PhysioBots: Engaging K-12 Students with Physiological Computing and Robotics

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Figure 1: Students designing and testing programs created with PhysioBots.

Abstract

The popularity of applications involving physiological sensing (e.g., brain and muscle activity) and robotics has continued to grow in recent years. However, empirical studies evaluating ways to expose K-12 students to physiological computing are limited. To address this gap, we present PhysioBots, an educational tool designed to introduce K-12 students to physiological computing and robotics. We evaluated PhysioBots with 27 high school students between the ages of 15 and 17 to compare the use of physiological (e.g., self-induced changes in brain or muscle activity) and conventional control (e.g., keyboard) of a robot during a STEM education activity. Our preliminary results suggest that PhysioBots may improve students' self-efficacy and programming confidence. Observations from open-ended survey questions also indicate that PhysioBots may support students in exploring ways to gamify emotional state manipulation. We discuss these findings and offer insights for future STEM education work involving physiological sensing and robotics.

CCS Concepts

• **Applied computing** → **Interactive learning environments**; • **Hardware** → *Neural systems.*

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Physiological Computing, Computers and Children, EEG, Brain-Computer Interface, CS Education, Physiological Computing Education

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1 Introduction

Human-Computer Interaction researchers have widely studied wearable sensing technologies in recent years. In particular, sensing technologies capable of measuring physiological signals [14, 47] from the body have been explored as a way to support user state evaluation [36, 47] and assistive technologies [30, 34, 44]. These signals are often used to measure activity associated with the brain (Electroencephalogram - EEG), heart (Electrocardiogram - ECG/EKG), and muscles (Electromyogram - EMG) [15]. Emerging research exploring ways to use wearable sensing technologies to support educational activities is becoming more common [25, 35, 63]. Previous work classified the use of wearable physiologial sensing technologies in educational settings into two categories: *evaluate* and *enrich* [23]. Work in the *evaluate* category focuses on using physiological sensing technologies to evaluate students' emotional state, physical activity, and other physiological metrics. Research in the *enrich* category focuses on using physiological sensing technologies to support students' learning of content areas such as science, technology, engineering, and mathematics (STEM). The work discussed in this paper contributes knowledge relevant to the enrich category. Furthermore, exploring the design of educational systems that integrate physiological sensing and robotics may assist in exposing more students to physiolgical-based cyber-physical human systems [42]. This approach may also support students in developing an interest in disciplines adjacent to STEM and medical fields. However, there is a lack of knowledge regarding ways to properly scaffold students with learning these skills which are typically not introduced until the university level due to their complexity.

To address the gap, we make two contributions:

- We present PhysioBots, an educational tool designed to introduce K-12 students to physiological computing and robotics.
- We provide the first preliminary study comparing students' experience constructing physiological (e.g. EEG) and conventional (e.g. keyboard) applications during STEM education activities.

2 Related Works

Researchers have begun to explore the use of physiological sensing technologies in educational settings. For example, previous work has explored the use of physiological sensing technologies to evaluate students' levels of engagement [3, 16, 20, 27, 33, 49, 54, 58, 59]. Previous work has also explored the use of physiological sensors to assist with self-regulation [4, 6, 51]. Researchers have also begun exploring ways to provide hands-on experience with physiological sensing technologies in educational settings. In particular, this 'hands-on' approach focuses on teaching students how physiological sensing technologies work and not simply leveraging the sensor for evaluation purposes [17, 18, 29, 37]. Previous work in this area has reported improvements in students' self-efficacy [23]. However, there is a lack of knowledge regarding whether this approach can improve students' programming confidence, interest in STEM, and motivation. This study aims to address this gap by evaluating students' responses to questions related to programming confidence and motivation. Furthermore, previous work in physiological computing education has primarily focused on exposing students to physiological systems that control virtual objects [24]. However, traditional physiological computing research has often focused on using physiological sensing technologies to control physical systems such as neuroprosthetics [34] and wheelchairs [9]. To address this gap, we present PhysioBots, an educational tool designed to introduce K-12 students to integrating physiological computing and robotics. In particular, PhysioBots supports students with hands-on experience using physiological sensing technologies (e.g. EEG) to control a physical robot. Our approach builds on constructionism, which extends constructivist theory by emphasizing that learning occurs through active creation and experimentation rather than passive receipt of knowledge [46]. To our knowledge, this is the first work featuring technology designed to expose students to integrating physiological sensing and robotics through a blocks-based programming interface.

While previous work typically featured one or the other, combining physiological sensing and robotics supports students in gaining hands-on experience designing simple physiological-based cyber-physical human systems [42]. Furthermore, this approach is supported by a wealth of previous work that has studied robotics in educational settings. In particular, researchers have explored the use of robots as learning companions [7, 10, 19, 26, 32, 43, 57, 61]. Additionally, previous work has explored leveraging robots to support students with building skills in areas such as artificial intelligence [13, 50], robotics [21, 22, 28, 31, 39, 40, 53], computational thinking [1, 41, 45, 55], mathematics [2], and cybersecurity [62]. The work presented in this paper extends previous research in educational robotics by exploring the integration of physiological sensing technologies, robotics, and visual programming environments. Furthermore, this paper presents the **first preliminary evaluation** of **rural K-12 students** constructing applications with **integrated physiological sensing and robotics components** via a **block-based programming environment**.

3 PhysioBots

We developed PhysioBots, a physiological computing education tool, to give students hands-on experience learning about physiological computing and robotics (see Figure 1). The following sections describe the tool's key components.

3.1 Real-Time Physiological Data Collection

The PhysioBots system uses the Muse 2 EEG device[1] to collect real-time data via a Web BLE connection. The Muse device has

[1]https://choosemuse.com/

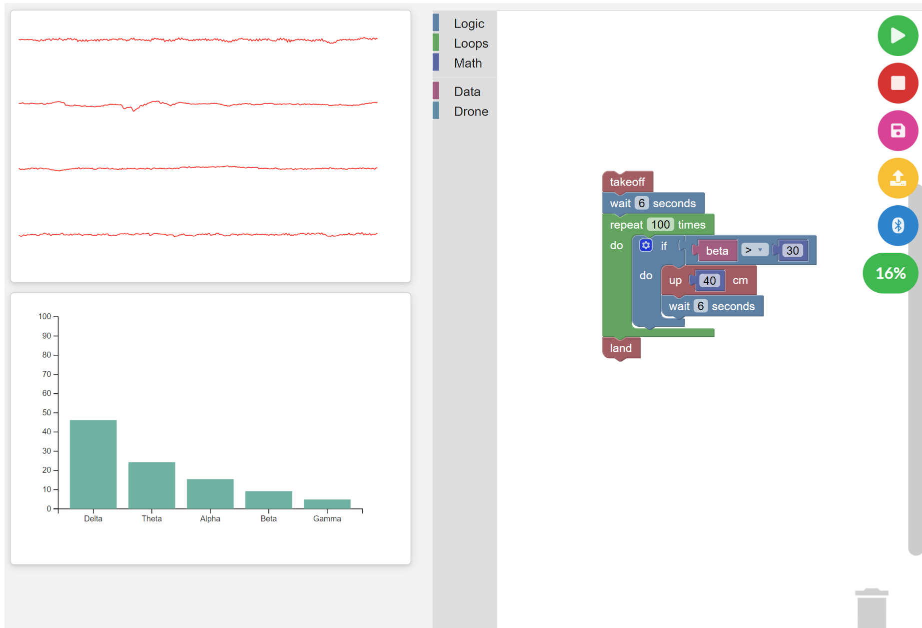

Figure 2: Example program created by a student that lifts the drone up when the beta frequency band power is above 30. (Top-Left) Interactive Graph displaying filtered EEG data. (Bottom-Left) Bar graphs of EEG frequency band power. (Right-Pane) block toolbox, scripting workspace, and menu buttons.

four channels (TP9, AF7, AF8, TP10) [48] and a sampling rate of 220 Hz. The EEG data is band-pass filtered between 0.5 and 30 Hz. Afterward, the data is separated into five different frequency bands (i.e., delta, theta, alpha, beta, and gamma) using a fast Fourier transform (FFT) and a modified periodogram with a Hann window. Band power information was averaged across the four channels to simplify the interface for novice users and presented as bar graphs that update in real-time (see Figure 2). Frequency band power patterns are commonly mapped to states such as attention, relaxation, and drowsiness [38]. The PhysioBots software enables students to utilize band power data using blocks in the data category. The interface also displayed real-time data from each EEG channel via a line graph. This aided with explaining basic concepts such as noise and artifacts common in EEG data. Exercises such as identifying how the interactive line graph changed when students moved or blinked their eyes provided hands-on experience with these concepts. The physiological sensing components, such as acquisition and signal processing, were implemented using the BCI.js library [56].

3.2 Robot Navigation

PhysioBots enabled students to create simple programs that mapped physiological changes to drone commands. The interface provided blocks for basic drone movements, including upward, downward, forward, and rotational control (clockwise and counterclockwise). We used the DJI Tello drone with PhysioBots during this study. However, PhysioBot's modular design allows for the integration of additional robotic platforms. The electron.js[2] framework was used to create a native application capable of communicating with the drone via a UDP socket connection.

3.3 Blocks Workspace

The PhysioBots interface allowed students to develop programs by dragging and dropping pre-defined blocks into a visual workspace. The workspace featured categories for physiological data, drone control, and basic programming concepts. Blocks for physiological data provided real-time data from EEG sensors, while drone control blocks enabled actions such as moving the drone and rotating it in specific directions. To create a program, students combined these blocks, often using conditional statements to trigger drone movements based on changes in physiological signals. For example, a student could use a block to check if the beta band power exceeded a threshold and, if so, execute a forward movement command (See Figure 2). This approach provided a hands-on experience with conditional logic, loops, and event-driven programming. Additionally, the interface included buttons for connecting to the Muse EEG sensor, starting and stopping the program, and displaying the drone's battery status. To our knowledge, this is the first work to implement physiological data and physical robot control via Blockly[3] in a single interface.

4 Method

We conducted a preliminary study to understand the differences between physiological computing (e.g., EEG) and conventional control (e.g., keyboard buttons) during STEM education activities. While previous work has shown that physiological computing

[2] https://www.electronjs.org/

[3] https://developers.google.com/blockly

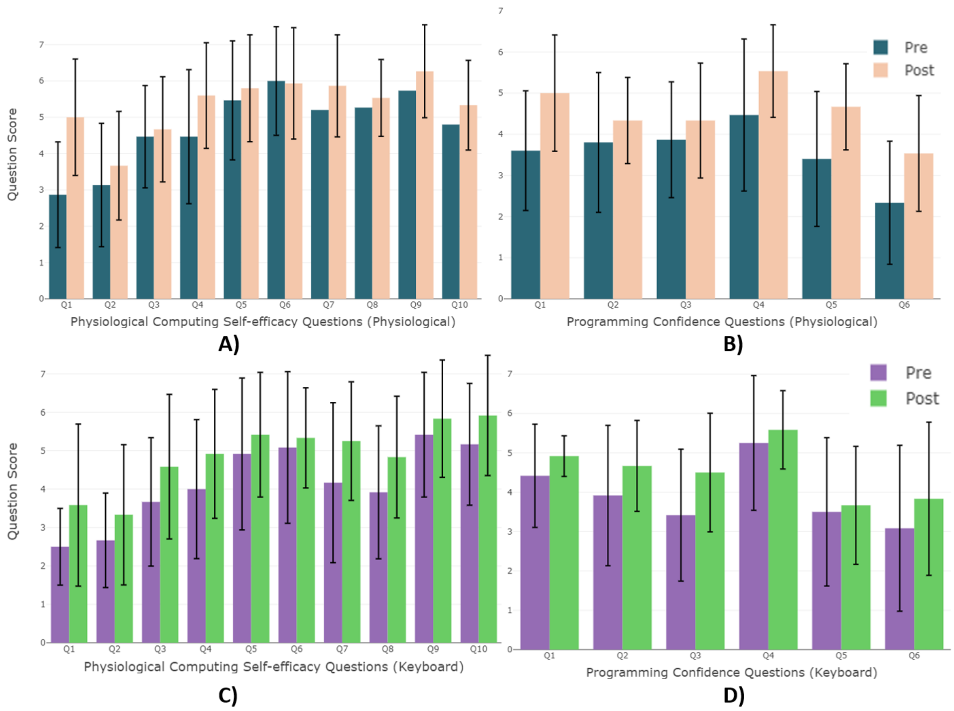

Figure 3: Self-efficacy scores for the physiological (A) and Keyboard (C) conditions. Programming confidence scores for the physiological (B) and keyboard (D) conditions.

could improve learning outcomes in STEM education activities, this is the first study comparing the use of physiological computing to conventional control in an educational context. The following research questions guided this study: **(RQ1)** To what extent does physiological-based control improve **self-efficacy** and **programming confidence** compared to conventional control?, **(RQ2)** To what extent does physiological-based control impact students' STEM **interest and motivation** compared to conventional control? **(RQ3)** How does physiological-based control affect students' **user experience** during STEM learning compared to conventional control?

4.1 Study Procedures

University of Alabama's Institutional Review Board (IRB) approved this study before data collection. A total of 27 (M=19, F=7, Gender Fluid=1) high school students between the ages of 15 and 17 were recruited. Recruitment was conducted in collaboration with educators from a local high school.

After providing an introductory presentation regarding the study, students completed consent forms and provided demographic information via a pre-study survey. The pre-survey also included questions related to students' self-efficacy and programming confidence. Afterwards students participated in a between-subject design study with two conditions: **physiological** and **keyboard-based** control. A total of 15 students participated in the physiological-based control condition and 12 in the keyboard control condition. Students were randomly assigned to each condition. The main difference between the two conditions was how the drone was controlled. During the physiological-based control condition, students developed programs that moved the drone based on changing frequency band power data measured by the Muse EEG device. Students developed programs that moved the drone based on keyboard inputs during the keyboard control condition. We provided students with a simple example program before asking them to create a new custom program during each condition. Students worked in pairs or groups of 3.

The study lasted approximately 90 minutes. The session began with a tutorial explaining how to use PhysioBots. Students were shown how to connect and mount the Muse EEG sensor during the physiological-based control condition. Students were also shown how to connect and control the drone using blocks in the workspace. Additional concepts such as loops, conditional statements, and event-driven programming were also introduced. A similar approach was used for the keyboard control condition, with the exception that students were shown how to control the drones using blocks mapped to keyboard inputs instead of physiological data. The study concluded with a post-survey.

4.2 Data Collection

After each condition students' self-efficacy, programming confidence, and STEM interest and motivation were measured via a post-study survey. Students also responded to open-ended questions regarding their experience with PhysioBots. To measure **self-efficacy**, a slightly modified version of Compaeau and Higgins validated computer self-efficacy scale was used [12]. In particular, the scale (7-point Likert scale) was made specific to applications featuring the use of physiological data for control. To better understand students' **programming confidence**, we leveraged questions (7-point Likert scale) that asked students how confident they were with the following programming concepts: (Q1) Variables, (Q2) Sequences, (Q3) Logic Structures (IF statements), (Q4) Functions, (Q5) Lists, and (Q6) Encapsulation. The Intrinsic **Motivation** Inventory instrument was also used to measure interest, competence, and effort during the post-survey (7-point Likert scale) [52]. Subscales related to interest/enjoyment, perceived competence, and effort/importance were leveraged to gather insights into how each condition impacted students. To measure **usability**, we captured students' responses to the System Usability Scale (SUS) after each condition [8]. We used the recommended format and scoring procedures for this instrument. Open-ended survey questions were used to gather additional insights into students' experiences using the tool. Questions were designed to gauge **interesting ideas** ("Write down an interesting thing that you did in your project and how you made it happen"), **difficulty** ("What things were hard when making your project?"), and **additional types of data** students would like to use ("If you did this activity again, what other types of data would you like to use?").

4.3 Data Analysis

R was used to analyze the quantitative data. Visual inspection and the Shapiro-Wilk normality test were used to check for normality. Skewness and kurtosis were also used to check for non-normality. Pre-post survey analysis related to self-efficacy and programming confidence were compared using a paired t-test for the physiological-based control condition. Independent t-tests were used to compare results between conditions for questions related to user experience (SUS), interest, and motivation. Self-efficacy and programming confidence responses were not normally distributed for the keyboard control condition and were analyzed using a Mann-Whitney U test. Similarly, self-efficacy and programming confidence pre-post responses were compared using a Mann-Whitney test for the keyboard control condition. Analysis of the open-ended survey questions was guided by Grounded Theory [60]. Recurring topics and themes were coded using a deductive approach to minimize bias. The list of codes was translated to themes that captured the core insights shared by participants.

5 Results

5.1 Self-Efficacy

We did not find a significant difference (p>0.05) in self-efficacy between the physiological (M=53.6, SD=7.3) and keyboard conditions (M=49.0, SD:12.6). Furthermore, no significant difference (p>0.05) was found between the pre (M=41.5, SD=13.6) and post (M=49, SD=12.6) survey responses for the keyboard condition. **However, we did find a significant difference (p=0.04) in self-efficacy between the Pre (M=47.4, SD=8.21) and Post (M=53.6, SD=7.22) survey responses for the physiological condition**.

5.2 Programming Confidence

Pre-post surveys explored changes in students' programming confidence after using physiological-based control and keyboard control (see Figure 3). Overall programming confidence was measured using the mean scores of the 6 questions related to programming confidence (e.g., variables, sequences, logic structures, functions, lists, and encapsulation). **Significant improvement was found in overall programming confidence for the physiological condition (Pre(M=21.4, SD=7.3), Post(M=27.4, SD=4.7))**. However, no significant improvement was found in programming confidence for the keyboard condition (Pre(M=23.5, SD=8.0), Post(M=27.1, SD=4.3)). Furthermore, no significant difference was found between the physiological condition (M=27.4, SD=4.7) and the keyboard condition (M=27.1, SD=4.3). When evaluating the 6 questions related to programming confidence individually, we found that the **physiological condition led to significant improvement in programming confidence for the following questions: Variables (Pre(M=3.6, SD=1.45), Post(M=5.0, SD=1.41), p=0.012), Lists (Pre(M=3.4, SD=1.63), Post(M=4.66, SD=1.04), p=0.018), and Encapsulation (Pre(M=2.33, SD=1.49), Pre(M=3.53, SD=1.40), p=0.026)**. Analysis of the 6 programming confidence questions for the keyboard condition did not reveal any significant improvement (p>0.05).

5.3 Interest, Motivation, and Usability

We did not find a difference (p>0.05) in interest/enjoyment between the physiological (M=6.02, SD=0.96) and keyboard conditions (M=6.15, SD=0.68). Furthermore, no significant difference (p>0.05) was found in perceived competence between the physiological (M=5.36, SD=0.98) and keyboard condition (M=5.92, SD=0.8). Similarly, no significant difference (p>0.05) was found in effort/importance between the physiological condition (M=5.15, SD=1.18) and keyboard condition (M=5.5, SD=1.41). We did not find a significant difference (p>0.05) in usability between the physiological (M=80.0, SD=16.8) and keyboard conditions (M=85.2, SD=18.6). Previous research suggest that usability scores above 68 are considered above average. This indicates that both conditions were rated higher than average.

5.4 Open-Ended Question Themes

Interesting Ideas. The most recurring theme during the physiological-based control condition was students exploring ***gamification of emotional state manipulation***. For example, one participant responded: *"Me and my partner decided to attempt at guessing the variable needed to control the craft, though he found a bypass by just thinking very hard."*. Another participant responded: *"One interesting thing that I did was make the drone go up very high, I made it happen by thinking of something that made me very angry"*. During the keyboard condition, the most recurring theme was students exploring ***navigation***. One participant stated: *"We made the drone go very high by changing [the code] and pressing the down button on our keyboard."* Other groups created challenge tasks using the obstacles in the classroom environment. For example, one participant responded: *"I made the drone land on a bench and table."*

Difficulty. The most common theme related to difficulty in the physiological condition was related to ***perceived self-regulation***

challenges. One participant responded that the following was something they found hard: *"Trying to stay focus to get the drone in the air"*. Another participant responded: *"A hard thing was getting a brainwave within a certain threshold to activate something while testing the code"*. While most participants did not report any difficulties during the keyboard condition (9 out of 15 participants), some reported issues related to **hardware challenges**. One participant stated: *"I crashed the drone and lost the propeller"*. Another participant stated: *"Trying to control the robot because of the low battery percentage"*.

Additional Data Types. Several responses to the question related to additional data types were related to a desire to use data related to ***movement***. One participant stated: *"Using like energy by running around or moving instead of sitting down"*. An additional notable response was the use of voice control.

6 Discussion and Conclusion

In this paper, we presented PhysioBots, an educational tool for introducing students to physiological computing and robotics. Our preliminary evaluation suggests PhysioBots may improve students' self-efficacy and programming confidence. These findings align with previous work relevant to physiological computing education [23]. While these results are promising, additional longitudinal studies are needed to understand if these attitudinal changes lead to improved performance and understanding. We did not observe differences in students' self-efficacy, programming confidence, interest, or motivation levels when comparing physiological and keyboard-based control. We plan to conduct future studies with a larger sample size to confirm findings from this preliminary study. While the keyboard condition was selected due to current technological constraints, future work should explore whether similar results are observed when including a joystick or mobile app for drone control. Robotics topics were restricted to robot navigation during this study due to time constraints. Future work should explore introducing topics related to robot perception alongside physiological sensing.

Analysis of the open-ended survey questions suggests that students found it interesting to gamify emotional state manipulation. This suggests that students may respond positively to educational activities designed to improve STEM and self-regulation skills. Previous work has observed promising results with similar approaches to self-regulation in educational contexts [4, 5, 11]. However, additional validation related to PhysioBot's support of self-regulation is needed since this was not the focus of the study. Students suggested that additional data types related to movement and voice control would be interesting to use with PhysioBots. This observation aligns with previous work involving sensor-based education tools [64, 65]. Furthermore, the use of sensors such as EMG that measure muscle activity may address concerns related to the self-regulaton challenges and signal-to-noise ratio limitations of EEG. In some instances, students intentionally introduced noise in the EEG signals by clenching their jaws or activating other muscles. While this is undesired in traditional EEG studies, we used this as a learning opportunity to demonstrate the limitations of current physiological sensor technologies.

During the keyboard condition, students' responses focused on the hardware challenges of the drone. However, during the physiological condition, students' responses focused more on manipulating their emotional state. This observation suggests that PhysioBots may be best suited for an interdisciplinary curriculum that combines physiology, computing, and robotics knowledge. In cases where educators are solely focused on traditional STEM education, PhysioBots may be best used as a supplementary tool for increased engagement and confidence.

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