The development of a PPG and in-ear EEG device for application in fatigue measurement

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***Abstract*-The need for proper fatigue detection and mitigation is made clear in research, with failure to detect fatigue resulting in significant societal health repercussions. Currently, there are limited hardware systems dedicated to the monitoring of fatigue-related biometrics. The devices that do attempt to provide this information are often impractical due to their size, required expertise and cost constraints. Access to these technologies by a broader population is therefore limited. Wearable health devices could provide a more practical solution. A data capture system was designed and implemented that records PPG and in-ear EEG information. The device was created to be inexpensive and portable. The in-ear EEG results obtained showed the detection of a statistically significant difference in alpha attenuation levels, which are closely associated with the state of alertness or drowsiness. While the acquired heart rate and blood oxygen saturation measurements showed a close correlation with an FDA approved pulse oximeter. Although the number of trials conducted was limited, the results show promising performance. This project is a stepping stone in the pursuit of an affordable fatigue monitoring solution that can mitigate the human-cost incurred on account of fatigue.**

I. INTRODUCTION

Fatigue can be described as a multidimensional phenomenon characterised by a deterioration of mental and physical performance. In modern industrial society, fatigue has become a common state in which people from all walks of life frequently find themselves. The most common fatigue symptoms include detrimental effects on reaction time, energy levels and the ability to focus [1]. High workplace demands, high stress levels, and insufficient sleep for extended periods increase the prevalence of an individual's fatigue and pose considerable societal health and safety risks [2], [3], [4], [5]. Over time, poor fatigue management increases the risk of work-related burnout, characterised by symptoms of extreme exhaustion, distress, and decreased effectiveness and communication [6]. Recently, job burnout has become an apparent cause of reduced working capacity in industrial and developing countries, with over 25% of employees exhibiting job burnout symptoms [7]. In dynamic and complex working environments involving extensive mental and physical demands, the need for fatigue management measures is clear [8].

Fatigue is a widespread societal problem and is currently one of the least researched human responses [9]. The lack of extensive research on fatigue is due to the inherent challenges found in fatigue research. These challenges include the absence of a well-defined theoretical framework, and a widely accepted definition of fatigue [10]. Therefore, fatigue has evolved into an umbrella term that comprises of various physiological, emotional, and behavioural factors that can result in chronic mental or physical states affecting an individual's capacity to perform tasks [11]. Fatigue has also become synonymous with terms such as drowsiness and sleepiness, which represent an intermediary stage between wakefulness and sleep [12].

The multifaceted nature of fatigue has made it difficult to measure and quantify, and as a result, there is no gold-standard measurement approach. The complex nature of fatigue requires measurements in different dimensions in the attempt to quantify it fully. The types of fatigue measurements can be divided into three groups: subjective, behavioural and objective measures [13]. Objective methods of fatigue measurement utilise well established diagnostic tools to monitor changes in vital signs. Commonly utilised methods include electroencephalogram (EEG), electrocardiogram (ECG) and photoplethysmography (PPG). For fatigue research, it is desirable to acquire neurological information in the time and frequency domain given the interconnection between fatigue and the brain [14]. EEG analysis has proven insightful in fatigue detection [15], [16], [17], [18]. Comparably, the body's cardiovascular function is also desirable given the connection between the autonomic nervous system and heart rhythms [19]. This relationship is the source of a group of useful biosignals such as heart rate (HR), heart rate variability (HRV), and average heart rate (AVR) [4]. Supplementary vital signs that can assist in fatigue detection include respiratory rate and blood oxygen

saturation, which a large variety of commercial sensors can measure[20]. Subjective measurements of fatigue have also been found to be useful in research [21], [22], [23]. These psychological self-report measures are dependent on the conditions being investigated. In the case of sleepiness, subjective sleepiness levels can be assessed by employing the Stanford Sleepiness Scale, and where fatigue is of interest, scales such as the Samn-Perelli checklist and Li's subjective fatigue scale can be used [24]. Other subjective measurements for fatigue that have been used include visual analogue scales (VAS), and the Brunel Mood Scale [17]. These subjective measurements provide meaningful insight into the way fatigue is experienced by individuals and has shown a positive correlation with objective measurements such as HRV and EEG [13], [14]. Behavioural or performance measurements are useful in fatigue research because they provide a means to evaluate fatigue's effect on an individual's decline in performance ability [25]. Simple reaction time measurements such as those utilised by the Psychomotor Vigilance Task (PVT) provide a repeatable metric used to evaluate decline in attention capacity [17], [26]. The accuracy of responses provided in tasks such as the AX-Continuous Performance Test (AX-CPT) and the Stroop Task also provide insight into the task's execution quality [27], [28], [23]. Along with objective and subjective measurements, these performance metrics should provide a reliable method to detect fatigue. These metrics would also be suitable for applications such as sleep monitoring, meditation, and general health [29], [30].

The process of measuring biometrics has often required excessive and large hardware setups and sufficient time away from daily responsibilities, but due to the large influx of wearable smart solutions, it has become much more possible to acquire the desired biometrics. Despite the increased popularity of wearable devices, there is yet to be a comprehensive monitoring system for fatigue-related biometrics. In this paper we present the development of an in-ear sensor that can potentially be used to monitor fatigue.

II. METHODS

A. EEG Hardware Design

Biosignals are often small in amplitude and contain undesired noise and interference. The accumulation of interference has an undesired effect of corrupting relevant information that may be of interest in the measured signal. Therefore, throughout the data acquisition pipeline, it is desirable that the data of the original biological signal remain uncontaminated. Since these signals contain vital information, the procedures of amplification, analogue filtering, and ADC are used for signal conditioning. The analog circuitry used to condition these analogue signals is often referred to as the analog front-end (AFE).

The design of a reliable, precision, high-accuracy ADC is not a trivial task, so commercial, off-the-shelf integrated circuits (IC) provide a decent base from which to start an AFE design. The use of ICs with integrated functions reduces the number of components required to design a data acquisition system. The use of ICs enables optimized and affordable designs with robust performance. The family of production-grade AFE produced by Texas Instruments is popular amongst researchers. Extensive evaluation of the AFE has been conducted in research [31], [32]. An initial prototype was developed in order to verify the schematic design and functioning of the IC before moving forward to a PCB design. The layout of the resulting PCB design was chosen such that the EMI is minimized by using bypass capacitors and separating analog and digital signal layers. The finished PCB design can be seen in figure 1. Three different in-ear electrode implementations were considered for the EEG signal acquisition. The features that were considered in order to determine the electrode feasibility were: Electrode contact; Comfort; Sensor material; Cost of production; Reusability; and Feasibility.

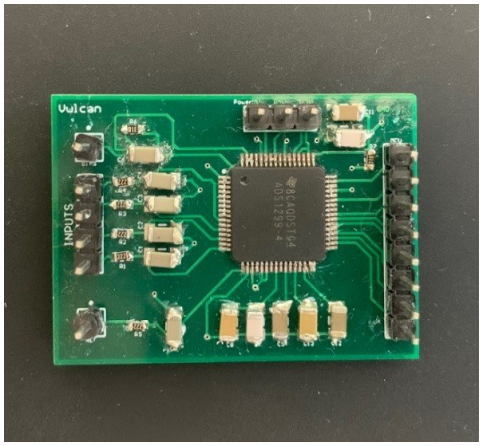


Figure 1: Finished PCB

With in-ear electrodes, there is no gold standard or design that works for everyone. The electrodes implemented need to be able to ensure reliable contact and low-impedance over time. The sensitive nature of the ear also requires that the electrodes be comfortable and safe to wear. There are two main approaches in electrode manufacturing: custom and generic. Custom electrodes provide the benefit that they are personally fitted for the specific participant and therefore ensure good contact, but they are expensive and difficult to manufacture.

Generic electrodes provide a more accessible and cheaper way to approach signal acquisition while sacrificing signal quality and comfort. Wet electrodes are often used to reduce the ESI by using conductive gels and improving signal acquisition. These conductive gels, however, dry over time, and their adhesion is easily lost during movement. Dry electrodes do not utilize an electrolytic substance and make direct contact with the skin. The main advantages of dry electrodes are that they are fast to place, do not require any additional instruments, and do not require extensive clean-up. There is also a clear distinction between active and passive electrodes. Active electrodes employ electronic circuitry between the sensor and the wire. The active electrodes provide a means to reduce possible line noise and therefore improve signal quality. The electronic elements used could add to noise if not correctly implemented. The cost of active electrodes is also high due to the circuitry's low noise and size requirements. Passive electrodes do not utilize circuitry between the sensor material and the wire. The last aspect of the electrode that needs to be considered is the sensor's material that will be the primary interface between the wire and the skin. The electrical and mechanical properties of the sensor material directly influence the design of the electrode.

The first electrode implemented was a custom electrode, as seen in figure 2, which was constructed by taking an impression of the ear to create an ear mould. The ear mould is then used to create a silicone-based earpiece. An audiologist often uses this process to create hearing aids. The ear mould is then used to create a silicone impression of the ear. Custom electrodes are desirable for their comfort and their ability to provide better contact over time. The downside of custom earpieces is that they are expensive to manufacture and that the time spent manufacturing them is also extensive. The electrode material selected for this implementation is conductive cloth. Cloth electrodes are highly flexible, conductive, soft, comfortable to wear and conform to changes in the earpieces' shape. The larger surface area of the custom earpiece makes it possible for the reference electrode and signal electrode to be located in the same ear. The reference electrode's location is targeted at the concha cymba, which has been shown to be an effective reference location in recent years [33], [34], [35]. The woven fabric has a low resistivity of 0.5 Ω/sq, making it highly conductive and formed into any shape required for the implementation.

The woven fabric is fixed to the earpiece substrate using a conductive adhesive. Soldering on fabric is infeasible; therefore, copper foil is implemented to bridge the wire and the fabric electrodes. Shielded cables were also used to enhance artifact rejection. The shielded wire's outer copper mesh was connected to the neutral part of the custom earpiece. It was found that the custom earpiece is comfortable to wear; however, the rigid nature of the earpiece made it prone to lose skin contact, which affects the signal quality.

The second earpiece that was considered was a foam earpiece design. Memory foam has the beneficial characteristic of being viscoelastic. The memory foam substrate's viscoelasticity ensures that an electrode can be safely and effectively inserted further into the ear canal than the custom earpiece. The earpiece can be compressed into a smaller shape and then inserted into the ear canal. Following insertion, the earpiece expands and redistributes pressure evenly along the entirety of its contact surface, thus providing a stable interface to the ear canal wall. The substrate's viscoelasticity also ensures that energy from abrupt motion such as pulsation is absorbed, thus minimally disturbing the electrode-skin contact. Sound-blocking earplugs utilize memory foam and are used for the viscoelastic substrate for this design. The electrodes must have similar flexible properties to accommodate the compression of the memory foam earplugs before insertion. A 6 *mm* x 10 *mm* square of conductive cloth is used as the electrode interface's top layer. Soldering directly onto conductive cloth would damage the material; therefore, the copper tape is used as a bridging material onto which wire can be soldered. A silicone ear hook was also implemented to assist in the contact functionality of the earpiece. An ear hook is a mechanical hook often found in hearing aids and sports earphones that improves an earpiece's stability during functioning. The implementation of the earpiece can be seen in figure 3.

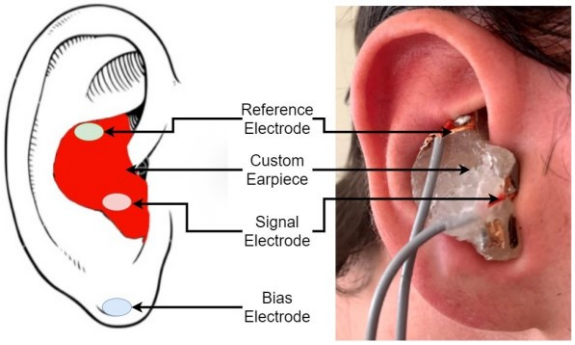
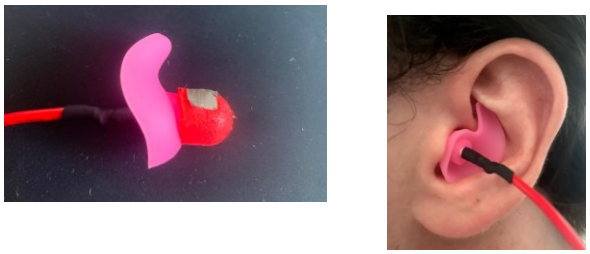


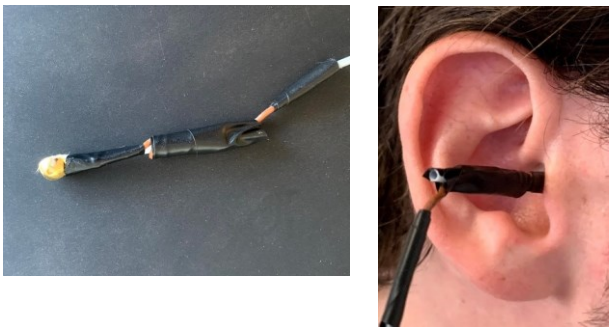
Figure 2: Custom Implemented earpiece conceptualization and Implementation with cloth electrodes



(a) (b)

Figure 3: (a) Foam earpiece implementation (b) Foam earpiece in ear

The final electrode that was implemented that provided the most consistently good results was the deep ear electrode. Utilising a smaller conductive area, the electrode can be inserted deeper into the ear canal. Inserting the electrode deeper into the ear canal provides an increase in signal quality and contact while possibly increasing the discomfort experienced. A gold-cup electrode was modified by reducing the overall size of the electrode and then positioned on an earbud to assist in positioning the electrode in the ear canal. The implemented deep ear electrode can be viewed in figure 4.



(a) (b)

Figure 4: (a) Deep ear electrode implementation (b) Deep electrode in ear

B. PPG Hardware Design

The typical PPG device contains a light source and a photodetector. The light source emits light onto the tissue, and the photodetector measures the light that is reflected or absorbed, depending on the configuration used. The most common PPG sensors are pulse oximeters used to measure blood oxygen saturation (SpO2). The choice of measuring mode would directly influence the viability of measuring sites. PPG sensors are commonly worn on the fingers in transmission mode due to the high signal amplitude that can be achieved compared to other sites [36]. This measuring site is not well-suited for extended sensing, as many activities of daily life involve the use of fingers. Earlobes are not compromised of cartilage and thus contain sufficient blood supply. Moreover, earlobes are far less vulnerable to the effects of motion artefacts compared to other extremities. Implementing a reflective PPG sensor with an ear clip on the earlobe was decided to be a suitable solution. The AFE that was selected for implementation is the MAX30102 from Maxim Integrated. The MAXREFDES117 is a reference design that utilizes the MAX30102 as an optical module and an integrated power supply and level translator. The MAXREFDES117 is an ideal sensor solution given its small size (12.7 *mm* x 12.7 *mm*) and low power design. A prototype was developed to use the earlobe as a measuring site. Clothes pegs provided an affordable solution to provide consistent contact to the earlobe for the MAXREFDES117 sensor module.

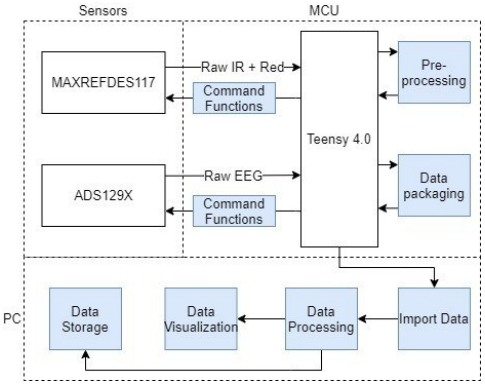


Figure 5: High-level Software Functional block diagram

Following successful prototyping, it was decided to implement a dedicated ear-clip design to ensure simpler reproducibility and improved sensor placement. The principle design of a clip is straight forward and ensures good contact. An initial clip design was implemented in Autodesk Inventor, featuring a dedicated sensor module location and a bias electrode location for the EEG setup.

C. Software Design

The implemented software was written for the MCU and the PC processing the data. The MCU software is based on *C++* and was developed using the Arduino Integrated Design Environment (IDE). The MCU software handles sensor communication, timing, selected processing functions and transmission of collected data. The PC software was developed in Python using Jupyter Notebook. The PC software reads the saved data, performs most of the processing required, and then displays the data stored

on the local hard drive. The high-level functional block diagram can be seen in figure 5.

Table I: Power supply verification by voltage probing

Voltage Probe	Expected Value	Measured Value
VREF	VREFP - VREFN = 4.5 *V*	4.496 *V*
VCAP1	GND + 1.2 V = 1.2 *V*	1.196 *V*
VCAP2	(AVDD + GND)/2 = 2.5 *V*	2.532 *V*
VCAP3	AVDD + 1.9 V = 6.9 *V*	6.941 *V*
VCAP4	VREF/2 = 2.25 *V*	2.249 *V*

Table II: Measured Noise Measurements compared to theoretical values for sample rate of 500 *SPS*

Input-referred noise Parameter	Datasheet (μV)	Measured value (μV)
V_{PP}	1.39	1.35
V_{RMS}	0.20	0.18

D. System Verification Tests

The design and implementation of the system were evaluated by performing incremental verification tests of the different subsystems. The tests are performed to identify the strengths and shortcomings of the designs. The AFE represents the intersection of analog and digital data. In the Software Design and Implementation section, successful communication between the AFE and MCU was verified by configuring the AFE and retrieving the Device ID. Verification of the analog data is still required to assess the functionality of the AFE. A suitable power supply to the AFE is crucial for acquiring analog data and is verified by measuring the internal voltage pins or the potential difference across the bypass capacitors. The bypass capacitors are essential for noise reduction in the AFE and, therefore, the output data quality. Table I shows the VREF voltage probe and the different bypass capacitors (VCAP1-VCAP4) and their expected voltages representing the appropriate power supply. The measured voltages across the bypass capacitors are also shown in table I. The resulting measurements show that the power distribution of the PCB design is satisfactory. Low noise levels from hardware improve signal acquisition for low-amplitude biosignals applications such as EEG. The noise measurements for the hardware was performed by shorting the inputs of the AFE and acquiring 5000 readings at a sample rate of 500 *SPS*. The test was repeated five times, and the results obtained were averaged over the number of tests. The resulting input-referred noise plot in the time domain can be seen in figure 6. The μV_{pp} value was calculated as 1.35 μV, and correspondingly the μV_{RMS} was calculated as 0.1856 μV. Table II compares the calculated noise measurements to the values stated in the ADS1299 datasheet.

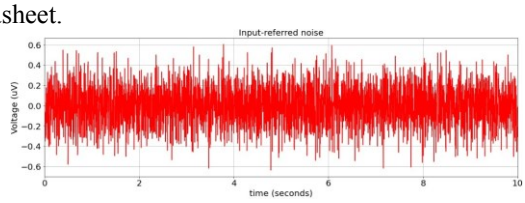


Figure 6: Averaged Input-referred Noise of AFE

E. EEG Measurements

The AAR was tested over twenty trials on one participant. Each trial's data was divided into the respective rhythm frequencies and then averaged over the twenty trials. The procedure was to keep the eyes open for 30 seconds and then close them for 30 seconds while in-ear EEG data is recorded.

F. PPG Measurements

For the testing of the SpO2 and HR parameters performance, data was simultaneously captured by an IMDK C101A3 pulse oximeter. The C101A3 is Food and Drug Administration (FDA) approved with an accuracy of ±2 % for SpO2 measurements and accuracy of ±2 *bpm* for heart rate data. The C101A3 uses fingers as measurings sites and utilises a transmissive PPG mode. For the measurements, the C101A3 was placed on the middle finger of the dominant hand. Trails were conducted to test the parameters' accuracy and consisted of a measurement period of 5 minutes per trail. The essential HR parameter tested is the instantaneous heart rate (IHR) or the Inter-Beat-Interval (IBI) HR-related values. This is because HRV is directly calculated from the IBI values. IHR uses the time difference between beats to estimate the heart rate.

III. Results

A. EEG Measurements

The resulting mean band amplitudes can be seen in figure 7 for eyes open and in figure 8 for eyes closed. Additionally, a single trail's frequency response can be seen in figure 9 to illustrate the increased activity in the alpha frequency range (8-13 *Hz*). Trails,

where excessive noise was present were discarded and repeated. The statistical analysis of the alpha band values over the twenty trails can be found in table III.

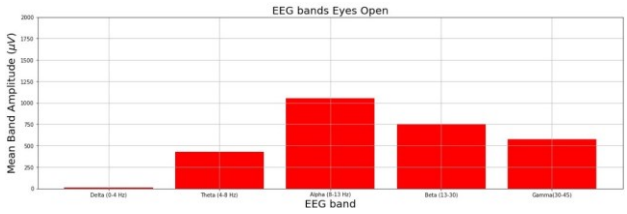


Figure 7: Mean band amplitude for EEG bands while eyes are open averaged over 20 trails.

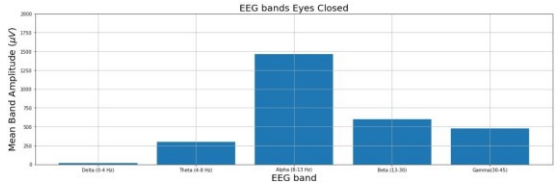


Figure 8: Mean band amplitude for EEG bands while eyes are closed averaged over 20 trails

Table III: Statistical analysis of EEG alpha band values over 20 trails

	Eyes Open	Eyes Closed
Mean	1466.47	1109.78
Standard deviation	600.14	399.99
p-value		0.0378

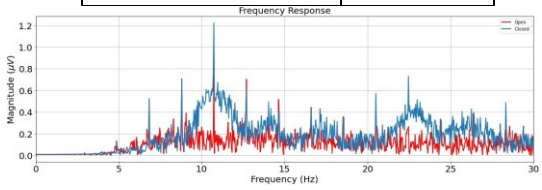


Figure 9: Frequency Response of an alpha attenuation trail



Figure 10: Comparison of raw IHR calculated values and HR values of C101A3 for trail period of 5minutes

B. PPG Measurements

Figure 10 compares the values between the raw IHR values obtained by the implemented PPG sensor and the calculated HR values of the C101A3 sensor for a single trail. While figure 11 shows the IHR values of the C101A3 sensor and the conditioned IHR values. The AHR for the trail illustrated in figures 10 and 11 was calculated as 65.2 *bpm*, while the C101A3 provided an AHR of 66.3 *bpm*. Five trials were performed and found similar results.

The typical range of SpO2 measurements for a healthy individual is between 95-100%. Measurements obtained from the IMDK pulse oximeter during the trials never dropped to under 95% as only healthy individuals participated in the trials. Similarly, the values obtained from the PPG sensor was also within the range of 95-100% and within a ±2 % error rate when compared with the IMDK pulse oximeter, as can be seen in table IV. The steps required for the proper inducing of hypoxia to achieve SpO2 levels under 95% are beyond the scope of this project and require additional equipment and ethical approval because of the associated health risks.



Figure 11: Comparison of conidtioned IHR values and HR values of C101A3 for trail period of 5 minutes

Table IV: Average SpO2 values over five trails

Trail	Average IMDK SpO2 (%)	Average PPG Sensor SpO2(%)
1	98.3	99.1
2	96.4	98.7
3	98.4	99.3
4	97.9	95.4
5	96.2	98.3

IV. DISCUSSION

A. *Interpretation of Results*

The results obtained provide insight into the system's functioning. The tests were performed to assess the validity of the designed systems' performance and its feasibility as an appropriate data capture device.

The first essential tests performed were the tests to verify the proper functioning and performance of the designed and implemented AFE. The first test was to verify the appropriate power supply to the AFE. The results obtained from the power supply verification was satisfactory and showed that the AFEs power requirements had been met. This is a necessary test to perform as improper power would affect the general functioning of the AFE, as the internal amplifiers, internal reference, and bias drive's performance would be compromised. After verifying the power supply, the noise performance of the AFE was evaluated. The system's input-referred noise was measured and compared to expected performance values, as stated in the ADS1299-x datasheet. The results obtained showed improved and comparable noise performance to that stated in the datasheet. The noise measurements show that the steps taken in the design process, such as using multiple PCB layers to minimize the noise between digital, analog and power signals, have ensured minimal system noise. The internal amplifiers' functioning was tested by generating an internal test signal fed into a selected channel's PGA. The internal test signal was successfully obtained and verified the connection between the PGAs and the internal ADC. The final verification test of the AFE consisted of supplying the system with a known external signal. The applied signal was successfully received and processed, verifying that the system setup, external input pins and analog filtering are functioning correctly. The collection of the results attained from the verification tests confirms that the AFE is working as intended and satisfies the performance requirements.

The two main components of the EEG system are the AFE and the in-ear electrodes. The AFE function has been verified; therefore, the focus shifted to electrodes and their performance. After extensive testing, it was found that the deep ear electrode provided the most consistent quality results. The custom electrodes did not provide constant contact over time and therefore yielded EEG signals contaminated with noise.

Similarly, it was found that the foam electrodes initially performed acceptably but suffered degradation of signal quality after extended use. The conductive cloth utilized as electrode material in the custom and foam electrode implementations provided more comfort but at the cost of signal quality. The gold material of the deep ear electrode implementation offers superior and consistent signal quality at the expense of user comfort. The deterioration in the conductive cloth's performance is likely due to the damaging of the conductive fibres, which increase the electrode's impedance and diminishes the signal quality. In contrast, the gold electrode's impedance is comparatively stable and therefore provides consistent quality signals.

When considering EEG analysis, the division is usually made between time and frequency domain based methods. After careful experimentation, it was found that the chosen approach did not compliment time-domain analysis methods such as the detection and analysis of MLAEP amplitude and latencies and was therefore not utilized. MLAEP responses are usually in the low (0-2) μV range and need to be captured 100 *ms* after the auditory stimulus. While MLAEP has seen promising results in monitoring anaesthesia levels, when considering the fatigue aimed application of the project, which inherently would require the participant to be awake, the MLAEP would too easily be contaminated with general physiological artifacts. The frequency analysis methods performed considerably better and have shown to be more resilient to artifacts. The alpha attenuation response is one of the methods chosen for detecting fatigue because alpha activity (8-13 *Hz*) increases when the eyes are closed and has been closely linked to the state of alertness or drowsiness. The tests performed yielded desirable results and showed an increase in alpha-band activity for the duration during which the eyes were closed. A t-test was performed on the alpha band data collected over twenty trials. It resulted in a p-value of 0.0378, which confirms that the device's results have a scientific, statistical significance.

The PPG measurements consisted of testing the IHR and SpO2 calculation of the implemented sensor configuration. The procedure consisted of determining the IHR and SpO2 values for 5 minutes while simultaneously recording the IMDK C101A3 pulse oximeter's HR and SpO2 values. This approach's motivation is that if the IHR values are accurately obtained, then the HRV values can easily be determined from the IHR values. For proper HRV implementation, a baseline measurement is required, and then the deviation from this baseline over time provides meaningful HRV data. The IHR values obtained from the trials were satisfactory and closely correlated with the IMDK pulse oximeter's HR values. Similarly, the SpO2 measurements of the implemented PPG sensor and the IMDK pulse oximeter were also very closely correlated. The utilization of the earlobe as a measuring site proved to be quite ideal as the site is less vulnerable to the effects of motion artifacts when compared to other measuring sites. This is because the earlobes do not contain cartilage, bone or

muscles and have sufficient blood supply. When considering the results obtained, the implemented earlobe PPG sensor would provide good HR and SpO2 biometrics for fatigue detection.

B. Comparison with Previous Literature

The overall project compares well with the findings of previous literature. Concerning the hardware development, there has been an increased interest in alternatives to conventional EEG systems. The most common implementations in recent EEG studies are off-the-shelf solutions such as the Open BCI biosensing boards and the more expensive medical grade bio-amplifiers. These EEG solutions offer adequate performance and have been shown to produce comparable results to conventional EEG systems.

The inherent dilemma of using a general EEG solution is that it is not application-specific. In-ear EEG studies also face this predicament and often use a general EEG solution, which leads to the underutilization of certain features and limits the use in specific research fields due to the obtrusive hardware. This is contradictory, given that the entire point of using in-ear EEG is to provide more flexibility to EEG research. Therefore, there is a clear need to develop dedicated hardware platforms to enable more mobile data acquisition. This project aims to contribute to this endeavour. There are very few dedicated hardware platforms for the in-ear EEG method as most in-ear EEG research focuses on electrode development and verification. Where in-ear fatigue, sleep, and drowsiness research is concerned, the utilized hardware is commercially available solutions [37], [33], [38], [27], [30]. The performance of the implemented EEG hardware in the project compares favourably with that found in the literature, exhibiting similar noise performance and can provide high-resolution EEG signals at a more than satisfactory sampling rate. Given the system's increased mobility, it is consequently more susceptible to environmental noise, which could degrade the system's performance if not adequately mitigated with shielding and filtering techniques.

The electrodes implemented in the project covered three different approaches that have been explored in research. The custom earpiece approach has proved to be a reliable method in the literature, given the excellent electrode contact and comfort. The custom earpiece in this project did not perform as well as the custom earpieces in the literature. This is mainly because the implemented custom earpiece featured some manufacturing limitations, such as not extending deeper into the ear canal. The utilization of conductive cloth as electrode material in literature has shown desirable results; however, the results obtained were inconsistent in the foam and custom earpieces. The most reliable electrode was the deep ear electrode and compared well with what was found in the literature. Inserting an electrode deeper into the ear canal provides better signal quality as it is closer to the source. The excellent conductivity of gold plated electrodes aids the signal quality obtained. The adequate electrode choice currently in research depends on the selected application and setting where the measurements will be taken. In-ear electrodes still need to be thoroughly researched in practice to determine a gold standard approach.

The results obtained from the selected EEG paradigms also compared well with tests conducted in research. It was shown that the AAR does indeed show an increase in alpha activity when the eyes are closed which is significant because the higher alpha band levels have been proven to be associated with a state of alertness or drowsiness [39]. This supports the use of the paradigm for fatigue detection application. Similarly, the ASSR results were desirable and illustrated the system's functionality and compare well with what has been found in other research studies. The system's shortcoming to detect MLAEP in a mobile setting is supported by research conducted by [40] and illustrates why MLAEPs are effective in idle applications such as an aesthesia monitoring.

The results obtained from the PPG measurements have also correlated well with the expected results from the literature. The choice of the earlobe as a measuring site for HR and SpO2 related measurements is suitable and is supported by similar findings in the literature [36]. The difficulty with verifying SpO2 measurements over an extended range (<95%) where hypoxia occurs is also a prevalent obstacle in SpO2 related studies.

C. Future Work and Improvements

From an EEG hardware perspective, the AFE is unmistakably one of the project's greatest strengths. The AFE provides high-quality EEG data in a small package, making it ideal for mobile applications, especially compared to off-the-shelf solutions and conventional EEG setups. The EEG hardware is also modular. It has a changeable sampling speed and support for up to four input channels giving it more versatility and ease of use if implemented in different applications. The weakness of the EEG hardware is the implemented electrodes. The variety of electrodes tested throughout the project emphasise the difficulty of implementing a reliable passive dry electrode for in-ear EEG data acquisition. The deep ear electrode that provided the most accurate and reliable results sacrificed comfort and would therefore not be convenient to wear for extended periods. The PPG hardware is also a distinct strength of the system.

Employing the earlobe as a measuring site with the implemented ear-clip provides comfortable and accurate measurement for extended periods. Some inherent disadvantages of most biometric acquisition systems are also featured in the hardware implementation, such as the susceptibility to noise and atrifacts despite passive noise reduction techniques. Another distinct advantage of the system is its cost. The entire system's hardware costs accumulate at around ± R2750 ($185), which is a decent reduction in price compared to the highly used 4-channel Open BCI ganglion board, which costs $250, and the project hardware also has PPG measurements. The system as a whole needs to be powered from a PC in its current state and does not feature onboard memory storage, which limits its existing range of applications.

The project achieved the objectives which it set out to do. However, there is the opportunity to improve the future versions of the device and similar devices. Some hardware improvements can be made to the system, which would significantly enhance the range of applications for which it can be used. These improvements include but is not limited to wireless connectivity, display for status monitoring, onboard memory and independent power supply. Implementing these features would significantly improve the ease of use and help isolate the system from the environment. The electrodes are a component where there is much room for improvement and innovation. Implementing a modular active electrode topology instead of passive electrodes would also assist in improving signal quality. Further optimisation and minimization of the hardware components would also help in promoting a mobile system. Additionally, more extensive testing can be performed. The complex nature of fatigue provides the opportunity to investigate multiple conditions associated with a state of drowsiness or sleepiness. These states' influences on the biometrics obtainable from the device could prove beneficial for future fatigue detection applications.

V. CONCLUSION

Fatigue is a condition developed as a result of extended wakefulness, increased workload, and sleep loss and is accompanied by the characteristic deterioration of mental and physical performance [13], [10]. In today's modern society, the demands of the workplace are extensive, and not enough attention is given to fatigue management. For some people, the improper management of fatigue has few societal consequences, while for others, such as doctors and drivers, the consequences can be severe. In order to effectively manage fatigue, it is first necessary to be able to detect it. Research has shown that fatigue is closely related to drowsiness and sleepiness, which can be identified with the correct combination of physiological and psychological biosignals [12], [41]. The tools required to measure these signals effectively are obtrusive and are impractical for daily monitoring. Furthermore, these tools are often expensive, limiting access to them [28]. The need for a low-cost and effective data capture device aimed at fatigue-related biosignals is evident. This project aimed to address this need. In-ear EEG provides an acceptable alternative to conventional EEG measures and has become increasingly popular due to its accessibility. Similarly, PPG technology has become prevalent in wearable health solutions and provides accurate cardiovascular and respiratory information. A data capture device was implemented utilizing in-ear EEG and PPG technology. The data capture device was designed with cost and size in mind to promote usability. Extensive testing was performed with the device to test its utility in the detection of fatigue-related biosignals. It was found that the device does measure the chosen fatigue-related biosignals with satisfactory accuracy. This is a significant result as it reinforces the feasibility of a fatigue monitoring device. Continued efforts to improve the understanding and detection of fatigue can ultimately lead to a device capable of mitigating the human cost of fatigue-related afflictions.

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