NeuroBoost

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Abstract

A novel smartwatch design is proposed for improving cognitive function on a daily basis. Integrating four physiological sensors paired with daily user input on activity and emotional wellbeing, machine learning algorithms are developed to model and understand patterns in cognitive function. The patterns are presented to the user on a mobile application and website interface, paired with suggestions for improvement. The report entails a thorough evaluation of prior research, product design, and setup of experimental trials to validate the product's technology, then followed by a thorough analysis of the product's global impact, scalability, and future iterations. NeuroBoost aspires to transform personal health monitoring by making cognitive health insights accessible on a daily basis, thereby improving everyday cognitive function. This integration of advanced technology with practical usability places NeuroBoost at the forefront of health innovation, promoting a proactive approach to mental wellness and setting a new, competitive standard in the wearable technology market.

Keywords: Cognitive Enhancement, Physiological Sensors, Machine Learning, EEG-Like Data Projection, Smartwatch

Contents

1. Introduction

Background & Significance

In recent years, wearable technology has gained prevalence and popularity among consumer groups through devices such as FitBits, Apple Watches, Garmin Watches, and Oura Ring. Many users adopt these devices as an extension of their smartphone's functionalities, as a fitness-centric tracker, or both. (Vijayalakshmi et al., 2018) As these devices commonly track health statistics, they frequently implement photoplethysmography (PPG) sensors and accelerometers for monitoring of heart rate and movement for stress, sleep, and fitness activity data. (Kaewkannate et al., 2016) More recently, Apple Watch implemented an electrocardiogram (ECG) sensor (measuring electrical activity of the heart) for more accurate measurements of atrial fibrillation in users with heart disease (Apple, 2023); FitBit added an electrodermal activity (EDA) sensor to provide a stress statistic derived from skin conductivity (FitBit, n.d.); and Oura Ring has integrated a Negative Temperature Coefficient (NTC) sensor to measure body temperature. (Oura, 2024)

Despite recent advancements in sensing capabilities, electroencephalogram (EEG) technology has not gained traction in the wearables market. The traditional EEG is currently used for medical diagnosis of epilepsy, sleep disorders, and brain tumors. (Casson et al., 2010) These can also be diagnosed from an ambulatory EEG done in a patient's home. (Klein et al. 2021) However, despite its removal from a hospital setting, an ambulatory system is usually bulky and limits the user to a specific area, resulting in a focus of the technology in medical diagnostics as well. There are currently vendors of comfortable and commercially available EEG headbands. (Carneiro et al., 2016) However, these wearable EEGs are mostly used for research purposes and have not gained traction in a consumer market most likely due to the specificity of

EEG sensors (measuring only neuronal activity local to where each sensor is placed) and the lack of implementation into a device which is unobtrusive and conveniently placed to the user (such as a watch).

Studies have shown strong correlation in EDA sensor data and EEG readings. (Lim et al., 1996) EDA sensors measure skin conductivity, which refers to the change in heat and electricity created by nerves and conducted by sweat within the skin. (National Cancer Institute, n.d.) Changes in skin conductance occur as a response to changes in the sympathetic nervous system. By using the correlation between skin conductance and neural activity, EDA sensor readings can be correlated with EEG readings. EDA sensors have been previously implemented into watches such as the Charge 5 by FitBit and the Epimonitor by Empatica. (Empatica, n.d.) As watches have been shown to be a successful form of commercially available wearable technology, implementing an EDA sensor with correlative algorithms to EEG data would create an EEG monitoring wearable device which is more likely to gain traction amongst consumers.

Here, we propose a new wearable device that, in addition to measuring the aforementioned signals that other marketed smartwatches sense, processes this EDA-based skin conductivity data through a machine learning algorithm to make predictions about a user's EEG data. This smartwatch, called Neuroboost, will offer this data to the user through an associated app interface. This increased data accessibility will allow users to understand the dynamics of their physiological landscape continuously throughout the day and during their various activities, such as exercise and stressful events. Together, these measurements and predictions will allow the user to make informed decisions about their lifestyle, health, and mental wellbeing by facilitating better understanding of how their physical and mental states coexist. In these ways,

Neuroboost will revolutionize both smartwatches and EEG technology and grant consumers more knowledge and power over their daily lives.

Project Objectives

NeuroBoost is a cognitive enhancement smartwatch that integrates several sensor technologies to monitor and analyze physiological and neurological data. The primary aim is to provide insights into the user's cognitive and emotional status, thus quantifying emotions and daily activities. The watch will enhance stress management and productivity by offering users actionable insights derived from the EDA, ECG, PPG, and accelerometer sensors. An essential objective of the product is to validate the integrated sensors' effectiveness in projecting EEG-like data within a compact wearable device, ensuring both reliability and precision within measurements. Together, this data will offer insights in overall brain activity, thus enabling users to better understand their cognitive states. The product uses innovative machine learning algorithms to predict cognitive patterns in memory retention and stress levels and will summarize these findings to the user via an application and website interface.

Scope of the Report

This scientific report comprehensively details the development and evaluation of NeuroBoost. The report begins with a motivation for the project, identifying the need for integrated cognitive and physiological monitoring in a wearable device. The literature review section examines current technologies in wearable EEG and related cognitive enhancement tools, identifying gaps that NeuroBoost aims to fill. Detailed descriptions of product design cover the integration of EDA, ECG, PPG, and accelerometer sensors, along with the architecture of the

associated data processing and machine learning algorithms. Experimental validation is meticulously documented and planned to demonstrate the efficacy and reliability of the sensor integration and the predictive capabilities of the machine learning models used. The report also explores the user experience design process, emphasizing ease of use and user engagement, critical for ensuring user adoption and satisfaction.

The project is grounded in a psychological approach, integrating biological, psychological, and social factors affecting health. Biologically, the smartwatch monitors physical indicators such as heart rate and skin conductance, which are linked to emotional and cognitive states. Psychologically, the device leverages these biometric readings to provide feedback that can influence and modify user behavior, such as promoting relaxation techniques when stress is detected. Socially, the insights generated by NeuroBoost aim to enhance the user's ability to interact effectively in their environment by optimizing their cognitive and emotional states, potentially improving productivity and social interactions. This interdisciplinary approach ensures that NeuroBoost is not only a technological innovation but also a practical tool for enhancing mental health and well-being in everyday life.

2. Product Design

Prototyping

Overall Design Philosophy

The overall design of the NeuroBoost was motivated by a high-level vision for a new generation of smart watches, founded upon the fundamentals of neuroscience to achieve the functions of a personal life assistant at the tip of one's arm. As such, it was necessary that the design was compact to allow for and encourage comfortable daily usage. Furthermore, it was important that the design was clean, minimalistic and elegant, for the purpose of being taken seriously by users and the broader market as a scientific instrument, as opposed to being a simple accessory for aesthetic purposes.

Driven by the aforementioned overall vision, some key requirements were laid out for the design of the NeuroBoost. First, and most importantly, there must be improved EDA, ECG and PPG measurements compared to other smartwatches on the current market. As mentioned earlier, the NeuroBoost is not simply an adaptation of a conventional smartwatch, but rather a state-of-the-art scientific instrument used to track and analyze an individual's daily life to a revolutionary degree of accuracy and precision. Therefore, it was necessary that the ECG and PPG measurements already implemented by current smartwatches be executed with higher standards, along with the novel introduction of EDA sensing that is not currently available on the smartwatch market. Second, it was necessary to allow for increased computational capabilities to facilitate complex and useful analyses of the obtained data. Physically, this meant that the body of the watch had to be of minimal mass and volume to provide the NeuroBoost computer with maximum space. The NeuroBoost computer consists of a printed circuit board (PCB), the design of which will be outlined in the next section, which will operate a machine learning algorithm

that will be discussed later on in this paper. Finally, leading on from the earlier vision of comfortable daily usage, it was required that the overall hardware was of low bulkiness to minimize any interference on the user's daily life.

Sensor Placement

Due to the main requirement of improved EDA sensing, a literature review was conducted to determine the optimal sensor placement on the NeuroBoost to obtain the most accurate and precise measurements. A 2018 study tested four different EDA sensor materials to investigate the optimal electrode positions: stainless steel, brass, silver and gold (Anusha et al., 2018). It explored a range of electrode placements across the arms of the participants, on both the dorsal side and the ventral side. The quality of the electrode placement was determined based on the stabilization time, which refers to the time taken for the EDA measurement to reach within 5% of the final value. Ultimately, the study found that an interelectrode separation of 4 cm achieved consistent measurement performance. As such, the decision was made to implement two EDA sensors on the NeuroBoost, one of the top of the wrist in the body of the watch and one on the bottom of the wrist in the strap of the watch, with an approximate separation of 4 cm.

Design Process

The design process was based on the fundamental PCB dimension of 40 x 35 mm. A first iteration of the design was initiated with the goal to simply create a robust foundation from which to further refine the design. Using Creo Parametric, a computer aided design (CAD) software, a simple skeleton watch was built—essentially just the watch body with straps on either side. The straps were obtained from an online open source (Webelogs, 2024), as the

complexity of the print-in-place flexibility mechanism could not be achieved within the timeline of this project. This initial design (Fig. 1) was 3D printed using polylactic acid (PLA) filament, a type of plastic. Upon discussion with the team, there was consensus that the design was based on solid foundations, and the main area for improvement was identified in the form of reducing the outer dimensions of the watch body. This was to align with the aforementioned requirement of minimizing bulkiness to achieve comfortable daily usage.

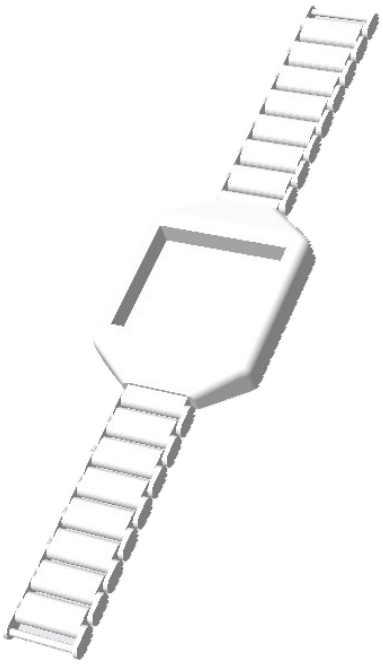


Figure 2a: Top view of the initial NeuroBoost design.

A second iteration was performed to implement the agreed adjustments. The watch body was downsized whilst maintaining the 40 x 35 mm dimension of the PCB, and EDA sensors were installed under the watch body, as well as within the watch strap. Specifically, the margins around the monitor screen were significantly reduced, given that the new thickness remained sufficient structural integrity. The final prototype design is summarized in the Results section below.

Printed Circuit Board (PCB)

Overview of Hardware Stack-Up & Component Placement

Like any smartwatch, our device requires a printed circuit board (PCB) to function. Our PCB integrates our various sensors, microprocessors, power lines, and amplifiers without use of bulky wires, ensuring components can communicate and function together seamlessly without being susceptible to noise that comes with long wires. Our PCB aims to culminate all of our research up until this point into a board that can be conveniently placed into our CAD design. The use of a PCB for interfacing with our devices allows for our smartwatch to be miniaturized and easily manufacturable on a mass-scale with fabrication companies like PCBWay or JCLPCB. Our electrical schematics and PCB layout are shown in Fig. 2b and our 3D model is shown in Fig 2c.

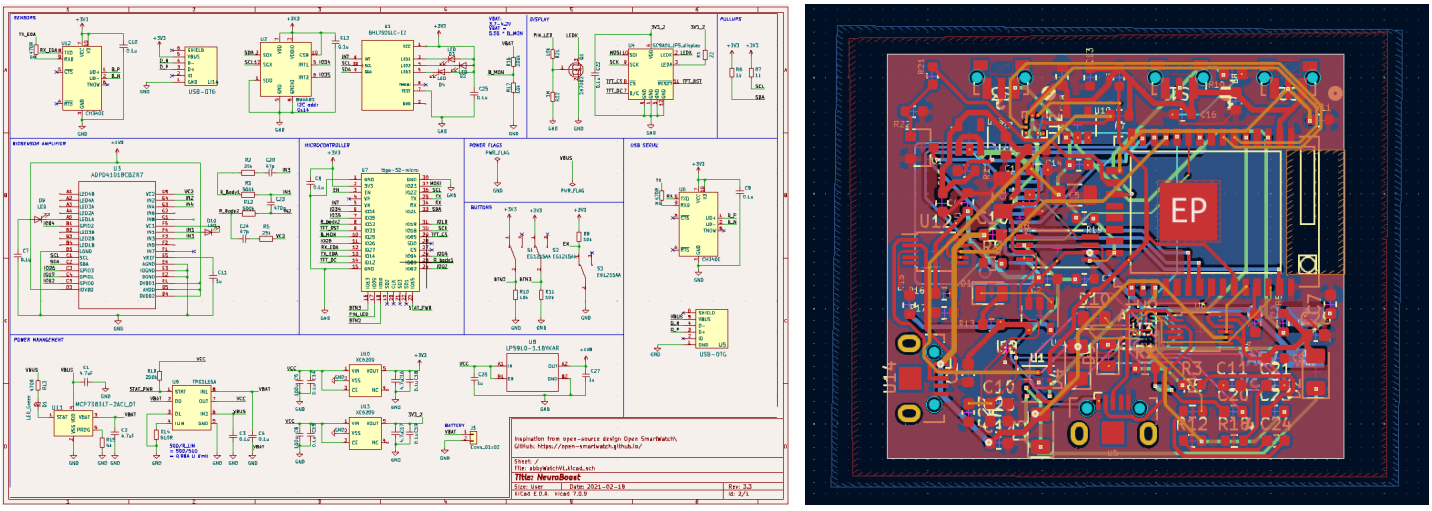


Figure 2b: Electrical schematic detailing device connections (left) and Stack-up of layout detailing physical placement and routing of devices (right).

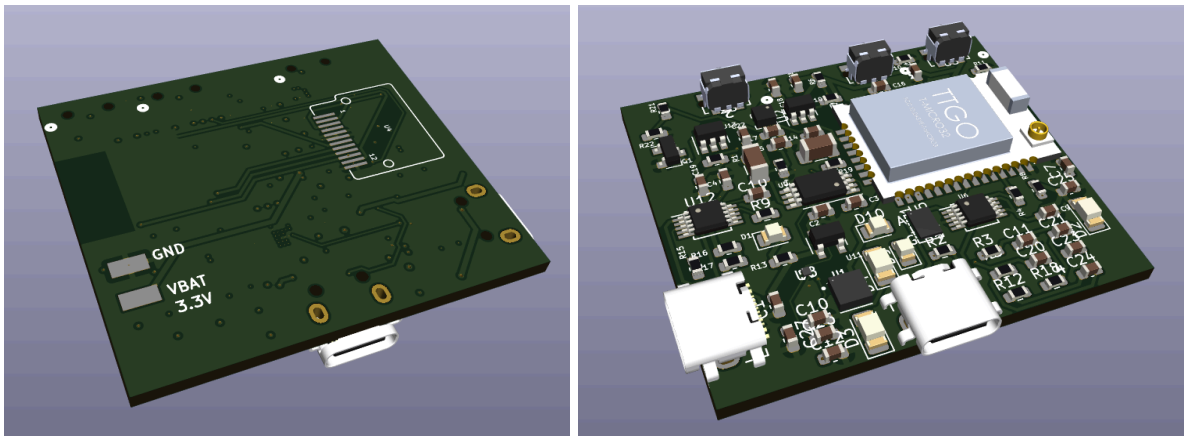


Figure 2c: Top view of the PCB, containing screen display interface and battery interface (left), and bottom view of the PCB, containing biosensors, processors, buttons, power management devices, and USB-C inserts (right).

As seen in Fig. 2d, our stack-up from top to bottom is as follows: screen interface and battery connection on top and biosensors on the bottom. It is imperative that the screen and battery are on the top of the board as opposed to the bottom so that we can access the wrist for the biosensors to get good measurements of the pulse and to have ease of access for externally interfacing with the EDA sensors mounted to the band of the NeuroBoost. Additionally, the top of the smartwatch will be the component visible to the user, so having the screen, interfaceable on the board with surface mount display (SMD) metal pads, run above the battery, which is stored underneath the screen. In this section, we will discuss power management. Following this, we will discuss the different sensors that we used to gain biometric data, including heart rate, blood oxygen levels, EDA signals, and activity tracking. We will then discuss our chosen microprocessor as well as our implementation of an amplifier for this sensor data to increase the accuracy of the readings. Our bill of materials (BOM) is depicted in Fig. 2e.

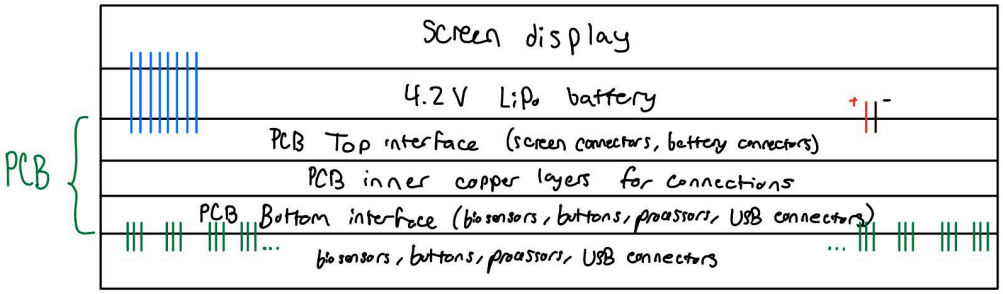


Figure 2d: Macro-level of internal placement of components in NeuroBoost. Horizontal black lines indicate separations of components. Vertical lines indicate connections, with green lines indicating solder joints connecting devices directly onto PCB and non-green lines indicate wires connecting devices externally.

Part Name	Quantity	PCB Designator	Part Number / Value	Mount Type	Informational Link
ECG/PPG Oximeter/Heart Rate Sensor	1	U1	BH1792GLC-E2	SMT	https://fscdn.rohm.com/en/products/databook/datasheet/ic/sensor/pulse_wave/bh1792glc-e.pdf
3.7V-3.3V Voltage Regulator	2	U10, U13	XC6209	SMT	https://www.digikey.com/en/htmldatasheets/production/637374/0/0/1/xc6209-xc6212-series
LiPo Charging Management Controller	1	U11	MCP73831T-2ACI_OT	SMT	https://ww1.microchip.com/downloads/en/DeviceDoc/MCP73831-Family-Data-Sheet-DS20001984H.pdf
USB to Serial Converter	2	U12, U6	CH340E	SMT	https://cdn.sparkfun.com/assets/5/0/a/8/5/CH340DS1.PDF
3-axis ultra-low power accelerometer	1	U2	BMA400	SMT	https://www.bosch-sensortec.com/media/boschsensortec/downloads/datasheets/bst-bma400-ds000.pdf
Multimodal Sensor Front End	1	U3	ADPD4101BCBZR7	SMT	https://www.analog.com/media/en/technical-documentation/data-sheets/adpd4100-4101.pdf
Screen Display	1	U4	GC9A01_IPS_display	THT	https://www.buydisplay.com/download/ic/GC9A01A.pdf
Microcontroller	1	U7	ttgo-32-micro	THT	https://www.espressif.com/en/products/socs/esp32#:~:text=ESP32%20can%20perform%20as%20a,SDIO%20or%20I2C%20%2F%20UART%20interfaces.
3.7V - 1.8V Voltage Regulator	1	U8	LP5910-1.1BYKAR	SMT	https://www.ti.com/lit/ds/symlink/lp5910.pdf?ts=1714981239240&ref_url=https%253A%252F%252Fwww.google.com%252F
Power Multiplexer	1	U9	TPS2115A	SMT	Autoswitching Power MUX . datasheet (Rev. F)
Transistor	1	Q1	2N7002	SMT	https://www.diodes.com/assets/Datasheets/ds11303.pdf
EDA Electrode Pair	1	-	3092020	External	https://support.pluxbiosignals.com/wp-content/uploads/2021/11/Electrodermal_Activity_EDA_Datasheet.pdf
LiPo Battery	1	-	3.7 V	External	https://www.digikey.com/en/products/detail/sparkfun-electronics/PRT-13851/6605199?utm_adgroup=&utm_source=google&utm_medium=cpc&utm_campaign=PMax%20Shopping_Product_Low%20ROAS%20Categories&utm_term=&utm_content=&utm_id=go_cmp-20243063506_adg-_ad-__dev-c_ext-_prd-6605199_sig-Cj0KCQjw_-GxBhC1ARIsADGgDjt93dG9hVPqnbUtD7hjrTTAj-Ey2GA9krVvYKulWxHlsy09tTirJuMaAosgEALw_wcB&gad_source=1&gclid=Cj0KCQjw_-GxBhC1ARIsADGgDjt93dG9hVPqnbUtD7hjrTTAj-Ey2GA9krVvYKulWx

					Hlsy09tTirJuMaAosgEALw_wcB
USB Connector	2	U14, U5	-	THT	general component
SPST Buttons	3	S1, S2, S3	-	SMT	general component
Capacitor	2	C1, C2	3.7uF	SMT	general component
Capacitor	5	C10, C11, C12, C26, C27	1u	SMT	general component
Capacitor	13	C10, C13, C14, C15, C18, C19, C22, C25, C3, C4, C7, C8, C9	0.1u	SMT	general component
Capacitor	2	C16, C17	4.7u	SMT	general component
Capacitor	3	C20, C21, C24	47p	SMT	general component
Capacitor	1	C23	470p	SMT	general component
Capacitor	2	C5, C6	100u	SMT	general component
LED	1	D1	-	SMT	general component
LED	2	D10, D9	-	SMT	general component
IR LED	3	D2, D3, D4	-	SMT	general component
Resistor	1	R1	22	SMT	general component
Resistor	5	R10, R11, R17, R21, R8	10k	SMT	general component
Resistor	2	R12, R3	500k	SMT	general component
Resistor	3	R13, R4, R9	470R	SMT	general component
Resistor	1	R14	510R	SMT	general component
Resistor	1	R15	5k	SMT	general component
Resistor	1	R16	200k	SMT	general component
Resistor	3	R18, R2, R5	25k	SMT	general component
Resistor	1	R19	220k	SMT	general component
Resistor	1	R22	1M	SMT	general component
Resistor	2	R6, R7	1k	SMT	general component

Figure 2e: PCB Bill of Materials (BOM) with datasheet and electronic distribution webpages depicting specifications for each electronic device.

Power Management

We are using a 3.7V lithium-polymer (LiPo battery) that has shorting protection for safety to power our entire circuit. All of our power management components, which we will discuss in this section, are viewable in Fig 2f. with the components from left to right being as

follows: charger controller, power multiplexer (mux), 2x 3.3V voltage regulators, input nodes for the positive and negative terminal of our 3.7V battery, and 1.8V voltage regulator.

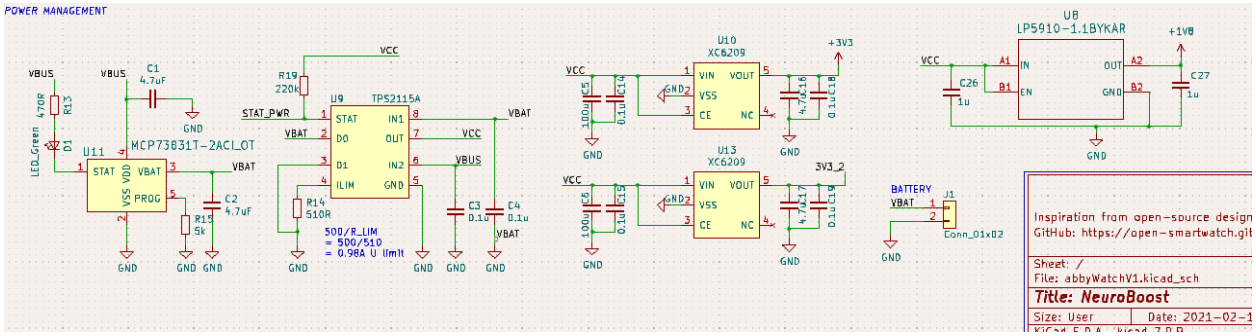


Figure 2f: Electrical Schematic with a focus on all power management device connections as well as the implementation detailing connecting to an external battery.

We are using a MCP73831 LiPo battery charger management controller as this device employs a constant-current and constant voltage charge algorithm with selectable preconditioning and charge termination to allow for more efficient and safe battery charging. This charging management controller also limits the charge current based on die temperature during high power or high ambient conditions, which optimizes the charge cycle time and also maintains device reliability with its ability to regulate the temperature of the devices when the battery is charging. This allows us to maximize battery life and ensure safe operation of our NeuroBoost smartwatch. This controller also includes circuitry to detect when the battery is fully charged. Once the battery reaches its full capacity, the charger automatically terminates the charging process to prevent overcharging, which can damage the battery or pose safety risks in the long term. Using the MCP73831 LiPo battery charger, we are able to connect the voltage running the current through the charger with USB adapter to the battery input, thus charging the battery whenever the battery level is low, thus allowing us to not have to switch the battery out whenever it runs out of power.

We are also employing a power mux, specifically the TPS2115A power mux, to select between multiple power sources, being either the voltage from the battery or the voltage from the USB connector going into the device. Its primary function is to switch between different power inputs based on certain conditions or requirements.. Specifically, per the datasheet for the TPS2115A power mux, the pins D0 and D1 determine which voltage value is transferred through the mux, being either the IN1 or IN2 input. Here we see that the value of the battery voltage determines which voltage value gets passed through to the rest of the circuit, specifically having the voltage battery, VBAT pass through to the rest of the circuit if the battery voltage is at a high enough value to power on the devices and the voltage coming from the USB connector passing through when the VBAT value is too low to operate.

We then have 3 voltage regulators to convert the 3.7V battery voltage to 3.3V and 1.8V for the lower voltage components, such as the biometric sensors, screen display, which all take 3.3V, and the biometric data signal amplifier, which operates at 1.8V. This voltage value information was found in these components' datasheets.

We also implemented the functionality of being able to monitor the voltage of the battery with the pin called B_MON. This voltage value is the output of a voltage divider, taking the voltage of the battery and putting the output B_MON between two resistors. From there, we are able to incorporate the following voltage divider equation into our firmware, in order to get the voltage value of the battery: B_MON = (VBAT * 200k) / (200k + 10k), as seen in Fig. 2g, the picture on the left being our implementation and one to the right being a basic breakdown of voltage divider circuit implementation. In our software we will take the read input of B_MON in our microcontroller, and then use the resistor values to solve for VBAT. The reason we do this, instead of simply connecting the battery to the input is because the resistor significantly reduces

the magnitude of the voltage value being read, which in turn causes lower power consumption, due to the fact that resistors are passive components. Functionality gives us the ability to display the battery level of the device, both on the display on the Watch, as well as the connected app, providing the user key information on the status of their NeuorBoost's battery life.

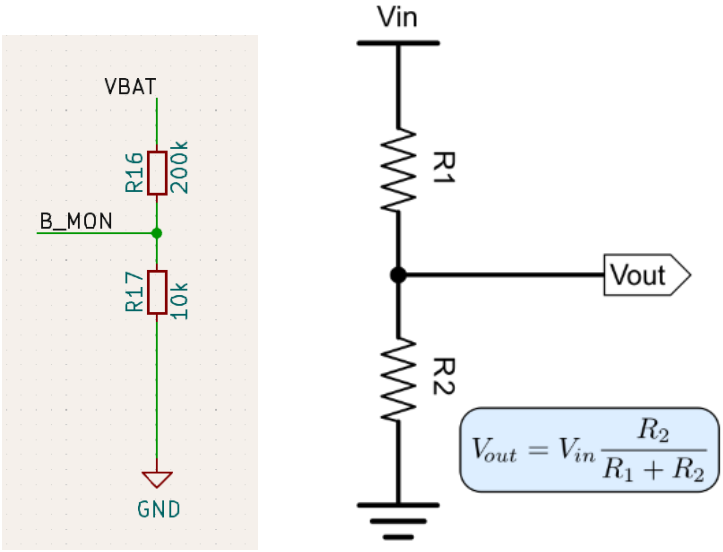


Figure 2g: Our implementation of a voltage divider to read the level of the battery connected to PCB (left) and equation with complimentary schematic providing the voltage divider equation (right) (Miles).

Biosensor Information Processing

We are able to upload the firmware to collect the data from the biosensors, send it to the microcontroller, and then wirelessly transfer it to our app via a USB connector, which runs to a CH340E USB to UART (Universal Asynchronous Receiver-Transmitter) bridge controller. This controller's UART interface allows it to communicate with devices using serial protocols as discussed later on in this section. When data is sent from the host device over USB, the CH340E converts it into serial data format suitable for transmission over the UART interface and then sends it to the microcontroller via the TX and RX lines.

For our microcontroller, we used the TTGO T-Micro32 V2.0, which functions just like a regular ESP32 microcontroller but has an area that is reduced by 45% compared to a regular ESP32 but has the same number of general purpose input/output (GPIO) pins (Fig. 2h), which helps us in our efforts to miniaturize the NeuroBoost while still being able to interface with many sensors. ESP32s have a hybrid Wi-Fi & Bluetooth Chip that allows us to transfer data to our app at high speeds. Our microcontroller has a hybrid Wi-Fi & Bluetooth Chip that allows us to transfer data to our app at high speeds. They also have robust thermal design with operating temperatures from –40°C to +125°C. Our microcontroller is also very efficient in power consumption, specifically through the use of fine-grained clock gating, which is removing the clock signal when portion of circuit isn't functioning; various power modes that provide dynamic power delegation throughout circuit, meaning that the microcontroller can cut power to parts of its internal circuit that does not need to use power or store any memory; and touch-sensing pins that can wake ESP32 from deep sleep. All of these dynamic power delegation functionalities give us the ability to preserve battery life of the device and perform more precise filters and more complex calculations without worrying about the battery life not lasting a sufficient amount of time.

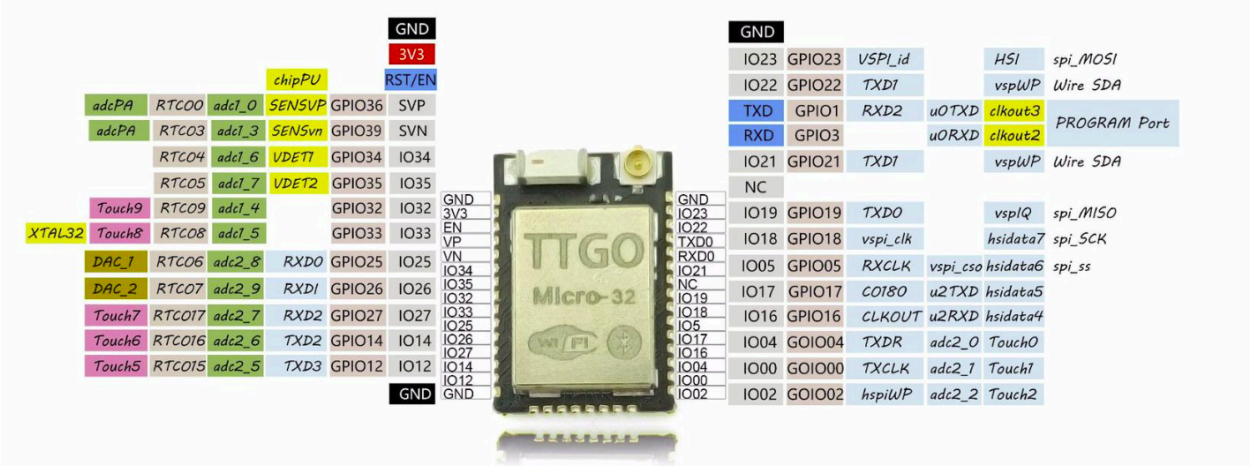


Figure 2h: Pinout of TTGO Micro-32 V2.0 Microprocessor. It has the same number of GPIO pins as a regular ESP32, including digital GPIOs, analog inputs, PWM outputs, UART, SPI, I2C, and other communication interfaces.

We also chose to employ the optical Analog Front End (AFE) ADPD4101BCBZR7 IC that integrates multiple photodetectors and photodiodes and uses them to measure the optical signals transmitted through or reflected from the human body. Specifically, for Fig. 2i, the left image is from the ADPD4101BCBZR7 datasheet and shows the set up for interfacing with 2 electrode inputs, in our case each pin E1 and E2 representing the input from one of the 2 external EDA electrodes. The resistor in the image to the left notates the resistance of the skin between said 2 electrodes, so this resistor is not included in our implementation to the right. Instead, these nodes, E1 and E2, are replaced with inputs coming from the microcontroller with information from each electrode, which connects to the microcontroller via UART communication. We chose to employ this AFE because it includes analog front-end circuitry for conditioning the optical signals detected by the photodetectors. It also includes a a digital signal processor (DSP) that can perform further processing on the conditioned signals, including filtering, noise reduction, signal extraction, and calculation of vital signs such as heart rate, oxygen saturation, and other biometric parameters that provides the NeuroBoost a lot more capacity for functionality of application with the biometric data obtained from the EDA and ECG/PPG sensors. Connecting

our EDA sensors to this module allows us to gain more accurate data on the emotional well being of our user to be able to better inform and assist them in their daily tasks.

Figure 56 shows a circuit that can be used for the two-electrode lead off detection measurement. R_{BODY} is the resistance of the body.

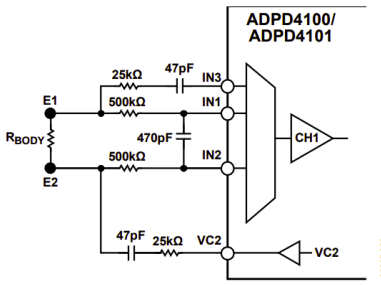


Figure 56. Circuit Used for Two-Electrode Lead Off Detection Measurement

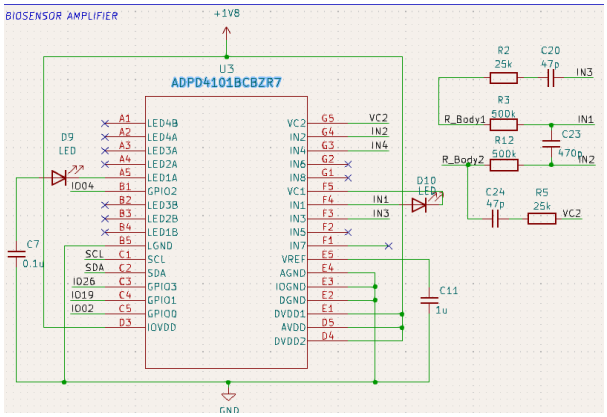


Figure 2i: Datasheet excerpt detailing wiring for Two-Electrode Lead Off Detection Measurement (left) and our implementation of this wiring in our schematic (right). R_body1 and R_body2 are received from the EDA electrodes.

We use 3 communications throughout our circuit, being SPI, I2C, and UART, each of which we will describe in this paragraph as well as where we implement each communication type and the reasoning behind each choice.

Serial Peripheral Interface (SPI) has one device controlling one or more devices. It requires at least four wires being a clock line (SCK), a master-out-slave-in line (MOSI), a master-in-slave-out line (MISO), and a slave select line (SS) for each slave device. We use SPI for our screen display as SPI is synchronous, meaning that data is transferred based on a clock signal (SCK) shared between the master and slave device(s), which allows us to have real-time multi-directional communication between our screen display, microcontroller, and app. This is also useful for our screen because SPI supports data being transmitted and received at the same time at fast data transfer rates, which is important for the screen on the device to display accurate information in real-time with the user's fast changing biometric data (Hopkins).

Inter-Integrated Circuit (I2C) has many devices controlling many devices on the same bus. It requires only two wires, which are a serial data line (SDA) and a serial clock line (SCL),

thus making it a very simple method of communication. We use an I2C-compatible amplifier as well as I2C-compatible biometric sensors over SPI amplifiers and sensors primarily because of a couple reasons. I2C supports having multiple devices connected to the same bus, each with its own unique address, which allows for simple integration of our many biosensors. With this, I2C can handle multiple master devices on the same bus, thus allowing us to perform more complex calculations and integrations with our many biosensors. Also I2C uses a clock line to synchronize data transfer between devices, ensuring reliable communication even at different clock speeds, while SPI doesn't have this and evidently sees timing issues in systems with devices running at different speeds. It should be noted that all of our SCL and SDA lines are pulled up to 3.3V via 1kOhm resistors, and this commonly done with I2C lines for 3 main reasons: it mitigates noise immunity by maintaining the lines at a defined logic level when no devices are actively pulling them low, thus preventing the lines from having no value, or being floating; allows for a check for a given device to see if other devices are communicating on the line through ensuring that the lines are high when no device is actively driving them low; and the fact that these pull-up resistors help in charging and discharging the capacitance of the lines, which helps acquire fast and stable signal transitions of the SCL and SDA lines, which is imperative as these lines drive the communication for our biosensors (Hopkins).

We use Universal Asynchronous Receiver-Transmitter (UART) for our external devices, including the charger/firmware-upload features of the USB connector as well as the USB connector carrying along data from our external EDA sensors to our microcontroller. UART communication involves two devices: a transmitter and a receiver, and therefore has two wires, being a transmit line (TX) for data transmission and a receive line (RX) for receiving data. It's a point-to-point communication protocol. UART is asynchronous, meaning that data is transmitted

with start and stop bits to denote the beginning and end of each byte. It supports full-duplex communication, allowing data to be transmitted and received simultaneously. UART is a very commonly used communication style and is commonly used for serial communication between devices. It should be noted that UART communication has lower overhead compared to SPI and I2C, making it efficient for transferring small amounts of data between devices. Therefore, in future iterations, we would look deeper into finding a different type of USC converter than our currently implemented USB-to-serial converter in orde3r to open up more capacity for the amount of data from the EDA sensors to be transferred to the microcontroller (Hopkins).

Other Electrical Components

We have 3 buttons that all have the same layout as a single pull-single throw (SPST) switch, which means that when the button is in the unpressed state, one of the two terminals that are supposed to connect to each other is floating, and it is only when the button is pressed that the latch within the button changes to connect the two terminals together. These buttons can be seen, both in schematic and 3D model view, in Fig. 2j.

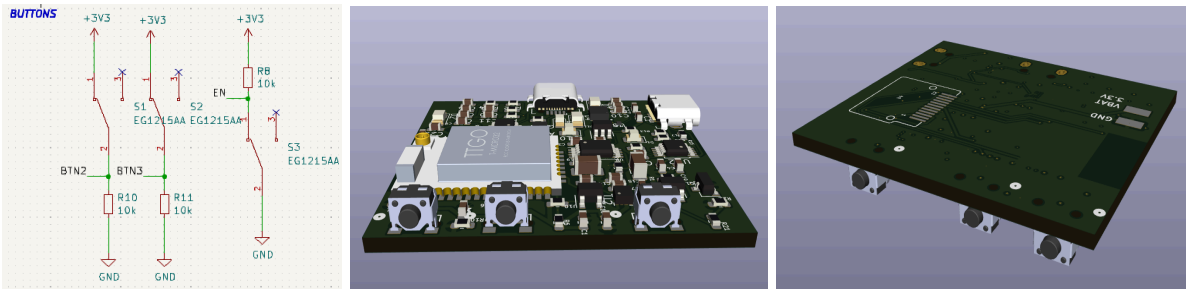


Figure 2j: Schematic of buttons for boolean user functions (left) and 3D models of buttons on the bottom side of the device (center and right). As seen in the 3D models, the buttons are side-mount buttons, with the button being perpendicular to its pins attaching to the PCB for the user to access outside of watch.

One button is to turn the device on and the two terminals that are connected are the enable pin EN of the TTGO 32 microprocessor and GND. When the button is not pressed, the EN pin is not connected to anything. In this state, the EN pin is pulled to a high logic level, being

to our 3.3V and therefore is in an inactive or disabled state. When the button is pressed, it creates a path to ground for the EN pin, pulling the EN pin to a logic low level, or GND, overriding the pull-up resistor. In implementation, our microcontroller would be programmed to detect changes on the EN pin, such as transitions from high to low with a rising edge or low to high with a falling edge detector, so that when the switch is pressed and the EN pin is pulled low, the microcontroller can respond to this event by executing specific code or triggering a particular action, specifically to turn the screen on and activate the sensors. It is important we have this button to allow for the microcontroller to turn off as it is connected to everything and delegates the power in the circuit, and with the microcontroller having the ability to be disabled, we are able to regulate the power supplied to different components, reducing the circuit's power consumption overtime when its not needed. In a similar implementation we have two buttons pulling two signals to two general digital signal inputs in the microcontroller for general purposes, spanning from calibrating the watch to hardcoding it from a physical UI perspective to send the data instantaneously over to the linked application interface using the ESP32 WiFI Bluetooth Module of the TTGO microprocessor.

We also chose to implement a GC9A01 for our IPS (In-Plane Switching) display, which supports parallel RGB (Red, Green, Blue) interface for communication with the host microcontroller, in our case the T-Micro32 V2.0. The GC9A01 acts as the main controller for the TFT LCD panel, managing the display refresh cycle, pixel data transmission, and various other functions required for driving the display. It supports various color depths and resolutions, thus giving us the ability to display immediate outputs on the watch interface to our user in the form of visual breathing exercises or information on their biometric statistics. We are using an IPS display because they offer superior color reproduction and wider viewing angles as evident in

Matsushima et al.'s implementation of these IPS screens in virtual reality technology whose realisticness relies on the ability for the screen to provide the user wide viewing angles, providing easily adjustable screen resolution when the user moves their head to view the screen display from a different angle (Matsushima et al.). Therefore, our selected IPS screen allows us to have a display with maintained consistent color and brightness across different viewing angles, which is useful for our application in the event the user is viewing the wrist watch screen from an abnormal angle and, in fact, never views the screen head on due to the placement of the device on the wrist. The schematic and layout views for this interface on the PCB that travels with wires to the screen sitting above the PCB can be viewed in Fig. 2k. The display has 2 backlight pins. LEDK (-) and LEDA (+). LEDA is connected to the 3.3V bus through R1. LEDK is connected to GND, but with a transistor Q1, which acts as a switch whose state is determined by the gate voltage, being in the on state when $V_g > V_{th} = 1V$ for the 2N7002, according to its datasheet. So this transistor adjusts current going into LEDK depending on the analog value of PIN_LED, which is coming from the microcontroller, and, when LEDK (-) is connected to GND, being when the gate voltage of the 2N7002 transistor, determined by PIN_LED using the same method as determined in the Power Management section on voltage divider, is above 1V, the brightness levels of the screen can be adjusted. We chose to utilize this feature of the GC9A01 IPS display in the event that the user needs to dim the screen of the display if they are in a dark setting that calls for that so that they can still use the screen features without having the screen at maximum brightness.

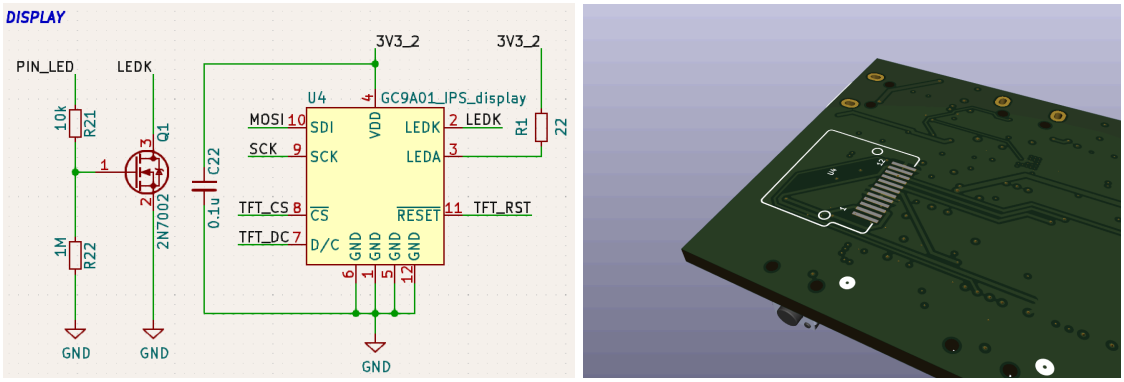


Figure 2k: Wiring of screen display (left) and 3D model of screen interface on the top of the PCB (right).

Sensor Integration

The overall design is the traditional model of wearable watch technology. In addition to their prevalence in a commercial setting, it has been shown in a case study at Georgia Tech that users tend to prefer wearable technology mounted to the wrist as opposed to other locations. (Profita et al., 2013)

The incorporation of EDA sensors creates a novel smart watch design. On its own, statistics about skin conductance can provide invaluable data with respect to the body's autonomic nervous system. This design will leverage both its stand-alone statistics as well as the proven correlation between EDA and EEG signals to provide insights into the connection between everyday activities (as recorded by the user), their neurological functions, and their physical exertion (recorded by the remaining sensors).

Despite recent promising research into optimizing EDA sensor signals through placement in areas besides the wrist, due to the widespread acceptance of wearable wrist technology and the aforementioned preference for it, a smart watch was chosen as the most marketable and precedented type of technology. As shown by a recent study, EDA sensors provide most optimal

measurements when used in tandem on the dorsal surface of the wrist with 4 cm interelectrode spacing. For this reason, the EDA sensors of our design were placed on the back of the watch face and on the back of the watch clasp, spaced apart and both allowing for sensor-to-skin contact.

- Fitness stats from accelerometer
- Heart rate stats can be turned into stress statistics
- PPG and ECG together can detect atrial fibrillation so using them both for ideal heart measurement (source 3)

The EDA sensors measure the changes in conductivity produced in the skin due to increases in the activity of sweat glands. They have a pre-conditioned analog output whose accuracy levels are medical-grade, and a high signal-to-noise ratio, meaning the noise is very minimal on the device. In choosing to implement the electrodes around the NeuroBoost band, we have the wires of the electrode converting from UC-E6 to USB-C, followed by plugging into the USB-C insert, followed by traces on the PCB routing the USB-C insert to a serial converter, which then sends the biometric data to our TTGO Micro-32 microprocessor (Fig. 2l). From here, the information gets processed in the Micro-32 and then sent to the optical ADE for additional amplification. With use of firmware algorithms, we can analyze this data to extract meaningful information about the wearer's emotional state by detecting patterns in the fluctuations of skin conductance over time, outputting stressed levels if the data has a large averaging of conductance or sharp changes over time or calm levels if there is a small level of average conductance or minimal sharp changes over time.

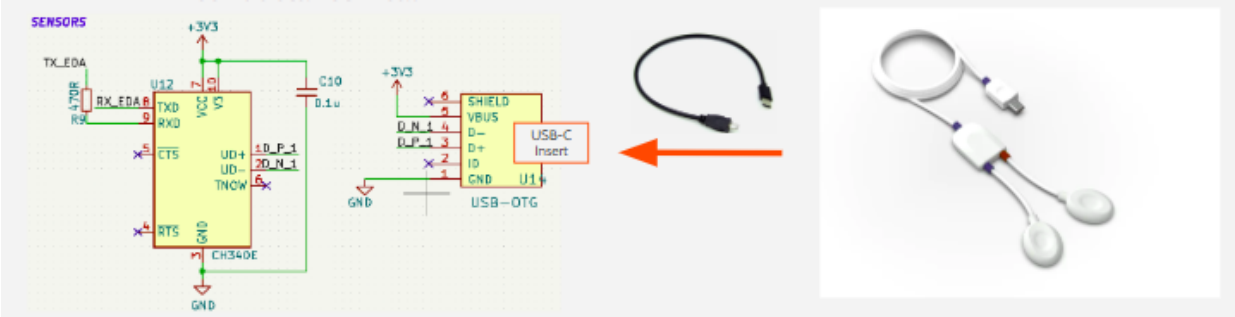


Figure 2l: Stages of interfacing with EDA electrodes, sending collected data from the electrodes (right) to the UC-E6 to USB-C converter to the USB-C insert to the USB-C to Serial converter to our TTGO Micro-32 microprocessor.

For our accelerometer, we chose the BMA400, which measures its own linear acceleration. In our firmware, we can use integration return velocity and further integration to return difference in position. The BMA400 communicates with I2C, which works with a clock line, a data line, and registers, in this device's case, providing data with a width of 12 bits at a time in registers. Registers are wire protected during a read access, meaning that its data content cannot be modified under normal operating conditions at this time, so it reads data in a single burst read. The boolean interrupt (INT) pin signals when it is time for the microprocessor to begin a single burst read. We coupled the BMA400 sensor with a bypass capacitor to stabilize the voltage level by filtering out high-frequency noise present and supplying instantaneous current to compensate for fluctuations in the main power supply caused by sudden changes in the load or by external noise sources. The wiring of the BMA400 accelerometer is depicted in Fig. 2m. This sensor offers the microprocessor more data on the linear movement of the user to rule out if the user's fast heart rate is due to physical movement as opposed to stress.

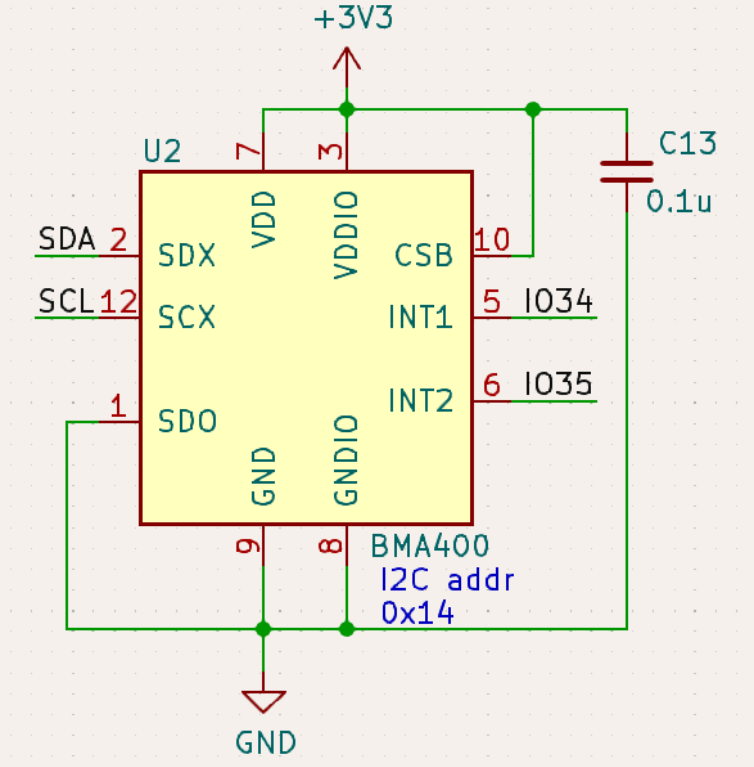


Figure 2m: Wiring of BMA400 accelerometer.

For our ECG/PPG sensor, we chose the BH1792GLC-E2 Heart rate/blood oxygen sensor, which receives data by taking in light from the body based on the changes of the blood flow in the wrist. IR detection photodiodes detect skin contact to obtain the pulse wave signal. The LEDs connected to the sensor light up based on the amount of light they receive from the blood flow in the wrist. Like the accelerometer, it uses I2C to communicate the date to the clock and data buses for the reasons that we mentioned in the *Biosensor Information Processin*g section, and uses an interrupt to begin reading the data. Similarly, it also has a bypass capacitor connected from the 3.3V input from the 3.3V voltage regulator output to GND for voltage stabilization through instantaneous current supply upon dips in voltage levels. We also have three LEDs connected to the LED outputs on the sensor, which internally connect to the LED drivers that use the data gathered from the change in blood flow to inform the brightness levels of the external LEDs

(Fig. 2n). Another reason why we chose this sensor was because it has First In, First Out (FIFO) memory, meaning that instead of sending all of the data to the microprocessor, it temporarily stores the data in its internal memory. This allows the sensor to continue capturing new data while the microcontroller processes the sent data. Also, FIFO allows for this data to be processed in the right order, which is incredibly important in our application as an error in the sequence of data can provide false sharp spikes in data, informing the processor that the user's heart rate is rapidly spiking when this is not the case. Our implementation for the BH1792GLC-E2 sensor is depicted in Fig. 2m.

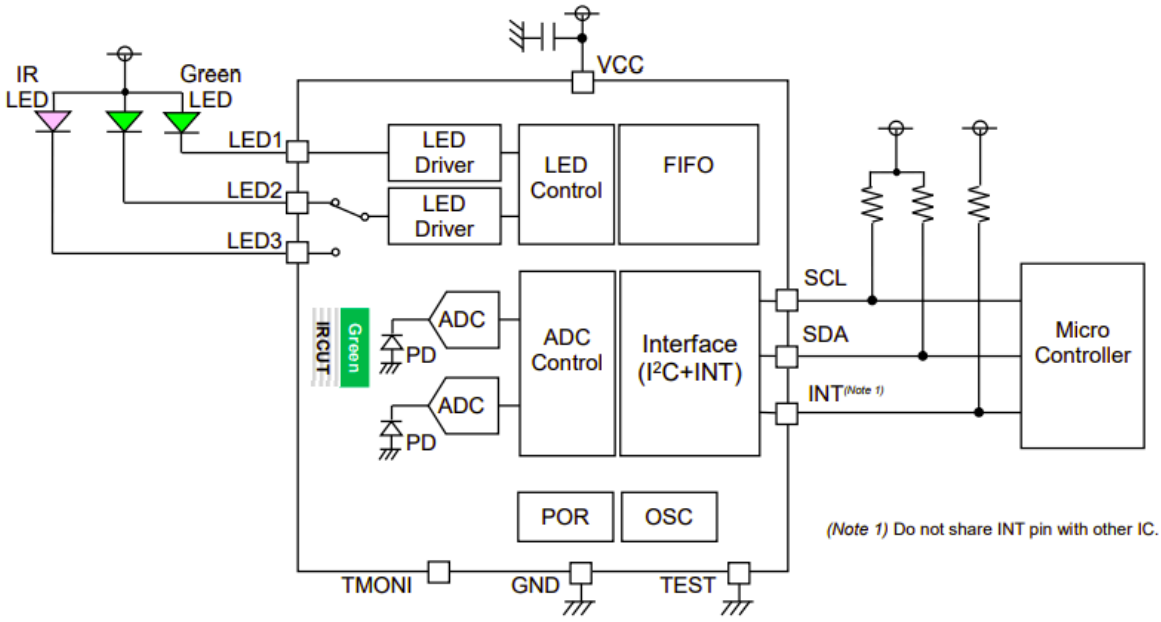


Figure 2n: Block Diagram of BH1792GLC-E2 PPG/ECG Sensor from Device's Datasheet.

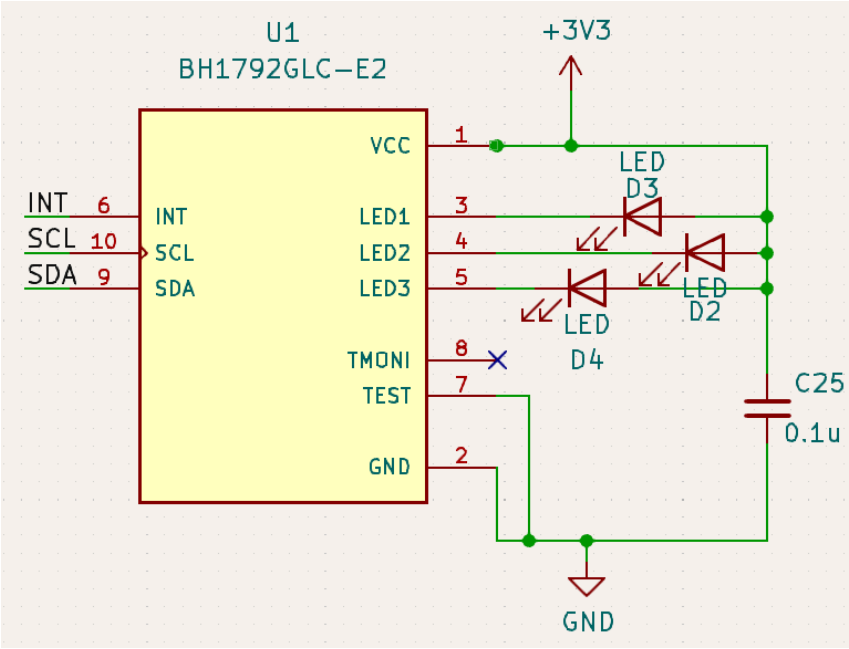


Figure 2m: Wiring of BH1792GLC-E2 PPG/ECG Sensor.

Sensors integrated into this system are summarized in the following table:

Sensor Type	Placement	Functionality
EDA	Back of watch face & within watch band clasp	Measures skin conductance which has been shown to have high levels of correlation with the alpha and beta bands of an EEG. This statistic is the input into a machine learning algorithm that correlates it to the corresponding EEG signals. (Lim et al., 1996)
Accelerometer	Within watch face	Measures acceleration which is convertible to fitness statistics (pedometer, miles walked, speed, etc.)
ECG	Back of watch face	ECG is the gold standard evaluation for heart rate measurement. It measures the electrical activity of a beating heart. 1-lead ECG will take measurements when prompted (Saarinen et al., 2023)
PPG	Back of watch face	Uses a light beam to continuously approximate volumetric changes in blood flow within the wrist which allow heart rate tracking (Castaneda et al., 2019)

The incorporation of EDA sensors with correlation to EEG readings creates a novel smart watch design. On its own, statistics about skin conductance can provide invaluable data with respect to the body's autonomic nervous system. This design will leverage both its stand-alone statistics as well as the proven correlation between EDA and EEG signals to provide insights into the connection between everyday activities (as recorded by the user), their neurological functions, and their physical exertion (recorded by the remaining sensors).

Despite recent promising research into optimizing EDA sensor signals through placement in areas besides the wrist, due to the widespread acceptance of wearable wrist technology and the aforementioned preference for it, a smart watch was chosen as the most marketable and precedented type of technology. (Hossain et al., 2022) As shown by a recent study, EDA sensors provide most optimal measurements when used in tandem on the dorsal surface of the wrist with 4 cm interelectrode spacing. (Anusha et al., 2021) For this reason, the EDA sensors of our design were placed on the back of the watch face and on the back of the watch clasp, spaced apart and both allowing for sensor-to-skin contact.

For a proof of concept prototype, we have selected to 3D print a standard watch face and band to visualize how the mechanical and electrical components of the design will fit together while maintaining the skin contact needed for particular sensors. The prototype allows the EDA sensors to extrude from the PCB on the watch face and the clasp in order to maintain skin contact. In order to ensure accurate measurements, users will need to wear the watch relatively tightly to ensure minimal movement. Future iterations of the watch will include an adjustable band size.

Similarly, the current prototype has a relatively large watch-face providing a housing location for the sensors and PCB. As iterations progress, the PCB will be refined and watch

shapes will be tested for durability, allowing the device to become a sleek screened face where the user can interact with their statistics.

Software Development

Mobile Application & Website Interface

The NeuroBoost mobile application and website are the primary interfaces for user interaction and data visualization. Future iterations of the current prototype will also have some features enabled on the smartwatch itself. Both the app and website platforms display a variety of physiological and cognitive data collected from the smartwatch sensors. Users can view historical data trends, receive personalized recommendations for cognitive enhancement, and manage settings for data collection and privacy.

Current features of the interfaces include a Personalized Dashboard that displays real-time and historical data on cognitive states, stress levels, and overall wellness. Several personalization settings are available for users to set preferences for data capture frequency, notification types, specific health goals, and consent-based wellness sharing opportunities with friends and family. A Recommendations Engine is also designed to offer customized, peer-review advice for improving cognitive function and managing stress, such as suggested breaks, mindfulness exercises, and physical activities.

Machine Learning Algorithms

The core of the NeuroBoost's software innovation lies in its use of ML algorithms that analyze data from multiple sensors to project patterns in brain activity. These algorithms are crucial for translating physiological signals and sensor readings into actionable cognitive

insights. Currently, a combination of Convolutional Neural Networks (CNNs) and Regressive Neural Networks (RNNs) are utilized to capture both spatial and temporal dependencies in the data. The integration of both CNNs and RNNs in NeuroBoost provides a robust framework for understanding both the spatial and temporal aspects of the physiological data. This dual approach allows the system to generate a comprehensive picture of a user's cognitive state and emotional health, based on the continuous stream of data collected from the smartwatch sensors. The machine learning framework not only projects what the brain activity might look like but also adapts and learns from the user's daily experiences and reported feelings, thereby enhancing the overall accuracy and personal relevance of its predictions.

Convolutional Neural Networks (CNNs)

CNNs are utilized in the NueroBoost system to process spatial patterns within the sensor data. The CNN's ability to handle multiple inputs simultaneously and recognize complex patterns makes it ideal for interpreting the intertwined signals that these sensors provide (O'Shea & Nash, 2015). For NeuroBoost, the CNN boasts feature extraction and data projection, where the model first efficiently identifies key features from raw sensor data which may indicate stress, relaxation, or other cognitive states. Then, the model projects these features into a format akin to EEG-like data, allowing the system to estimate brain activity without direct EEG measurements. This projection is refined continually via the RNN, thus ensuring accuracy and relevance to the user's current state.

Regressive Neural Networks (RNNs)

RNNs are successful in handling sequential data, thus making it a perfect model for analyzing temporal dependencies and changes in sensor data over time (Specht, 1991). Physiological responses can vary significantly across different times and situations, thus RNNs can be used to capture these temporal patterns and learn from them effectively. For NeuroBoost, the RNN enables temporal pattern recognition and feedback integration, where the model first recognizes and learns from the sequence of sensor data points collected over time, understanding how the user's physiological responses evolve in various cognitive and emotional contexts. Then, the model utilizes a feedback loop from users, who provide daily input about their activities and feelings. This input helps the RNN adjust its predictions, making the model more personalized and responsive to individual user needs.

Algorithmic Approach

The algorithmic approach begins with data preprocessing, in which the raw sensor data from the EDA, ECG, PPG, and Accelerometer sensors is first sorted and standardized to ensure quality inputs for model training. Feature Engineering is then the next step, which identifies and isolates features that strongly correlate with cognitive states and stress levels. Model Training then proceeds by utilizing the CNNs and RNNs to extract features from sensor data indicative of cognitive states or activities, thus creating a projection of EEG-like data, which captures brain activity. Then, the feedback loop integrates user feedback to refine model predictions, continuously improving and adapting to individual variability in physiological and cognitive responses.

Software Integration

Robust software architecture is required to seamlessly integrate the mobile application, web platform, and predictive analytics via the ML models. Data synchronization across these components will ensure that users have a cohesive and integrated experience, whether accessing their data via a smartphone or computer. Key integration points will include secure APIs for real-time data transfer between the smartwatch and the software platforms, ensuring data integrity and privacy. User authentication and encryption protocols will also be implemented to protect and secure user data. Cloud solutions for scalable data storage and powerful computing resources will be needed for machine learning operations.

Overall, the development of the NeuroBoost software components is guided by the principles of user-centric design, data security, and innovative use of technology. The integration of the app, website, and machine learning algorithms not only enhances the functionality of the NeuroBoost smartwatch but also empowers users to take proactive steps towards improving their mental health and cognitive function. This holistic approach to software integration and particular use of ML data modeling in neurotech sets a novel standard in the domain of cognitive-enhancing wearable technology.

Final Product

NeuroBoost inventively combines aspects of previous successful consumer technologies and new cutting edge research by leveraging a smartwatch platform to correlate skin conductivity to EEG sensor data. Sensors aside from EDA have been previously implemented in other platforms to successfully measure physiological data as mentioned in the introduction. NeuroBoost's novelty is derived from the unique back end machine learning processing,

converting EDA to EEG signals and correlating them with how to optimize a user's actions. The feasibility of developing these algorithms is shown by an array of past research showing the strong correlative relationship between the two and the abundance of data collected in the projected clinical trials to build and verify the accuracy of the device.

3. Experimental Trials and Expected Results

Validating the use of NeuroBoost data as insightful about the brain is ambitious. As such, several clinical trials would be run that would test the accuracy of the data produced by NeuroBoost. These experimental trials aim to bring in potential users of NeuroBoost and compare their monitored brain data while they use the device, in order to make later correlations between the data that each records. In essence, our watch claims that EEG, fMRI, and Eye-Tracking data can be detected by signals on a wrist, but in order to assess the reliability of this correlation, the following trial will be run.

1,000 participants representing a national distribution of Socio-Economic Status (SES), age, gender, and ethnic and racial identities will be recruited for the trials. Each subject will attend two sessions at their local NeuroBoost Labs twice. In each session, subjects will be tasked with a set of activities that target specific brain regions. This is done in order to monitor as many cortical areas as possible within the time frame of a session. Each session will contain the same tasks, but the specific content of each task will vary in order to maintain subjects engaged in the study. In the first session, brain and physiological activity will be measured by EEG, Eye-Tracking, a behavioral test, and the NeuroBoost standard sensors. In the second session, fMRI will replace EEG, and NeuroBoost's traditional sensors will be replaced by dry non-metallic sensors. The rationale behind having two sessions for each subject is the following: 1) attain greater data and resolution for the targeted brain regions across different days in order to minimize day-specific patterns of activity, and 2) enable the measurement of both EEG and fMRI across the same set of tasks and recruitment of brain regions, given that both cannot be employed simultaneously.

Experimental Tasks

The following tasks will be assigned to each subject on each session:

Movie-viewing with Natural Event Segmentation

This task involves participants watching a movie, which engages multiple sensory areas due to the audiovisual nature of the content. The task is particularly effective in stimulating regions responsible for processing visual and auditory information, as well as those areas involved in higher-level processing such as event segmentation and comprehension. Since event segmentation— which subjects will be tasked to actively engage in— occurs in a nested manner across cortical areas, it's a particularly insightful task to gain brain data when analyzed with models such as a Hidden Markov Model (HMM) (Baldassano et al., 2018).

Recognition Test

A recognition test will be conducted about the movie after watching, where participants will undergo a recognition test to identify scenes or elements from the film. This task primarily activates the perirhinal cortex, a region associated with recognition memory, especially for scenes, along with other memory-related areas.

Free Recall of Experimenter

Participants will be asked to "free recall" information about the experimenter without any prompts. This task predominantly involves the hippocampus, which is crucial for the retrieval of episodic memories and personal experiences.

Emotional Autobiographical Interview

During this interview, participants will discuss emotional events from their own lives. This introspective activity engages the Default Mode Network (DMN) and the amygdala. The DMN is involved in self-referencing thoughts and emotional reflection, while the amygdala handles the emotional aspects of many memories.

Time Rushed Arithmetic Test

This task requires participants to solve arithmetic problems under time constraints, which particularly stimulates the prefrontal cortex (PFC). The PFC is essential for problem-solving, decision-making, and working memory, especially under stress. It loads and unloads task sets, which serve as guides in the executive functioning of our immediate cognitive needs. It works like a gate (see: GateBoss), whereby useful information is let in and let out according to the loaded task. It's important to record this region in action, as it guides much of our action itself.

Emailing + Multitasking: Task-Switching

In this complex task, participants will manage emails while simultaneously engaging in other tasks, requiring constant task-switching. This activity extensively involves the PFC for managing multiple tasks and the medial temporal lobe for memory integration and retrieval.

All of these tasks have been carefully selected to engage specific brain regions known for their involvement in distinct cognitive processes, providing a comprehensive overview of brain function across different contexts and activities. Participants' brain data from both the EEG+ and the fMRI+ sessions will be fed into the NeuroBoost algorithm that will run the correlations to

understand how one of the measurement's activation patterns relate to patterns from the other measurement tools.

Data Analysis

The experimental trials are structured to synchronize the data collection from fMRI, EEG, Eye Tracking, and behavioral tests with NeuroBoost's sensor outputs at precise moments during each task. For instance, during the movie-viewing task, as subjects watch the film, both fMRI and NeuroBoost sensors continuously record data. This multiple-modality approach allows us to directly compare the brain activity captured by fMRI, known for its high spatial resolution, with the physiological data detected by the NeuroBoost at identical time points.

This direct comparison is key. In this case, it involves correlating the high-resolution images of brain activity from the fMRI scans with the patterns identified by the NeuroBoost sensors during the same tasks or stimuli. For example, when a participant experiences a particularly emotional scene in a movie, both the fMRI and NeuroBoost sensors capture information. Later, we can analyze how closely the changes in brain activity (as shown by fMRI) correlate with changes detected by NeuroBoost's sensors. Indeed, that's what we'll see later on in our expected figures.

By mapping these correlations across various tasks and all measurement types (including EEG, Eye-Tracking, and the different sensor modalities of NeuroBoost), we can develop predictive models (see Yu et al., 2016; Mele et al., 2019). These models, while not detailed in this section, would use NeuroBoost's sensor data to approximate what the fMRI would have recorded at that moment. A good correlation not only validates the efficacy of NeuroBoost's sensors but also enhances its predictive power for later use (as feedback). The ultimate goal is to

enable NeuroBoost to predict detailed brain activity that would normally only be visible via techniques like fMRI, solely based on sensor data.

Validation of Predictive Models

How could we test whether these predictive models actually work? By comparing the data collected by real spatially and temporally high-resolution imaging, such as fMRI and EEG, with the predictive model's prediction of the neural activity for those same imaging methods at the same moments within a task.

More specifically, we will be drawing from Representational Similarity Analysis (RSA) (Kriegeskorte et al., 2008), which is used in neuroscience to compare neural activity patterns across different regions, stimuli, or methods. In the way we intend to use it, it involves constructing a dissimilarity matrix that quantifies the difference between the average neural responses for a given moment in a task measured by fMRI/EEG/Eye Tracking and the neural responses "imagined" by the predictive model, all across nine different brain regions. RSAs are excellent for showing the spatial and temporal resolution and predictive accuracy of NeuroBoost.

Here, the expected findings from the RSA should show low dissimilarity scores when comparing only the same brain regions. It is also important to note that each dissimilarity matrix corresponds to a specific moment within a task, such as a scene during the movie-viewing task. Looking at a concrete example, let's examine this: if we're looking at a subject's brain during the second calculation of the arithmetic test task, and the EEG data from Region 4 and the predictive model's imagined data for Region 4 are similar, then the dissimilarity score will be low. This indicates high similarity between the activity measured, and the activity predicted, and shows high accuracy in the model's predictions specific to that region. This specific match is in fact a

very positive outcome, demonstrating that the device's predictions are region-specific and reliable. Conversely, if we observed low dissimilarity scores between different regions (e.g., fMRI data from Region 4 compared to the predictive model's imagined fMRI data for Region 8 for that same moment), it would suggest a lack of spatial specificity in the model. The consistency of low dissimilarity scores across the correct regions in all analyses, including fMRI, EEG, and Eye Tracking, would confirm NeuroBoost's high spatial resolution, underscoring its capability to accurately map and predict neural activities within the exact regions being studied.

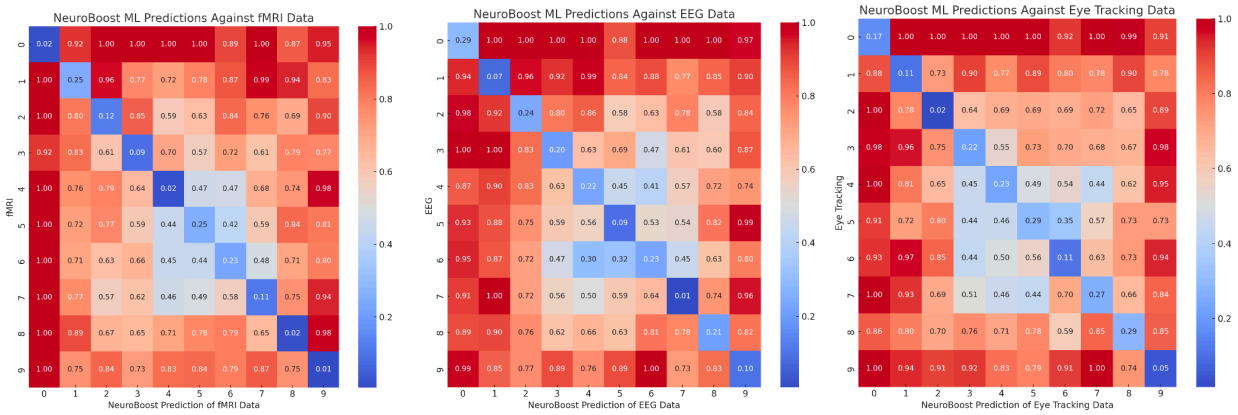


Figure 3a. - RSA Dissimilarity Matrix for a Given Episode.

Using the same method, we can assess the temporal resolution of the NeuroBoost predictive model. In order to achieve this, we would run a dissimilarity matrix, including all the same nine regions, between the neural data measured by EEG/fMRI/Eye-Tracking and the predictive model's prediction of the same— with one exception. Instead of comparing the same episode (moment within a task, such as a math question or a scene in the movie), the comparison is between an episode and its preceding episode. If this analysis yields similar results as the ones described above, then the model would have good spatial resolution, but the spatial resolution wouldn't be good enough to discriminate between activity across an event boundary. However, as seen in figure 3b, when running a dissimilarity matrix for two distinct episodes, any trace of

low dissimilarity for the same brain region would be expected to disappear. This would show that beyond being area-specific, NeuroBoost's predictive model only makes the right prediction at the right moment.

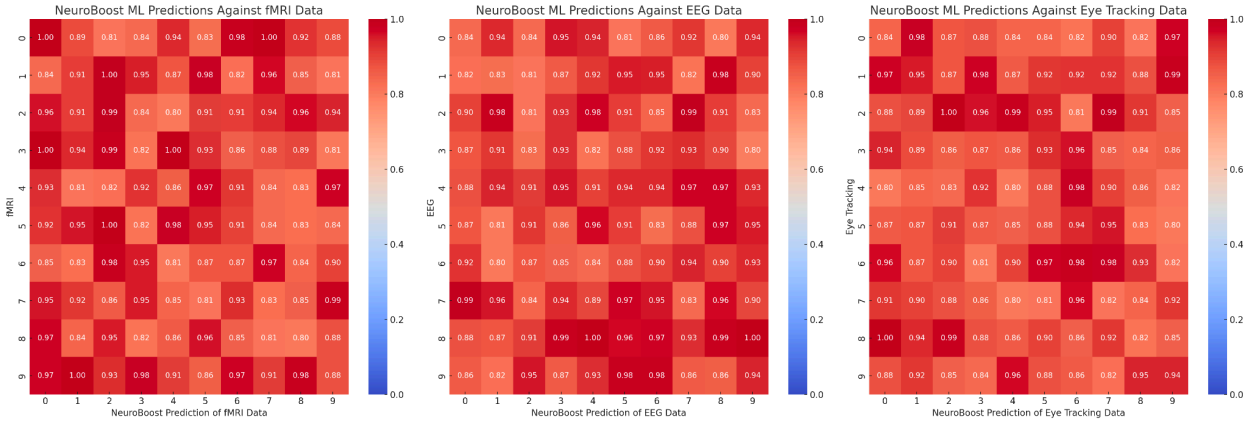


Figure 3b. - RSA Dissimilarity Matrix for Different Episodes.

The next statistical analysis we would run is a Bland-Altman plot (Bland & Altman, 1986), with which we aim to assess the validity of the NeuroBoost predictive model by comparing its output (its imagined values for specific episodes) with actual measurements from EEG and MRI data for those episodes. The Bland-Altman plot, a method typically used to measure agreement between two quantitative measurements, would help illustrate the extent of bias and the accuracy of the NeuroBoost model across various levels of neural activity.

We expect the plot to show most data points oscillating around the zero line, which would indicate minimal difference between the predicted values by our model and the actual neural activity recorded. This pattern should hold true regardless of the neural activity's "intensity", suggesting consistent model accuracy during both high and low activity phases. Ideally, the data points would distribute equally above and below the zero line, reinforcing the model's reliability

and unbiased nature (as opposed to the model consistently predicting higher activity than that actually measured, for example).

Furthermore, we plan to establish operational limits on the Bland-Altman plot, essentially setting subjective thresholds within which the data points should fall in order for the model to be deemed useful. These limits will define the acceptable range of variance, and we hypothesize that the majority of data points will reside within these boundaries, supporting the model's precision. Should this be the case, the accompanying 95% confidence interval, statistically derived from the plot's data points, would likely fall within or close to the operational limits and confirm that our model accurately reflects actual brain activity.

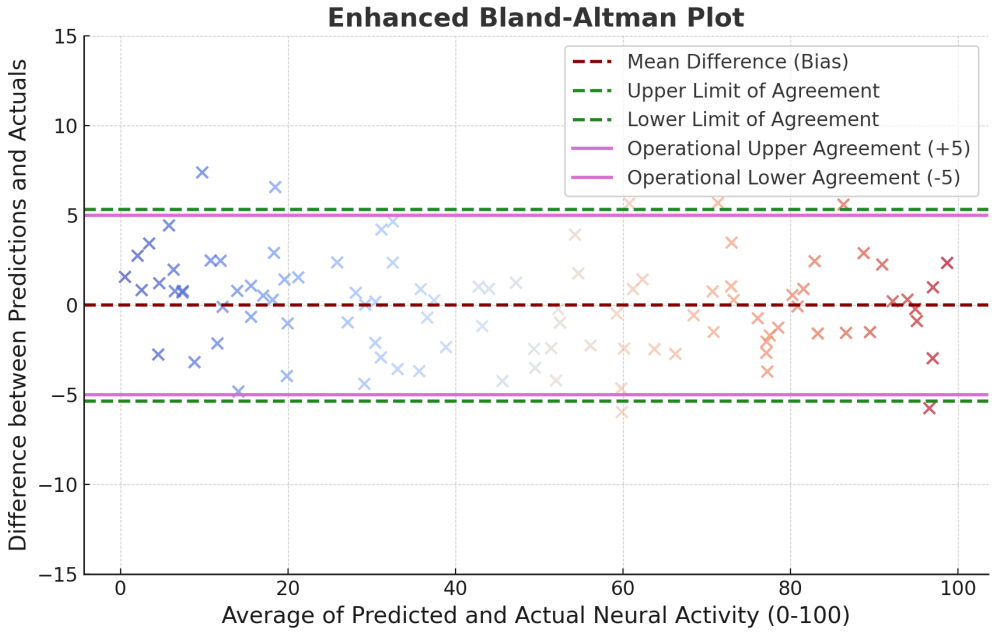


Figure 3c - Bland-Altman plot showing difference between measurement and prediction across activation intensity levels.

Data collected from clinical trials would be used in establishing a robust baseline understanding of neural activity across tasks and regions. This data would only be drawn from upon clinical trial users' consent. To enrich and personalize the accuracy of the baseline's general predictions, it is envisioned that new users of NeuroBoost devices would participate in an initial 'fitting' session at their local NeuroBoost lab partner. Here, their brain activities would be mapped and compared against the baseline data derived from the clinical trials in order to tailor the algorithm and ensure that each user's NeuroBoost device is finely tuned to their unique neurological patterns. Moreover, ongoing collection and integration of data— upon consent— from these individual sessions would continuously refine the general predictive model, enhancing its sensitivity and accuracy for all users. This iterative process, rooted in a strong initial dataset and enriched with each new user's data, would ideally lead to a highly accurate and responsive tool capable of detecting nuanced patterns and changes in brain activity. This would allow for the model's independence of fMRI measurement eventually, which is costly and leads to overall increases in price and subsequent decreases in accessibility for the product. This is partially possible due to recent findings that people's neural representation of semantic events and information is region-specific across people (Zadbood et al., 2017), essentially suggesting that people represent information about the world in the same parts of their brains, countering the belief that every brain is idiosyncratically wired and activated. Given these results, by integrating rigorous clinical methodologies with advanced algorithmic analysis, these trials will significantly enhance the NeuroBoost's capability to provide accurate and personalized cognitive insights, possibly requiring less scanning than expected.

4. Results

Physical Prototype

The final prototype design of the NeuroBoost is presented in Figures 2-4. Figure 2 shows the top side of the overall watch, whilst Figure 3 depicts the bottom side of the overall watch. The key features in Figure 3 are two EDA sensors in direct contact with the user's skin, one on the watch body and the other on the strap. Finally, Figure 4 portrays a close up of the internal PCB within the watch body. The details of this PCB are available in the next section of this paper. The entire prototype was 3D printed with PLA filament, including the monitor screen, the PCB and most importantly the EDA sensors. This physical prototype was provided at the final presentation to allow for the most direct and intuitive understanding of the NeuroBoost product by the audience.

Figure 2: Top view of the NeuroBoost.

Figure 3: Bottom view of the NeuroBoost.

Figure 4: Zoomed-in view of the NeuroBoost PCB.

Future Improvements

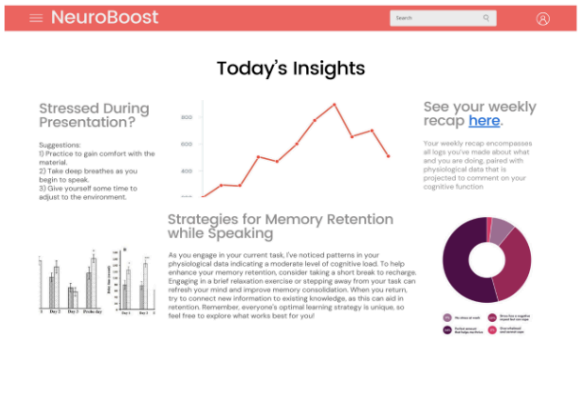
It should be noted that this design is solely a prototype at this current stage of development. Therefore, there is significant scope for improvements in the future. As highlighted earlier, the primary focus of this physical design is to optimize sensor measurements, in particular through the EDA electrodes. There is still capacity for the electrode separation to be optimized, with the potential to implement them at any location throughout the entire length of the strap instead of just at the bottom. Furthermore, there may be improved performance by implementing a larger number of electrodes, as opposed to just two. Similarly, the material of the electrodes could be explored to achieve better electric conductance with the user's skin. However, there must also be consideration for the possibility of electrical interference with other components on the watch.

Software Interfaces & Validation of Predictive Modeling

The current software iteration of the NeuroBoost interfaces consists of wireframes and intended testing methodologies to improve the front-end and back-end of user experience and interaction.

Mobile Application & Website Interface

Current wireframes for the two interfaces are the foundation for visualizing the user interface and user experience (UI/UX) design. These wireframes are instrumental in outline



Website Dashboard | **Mobile Dashboard**

the structure and flow of interaction within the app and website, providing a clear map of how features are organized and accessed by users.

The website wireframe is designed to provide a comprehensive overview of the user's health data and cognitive trends over time. It features an expansive layout that includes detailed charts and graphs for an in-depth analysis of cognitive states, paired with educational content to help users better understand their data. The website is optimized for accessibility across both desktop and mobile platforms, ensuring that users receive a consistent and seamless experience regardless of which device they use. This current design enables users to track their progress and set health goals, while gaining insights on their cognitive and emotional health.

The mobile application wireframe offers a more focused and streamlined user experience tailored for on-the-go interactions. The mobile app features a home screen that provides a summary of daily cognitive and emotional health metrics, along with quick navigation options to historical data and personal settings. Detailed pages within the app will allow users to view specific health insights and receive personalized recommendations based on their data. The mobile app is designed with user convenience in mind, placing essential health management tools at the fingertips of the user, thus promoting regular engagement and proactive health management.

Together, these wireframes lay the foundation of NeuroBoost's user interface design, aiming to enhance user experience by providing intuitive navigation and meaningful health insights on both platforms.

Software Testing & Validation

Usability tests for the NeuroBoost project are to be designed to further evaluate the effectiveness and user-friendliness of the app and website interfaces, as well as the accuracy and responsiveness of the back-end machine learning algorithms. This step is a critical component in the development of the product software, as they are designed to assess several facets of user interaction and algorithm performance, providing crucial insights that will guide the iterative refinement of the system. Expected outcomes of these tests will highlight user engagement challenges and accessibility issues which can be refined in the next iteration of the software.

Similar testing for the ML algorithms will focus on the accuracy of predictions and adaptability of the models of new data and user feedback. This involves particularly assessing how well the CNNs and RNNs process and interpret physiological data from sensors to predict cognitive and emotional states. The tests will validate the precision of the models against controlled conditions and measure their ability to learn from ongoing user interactions to enhance their predictive accuracy over time. These insights are expected to validate the algorithm's theoretical effectiveness, thus guiding further development to ensure they meet practical needs and provide meaningful insights to users in the real-world application.

5. Discussion

Product Challenges & Limitations

Integration of EEG-Like Functionality

One of the primary challenges faced during the development of NeuroBoost was the integration of EEG-like functionality onto a wrist-worn device. Traditionally, EEG measurements require extensive electrode setups across the scalp and forehead to accurately capture brain activity. To address this challenge, we pivoted from direct EEG integration to leveraging a combination of other biometric sensors: EDA, ECG, PPG, and accelerometer, which could indirectly provide insights of cognitive activity.

Machine Learning for Data Synthesis

Inspired by the research conducted by Poh et al. (2012), which demonstrated the utility of wrist-worn sensors in monitoring autonomic changes associated with seizures, NeuroBoost seeks to extend that approach to broader cognitive monitoring. In the Poh et al. study, wrist sensors effectively recorded EDA and heart rate variability, parameters that indirectly correlate with brain activity during and after seizures[1]. This concept was a foundation in our development, and we employed machine learning models to project EEG-like data. Several models and algorithms were subject to review, and a combination of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) were determined to best model the relationship between the sensor data and expected EEG results. These models were selected for their ability to handle large data sets and success in learning complex patterns in physiological data, thus rendering them ideal for predicting neurological conditions from physiological measurements.

Sensor Calibration & Data Integrity

Ensuring accurate and consistent sensor readings is paramount to project success, as the data offers crucial health insights. The project must implement rigorous calibration procedures during initial setup and regular monitoring throughout the device's operation. These steps will be essential in maintaining data integrity and ensuring the reliability of the health insights provided.

By the same respect, the machine learning models implemented require substantial volumes of high-quality training data. To secure such amounts of data, the project must undergo thorough clinical trials and gain access to anonymized physiological and neurological data to generate trends and patterns. This arrangement will allow for the predictive models to be accurate and reliable, while maintaining diversity in the data set to reflect a broad spectrum of physiological and cognitive patterns.

User Comfort & Device Aesthetics

Integrating multiple sensors into a single wearable device introduced design challenges in assessing the tradeoff between functionality and comfort. The sensor layout was optimized to be lightweight and comfortable for the user, and future iterations of the current prototype will utilize skin-friendly materials that also preserve the product's functionality, comfort, and aesthetic.

Comparison to Existing Technologies

Despite the limitations and challenges, NeuroBoost introduces a novel approach in the wearable technology landscape by implementing EEG-like projections to monitor cognitive functions, setting itself apart from existing devices that typically rely on direct EEG measurements or other physiological sensors. This innovative approach utilizes a combination of

other biometric sensors (EDA, ECG, PPG, and accelerometers), which collectively contribute to creating a sophisticated model of the user's brain activity without the need for cumbersome EEG setups. This methodology not only simplifies the user experience but also expands the practicality of cognitive monitoring to everyday wear, making advanced neurological insights accessible and actionable in real-time through a user-friendly smartwatch interface.

Compared to existing technologies reviewed in our literature, such as EEG headbands or dedicated medical devices that directly measure brain activity, NeuroBoost offers a unique blend of convenience and functionality. For instance, while traditional EEG devices provide detailed brain activity monitoring, they are often limited by their intrusiveness and are not suited for continuous, long-term wear outside clinical settings. NeuroBoost resolves these limitations by approximating EEG data through machine learning, thus providing users with valuable insights into their cognitive state without the typical constraints of EEG devices.

The integration of machine learning algorithms enables NeuroBoost to not just passively monitor but actively predict and respond to cognitive patterns based on the aggregated sensor data. This predictive capability is a significant advancement over other wearables, which are generally limited to simpler health metrics. By leveraging these algorithms, NeuroBoost can first create EEG-like projections using physiological data, then offer personalized suggestions for cognitive enhancement and stress management, positioning it at the forefront of a new generation of wearables that do more than just track physical health - they enhance mental well-being and cognitive performance. This strategic use of EEG-like projections in place of direct EEG measurements allows NeuroBoost to maintain a balance between user accessibility and sophisticated functionality, pushing the boundaries of what wearable devices can achieve in terms of cognitive health monitoring.

6. Global Impact & Market Readiness

Potential Global Impacts

Wearable technologies like smartwatches come with many benefits as they help users track their data throughout their day that they may then use to make decisions about their health and lifestyle. As smartwatches become increasingly prevalent for consumers, they are likely to have a higher impact on social behaviors (Lu, 2024). For instance, some apps associated with current fitness trackers integrated in smartwatches encourage users to connect their data with other users they may know, adding a social aspect to wearables that supposedly motivates users to stay on track with things such as step count goals, and allows them to challenge friends and family members to complete new fitness goals in an interactive way (Samsung). This type of sociability feature is one that could be implemented in future iterations of our website and application, inspiring social connections over fitness-related performances by our product, similar to previous smartwatch models. Concerns have been raised regarding this digitization of lifestyle and social interactions. For example, consumers may opt to exercise independently and rely on digital data sharing rather than in-person interactions for social activity and staying connected with others. Realistically, this is a matter of user preference and increases convenience of social exercise habits when obstacles such as distance or timing arise, enhancing social landscapes. We trust that consumers will maintain the level of in-person social activity and availability that they prefer, even when presented with a digital option. Other concerns include how a user may establish their digital wellness data as a so-called personal narrative that they fear shifting from (Lu et al., 2024). It is true that in one study, smartwatch users cited feeling pressured to conform to standards set by their wearable technology (Lu et al., 2024). To overcome the risks associated with this, users of our device will be encouraged to set goals that

are useful and realistic for their preferred lifestyle, so achieving these goals will largely benefit them and will not lead to overexertion for the sake of fitting a pre-established expectation that is not practical for the user.

Data collected by wearables in addition to fitness tracking often correlates to data that may be collected in a clinic, for example, an ECG. Importantly, a smartwatch is not a replacement for clinical testing. Research in the past has indicated that data collected by a smartwatch, compared to clinical test data, had some areas of advantage, namely, it can collect continuously, allowing understanding of what may be occurring at different times of day or when not in a stable environment such as a clinic (Dunn et al., 2021). However, certain types of information can be less accurate when obtained by a smartwatch instead of tried and true testing devices found in medical settings (Dunn et al., 2021). As such, current smartwatches are not considered medical devices, nor do they qualify as collecting health data (Niskirat et al., 2024). Instead, it has been proposed that information measured by a smartwatch may be voluntarily offered to a medical professional if concerns arise as an early warning sign, and users along with physicians may use or discard this data in establishing health and wellness plans as they deem fit (Olsen, 2021). In the future, as sensors develop greater accuracy capabilities, it may be possible to integrate smartwatch data more firmly with medicine, but current models do not serve this purpose. Thus, our goal is not to collect medical data, rather to provide approximations about users' physical state throughout their day that they may choose to make unbiased decisions about.

In order to allow for such approximations, wearables must store a large amount of user data. Inherent in the storage of user data comes concerns regarding third-party usage. Wearable tech currently on the market, including smartwatches, have a wide range of sensing abilities,

including geolocation and heart monitoring, for example. Current legislation prevents privacy breaches to only a limited extent (Gutierrez, 2022). Unlike a true clinical setting where doctors are prevented from disclosing medical information without explicit patient consent, companies that develop wearables are within their rights to freely share the data they collect when it is not considered health data (Gutierrez, 2022). Typically, information gathered from a wearable, including data that may be considered sensitive and may be used to make inferences about health, can be sold for profit to third-party sources (Gutierrez, 2022). Throughout the development process, we are dedicated to providing the best possible user experience, and thus will only store user data for the purpose of providing information about lifestyle to the user. However, this represents a bigger problem in the realm of wearable technology. Data collected by a wearable is not currently regulated in a similar fashion to data collected in a medical setting (Niksirat et al., 2024). Regardless, third parties are capable of drawing conclusions about user data that a user may not be aware of or comfortable with, and that may pertain to a certain health landscape. The definitive solution to this issue is a more stringent policy regarding usage of data collected from wearables, which is, unfortunately, beyond the scope of this project, but an important area to be aware of throughout the development and implementation process. Respect for client satisfaction and confidentiality is a value we take seriously as we develop our device.

Studies have found that there are a very wide range of risks associated with security and privacy when using wearable technology. A primary reason for this is a lack of awareness of potential uses for wearer information (Niksirat et al., 2024). The exchange of personal data may often be unknowingly consented to by users, as informed consent documents (such as “Terms and conditions”) are lengthy, jargony, and inaccessible to a standard consumer. We are committed to transparency, and aim for straightforward communication with anyone who may be

entrusting the device to measure their personal information. Future iterations of our product aim to collect several different types of data, and users will be presented with the choice to opt in and out of collection and storage services, where possible, in an easy- and quick-to-read dialog.

Importantly, the design of most wearable devices leads to the device being susceptible to security breaches (Niksirat et al., 2024). Low computational power and high cost of security enhancement are cited as potential causes of security failings in wearable technologies (Niksirat et al., 2024). These factors pose another significant risk for privacy violations for users. Those who are consenting to the use and storage of their personal data should be made aware of the inherent risks associated with the use of their devices. This risk is also encountered in other wearable devices designed specifically to collect health data, cementing it as a broadly applicable flaw in the current model of wearables that passively collect sensitive personal data (Mukhopadhyay et al., 2022). While there is no guarantee that this will pose a challenge for the development or even the application of our product, the inherent risks associated with the security of wearable devices is a concern that we will take into account throughout future iterations in the development process.

In addition to augmenting smartwatch technology, our product builds upon existing EEG technology. While not taking EEG measurements directly, our machine learning algorithm is intended to map skin conductance signals onto an expected EEG reading. This will provide widespread remote access to approximate EEG data, which is, as of yet, restricted. In fact, examples like the COVID-19 pandemic highlight the importance of remote options for acquiring medical data (Freund & Feyissa, 2022). In a resource-limited environment such as that of the pandemic, EEG-based healthcare is forced to grind to a halt (Freund & Feyissa, 2022). Thus, large populations of patients, including those with epilepsy or experiencing other forms of

seizures would have lesser access to diagnostics to help patients manage their condition (Freund & Feyissa, 2022). To address this, Neuroboost offers access to approximations of EEG readings on a broad scale. While this cannot be asserted as foolproof medical diagnostic data, it offers users and physicians an alternative route from which to proceed in understanding user circumstances when classical methods of EEG are not available.

This will also be useful for more widely applicable examples of difficulty accessing EEG-related care, such as for users who are located inconveniently or inaccessibly far from centers that could take EEG measurements. Another reason why patients may be discouraged from consistent EEG care is the difficulty of the procedure. Even a simple EEG involves bulky headgear and asks that the patient remains as still as possible for a lengthy amount of time (Rayi & Murr, 2022; Casson, 2019). This lack of convenience is remedied by our device taking the form of a wristwatch that measures as you perform regular, unrestricted daily activities. In addition, because our technology is designed to collect data continuously, it is able to detect a far greater amount of signal than typical EEG may, which paints a more complete picture of the user's physiological state than when they enter an artificial environment for testing during a limited time window. With this, a user may catch on to compelling data points that they may wish to address with a physician earlier on than if they rely solely on results taken in a testing center. Altogether, our device will significantly improve access to physiological data about a user, which may otherwise go undetected, that can assist in making health and lifestyle decisions.

Intended User Experience

Patient empowerment has been well discussed in the literature of clinical outcomes. The most commonly cited definitions of patient empowerment indicate that "Patient empowerment

starts from the principle of one's inherent capacity to be responsible for one's own life, and can be described as a complex experience of personal change, possibly facilitated by health care providers" (Tang et. al. 2010). Other researchers have proposed that patient empowerment encompasses activities that foster self-management (Werbrouck et. al. 2008). Participatory health informatics (PHI) considers the role of technology in assisting individuals with self-management and decision-making by also improving health literacy and the physician-patient relationship so that individuals can become more involved in the aspects of their health and care (Werbrouch et. al. 2008). Historically, research in the PHI field has predominantly been based on social media and internet-based applications, with patient empowerment having been identified as the most common theme in this body of research (Denecke et. al. 2020). However, wearables are just beginning to be considered as part of PHI given recent technological advancements (Denecke et. al. 2020). Therefore, similar research is now required to examine whether wearables can empower individuals in ways similar to those mentioned earlier regarding domains such as self-management, decision-making, and the physician-patient relationship. Integrating data from wearable technology into the biopsychosocial model of holistic well-being offers a comprehensive approach that considers biological, psychological, and social factors in patient care and life improvement that can be paired with PHI in Neuroboost's system of care. This model emphasizes the importance of treating the whole person rather than just the symptoms of a disease and is often used as a treatment plan for social work, clinical psychology and healthcare professions. Integration through wearable technology can significantly enhance this model, especially in the domain of mental well-being, as emphasized in the Neuroboost product.

Consider how Neuroboost tracks various physiological and activity metrics, such as heart rate variability, sleep patterns, and physical activity levels, all of which can provide insights into

a user's health. Consider also how Neuroboosts EEG-emulating data can provide those same metrics on mental health. Both psychological and physical data becomes accessible in improved ways, as well as opening up the possibility for improved relational dynamics. Here, data integration can foster a supportive social environment, which is crucial for mental well-being. If a patient sets goals related to improving their mental health (e.g., regular meditation, achieving better sleep patterns, or more daily physical activity), these goals can be shared with friends and family through a connected app. As friends see these goals and the patient's progress, they can offer encouragement and support. The feedback of continued user engagement, community support and data-gathering improves continued, data-backed experience with the Neuroboost product in which the algorithm can be tailored to best reproduce those positively-correlated actions that lead to improved wellness.

This social interaction has multiple benefits, namely in encouragement and Accountability where friends cheer on the patient, boosting their motivation to pursue and achieve set goals, and providing a sense of accountability. In addition, social touchpoints increase alongside clinical touchpoints with increased interactions with friends and family can combat feelings of isolation or loneliness (a common symptom in many mental health conditions). In addition, user engagement and compliance is improved with positive reinforcement where achievements, even small ones, can be celebrated within the patient’s social network, providing positive reinforcement that is essential for building self-esteem and promoting mental well-being.

Integrating wearable technology data into the biopsychosocial model highlights Neuroboost’s unique holistic patient care model by leveraging biological, psychological, and social insights that aligns with goals of current health and wellness practitioners. This integrated

approach, particularly when combined with supportive social interactions through technology, can significantly improve the management and outcomes of mental health conditions as well as physical conditions. It aligns with modern healthcare strategies that emphasize preventive care and the active involvement of patients and their communities in the health management process, and demonstrates Neuroboost's unprecedented commitment to holistic data improving the lives of individuals in complete and holistic ways.

Scalability & Market Readiness

The integration of wearable technology into healthcare has paved the way for Neuroboost to capitalize on existing frameworks. Clinical, legal, market and technology pipelines have shown the promising potential in healthcare-focused wearables improving patient outcomes, enhancing preventive care, and facilitating more personalized medicine (Lu, et. al. 2020). Through utilization of this existing research and market footprint of consumer wearables such as Fitbit, several key categories are emphasized for improved functionality and scalability for users of Neuroboost.

Remote Monitoring and Chronic Disease Management in current clinical trials data provide a powerful repository of valuable user feedback that wearable devices can effectively monitor conditions such as diabetes, cardiovascular diseases, and respiratory disorders outside of clinical settings. This remote monitoring capability enables continuous care, allowing healthcare providers to adjust treatments based on real-time data, but also allows users a key interaction with their own data. This provides both Predictive Analytics, as well as potential for improving user compliance with better health outcomes. Utilizing AI to analyze collected data and provide personalized health advice and alerts. For example, if the device detects signs of an impending

health issue, it could advise the user to take specific actions or consult their doctor. The user interface could adapt based on the user's interaction patterns and health literacy level. For those who need simple interfaces, it could show basic health information, while for more tech-savvy users, it could display detailed data analytics. While the focus of such devices in the clinical setting are increasingly equipped with sensors and AI-driven analytics to predict health events before they occur (i.e. algorithms can analyze data from heart rate variability (HRV) to predict the risk of cardiac events), they can greatly help in the overall engagement and compliance with potential health responses. This goal also includes making devices more comfortable, ensuring longer battery life, and developing intuitive user interfaces that provide actionable health insights that increase likelihood of user response. Iterations in the hundreds of several controlled trials could be used to feed our algorithm enough user feedback to tailor device reminders and responses towards this end.

In addition to user experience, existing clinical data provides additional benefit to the rolling out of Neuroboost. Integration with Healthcare Systems research also emphasizes the integration of wearables into existing healthcare infrastructures, abiding by HIPAA, and tested within live hospital networks, minimizing cost and time to implement. Incorporating advanced encryption and user consent protocols directly into the device's architecture to address privacy concerns effectively can be applied in similar methods as to what current health records protocols at existing hospital networks provide (Wiljer, 2008). This data allows us to develop standards and protocols for data sharing between wearable devices and electronic health records (EHRs) at a fraction of the time required by most startups in a similar market, with compliance standards met in a tricky market such as those that deal with immense privacy concerns. This also allows seamless integration into improved healthcare pipelines where users data can be

easily integrated into EHRs, allowing healthcare providers immediate access to the user's updated health status. Feedback time for both parties is decreased, and touchpoints (a common metric in healthcare standards) are increased, allowing for greater accessibility to one's health, health data and improved health care outcomes.

While considerable literature findings suggest that wearables can empower individuals by assisting with diagnosis, behavior change, and self-monitoring, greater adoption of wearables and engagement with wearable devices depend on other factors as well, including promotion and support from providers to encourage uptake, increased short-term investment to upskill staff, especially in the area of data analysis, and overcoming the barriers to use, particularly by improving device accuracy. Acting on these suggestions will require investment and constructive input from key stakeholders, namely users, health care professionals, and designers of the technology, though with help from existing frameworks as a launch point for improved success.. As advancements in technology to make wearables viable health care devices have only come about recently, further studies will be important for measuring the effectiveness of wearables in empowering individuals. Nevertheless, a significant challenge will be in the publication of research to keep pace with rapid developments related to wearable health technology.

7. Conclusion

Product Summary

The NeuroBoost project significantly advances the field of wearable technology and healthcare by integrating EEG-like projections into a consumer-friendly smartwatch, effectively bridging the gap between advanced health monitoring and daily usability. This innovative approach not only enhances the functionality of wearable devices by providing non-invasive, continuous cognitive health monitoring but also democratizes access to sophisticated health metrics, empowering users to manage and improve their cognitive functions in real-time. By utilizing indirect EEG-like data combined with machine learning algorithms, NeuroBoost offers personalized insights and actionable recommendations tailored to individual physiological patterns, thereby promoting a proactive approach to mental health and cognitive performance. The project's emphasis on user-centered design ensures that this advanced technology is accessible and practical for everyday use, encouraging widespread adoption and sustained engagement. Overall, NeuroBoost's contributions to wearable technology for improved cognitive function are transformative, marking a significant step forward in integrating cognitive health insights into everyday life, thus fostering a healthier, more informed society.

Future Work & Next Steps

Similar to any novel technology, this device has significant room for future development. The current prototype model allows for basic functionality but disregards comfort and style. In order to appeal to a wide range of users, sleek, comfortable, and adjustable watch bands would be integrated into the first version of the watch that goes to market. This is necessary not only to match any individual’s style, but more importantly, since EDA sensors require skin contact, an

effective version of the watch would need to closely match a user's wrist size while maintaining constant known distance between the sensors for backend calculations. As such, bands would be sold in varying sizes, while each size will have a small range of adjustability for fit and comfort.

Furthermore, our current mock-ups of the watch are bulky and unrefined. A commercial version of the watch would face electronics miniaturization as well as a more sleek watch shape to encourage users to incorporate this wearable device into their everyday life.

With regards to watch functionalities, future developments would focus on optimizing the data provided to the user. This would include backend improvements to machine learning algorithms as more data sets are acquired for both learning and testing purposes. Furthermore, recent studies have questioned the ideal placement for an EDA sensor to render the most clear cut data. One such study claimed that sensor placement on either the base of one's fingers and the foot would provide improved readings as compared to the wrist. (Hossain et al., 2022) As such, further research should be done to evaluate the utility of implementing remote sensors within athletic tape or ring wearables for the hands or attachments to socks for the feet.

It is worth noting that the success of this groundbreaking integration of EDA sensing and wearable technology hinges on the fact that EDA and EEG signals can be successfully correlated, as has been shown in research. However, due diligence on the effectiveness of correlating an individual's EDA signals to a projected EEG reading based on an algorithm trained with data sets from experimental trials (discussed in further detail in section 3) may or may not be entirely accurate. For more exact data extraction, the use of actual EEG technology would be ideal to provide correlations more specific to input based on each individual user. In which case, an EEG cap or headband, made for use around the user's house, could extract data with greater specificity to neuronal groupings and their particular neurological functioning.

Depending on the efficacy of the machine learning algorithm, this may prove to be repetitive and unnecessary to accurate readings; however, in the case that these correlations vary based on each individual or that EEGs still provide a greater level of detail, they may improve the accuracy of the device for the user.

Furthermore, data extracted from the EDA sensors within the wearable device could be optimized to provide a clearer correlation between skin conductivity and neural activity. Currently, EDA sensor quantity and placement (as previously discussed) is derived from an array of previous studies. However, for the specific application of the watch, observing how many sensors and what locations they are placed in gives the most consistent EDA readings could improve the performance of the overall system.

Neuroboost uses an array of sensors (PPG, EDA, ECG, Accelerometer) to correlate your mental and emotional state to your physical state through measurements of heart rate, physical activity, stress monitoring, and neural activity. However, there are an array of further biomarkers that could be implemented to further optimize a user's tracking of their mental and physical health. The Accelerometer, already implemented into other wearable systems, could be used to extract sleep data, specifically length of deep sleep cycles, based on user movement or lack thereof.

Moreover, as previously described, Oura Ring implemented a body temperature sensor which provides a check as to how the body is reacting in response to physical activity or falling ill. (Oura, n.d.) Furthermore, accurate measurement of body temperature allows for menstrual cycle tracking which is more accurate than the traditional diary tracking (specifically for users with irregular menstrual cycles or unregulated hormone activity). (Yu et al., 2022) Still, body temperatures can fluctuate as a result of environmental factors or physical activity so a direct

measure of hormone fluctuations would provide optimal cycle tracking. Recently, Ye et al. developed a reusable hormone sensor which measures estradiol in the skin. (Ye et al., 2024) As this technology develops, implementation into the wearable device would allow users to access trends on how different phases in the menstrual cycle impact their mental and physical functioning.

Finally, in future iterations (and following necessary approvals), interfacing the NeuroBoost with doctors' offices would allow for quicker diagnostics and improved efficiency in monitoring of a variety of neurological conditions such as migraines, dysautonomia, epilepsy, sleep conditions, and brain tumors, which cause fluctuations in the readings of EDA sensors or the resulting derived EEG data. Furthermore, with patient consent, neurological patients whose EDA and EEG data was taken constantly could provide a copious amount of data applicable to an array of research topics. By creating an interface with doctors' offices, this data (at the discretion of the user) could be shared with clinical researchers studying these disorders.

8. References

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