instruments	2	$1.33
TDE-430 ear clips†	Florida Research Instruments	2	$45.90
No. 4, 3/8” Screws	McMaster-Carr	8	$0.53
Lipo Battery	Adafruit	1	$7.95
Micro Lipo Charger	Adafruit	1	$5.95
3” Jumper wires	Adafruit	2	$0.20
6” Jumper wires	Adafruit	4	$0.39
12” Jumper wires	Adafruit	2	$0.40
19.7” Jumper wires	Amazon	10	$1.17
Velcro Strap	Amazon	1	$1.42
1” Flat elastics	Amazon	50 cm	$0.49
1/8” Round elastics	Amazon	60 cm	$0.10
		Total Cost per EEG Headset	$569.49

* Assuming assembly of 30 EEG headsets, not including tax or shipping, rounded to the nearest cent

† Will be redesigned in future work

APPENDIX C
RAW DATA FOR INDIVIDUAL PARTICIPANTS

	Proportion of noise (%)	Signal to noise ratio (dB)	Parietal alpha band power difference: Easy vs demanding tasks (uV^2)	Frontal theta band power difference: Easy vs demanding tasks (uV^2)	Parietal alpha band power difference: Eyes closed vs eyes open (uV^2)
Commercial Headset	0.40	2.74	1.64	-5.90	3.54
	0.42	6.11	0.03	37.02	N/A *
	0.76	-5.03	3.57	80.87	N/A *
	0.25	-4.61	-0.63	-0.82	29.39
	0.24	4.91	-0.05	1.98	0.39
	0.55	11.61	0.13	0.10	6.82
Average	0.44	2.62	0.78	18.87	10.04
St Dev	0.19	6.47	1.56	34.09	13.17
EEG Prototype	0.25	5.88	2.07	-5.17	1.19
	0.52	11.20	1.99	25.14	N/A *
	0.55	-2.27	16.15	-24.39	N/A *
	0.50	-13.90	0.91	1.10	33.03
	0.33	8.90	3.24	-0.08	23.40
	0.41	6.50	0.12	-0.43	3.40
Average	0.43	2.72	4.08	-0.64	15.26
St Dev	0.12	9.33	6.01	15.83	15.50

* With the development of experimental technique, the parietal alpha band power of eyes closed and eyes open were not collected for two initial participants. Therefore, only four sets of data were available for this signal quality feature