Wheelchair Exercise Monitor

Preliminary Design Review Report

Senior Design 2017-2018

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Abstract

The objective of our project is to develop a mobile exergaming and fitness tracking system for individuals who use wheelchairs, due to spinal cord injury (SCI). Decreased mobility leads to physical and psychological health problems, thereby affecting their quality of life. Increasing and encouraging regular cardiovascular exercise can prevent long term health risks as well as give patients a better quality of life by encouraging a more active lifestyle. Our goal is to encourage individuals to work out and to facilitate exercises at home without a physical trainer. The idea is to gamify pre-defined/physician-recommended workout protocols so that the user will be more focused on winning the games and in doing so, complete the workouts. Current activity monitors and fitness trackers have limitations as far as accurately monitoring fitness, and to our knowledge, none have been customized to appropriately incentivize exercise for individuals in wheelchairs. We are therefore developing a multimodal energy expenditure metric, derived from multiple body-worn sensors, that will drive mobile app games. Based on tests performed, heart rate alone is not a reliable metric and therefore, other sensors such as electromyography will be explored to seek more accurate results. We were able to estimate energy expenditure using volume of oxygen consumed (VO_2) in correlation with heart rate and muscle activity, but it did not increase the accuracy as much as we hoped.

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Statement of the Problem

Spinal Cord Injury Health Problems

When the spinal cord or nerves at the end of the spine are damaged, spinal cord injury (SCI) leads to paralysis and the inability to walk. SCI is commonly caused by a traumatic sudden blow to the spine, causing a permanent loss of strength, sensation, and functionality of the injured area. Patients who suffer from SCI are at greater risk of developing cardiometabolic and cardiovascular disorders. Cardiometabolic syndrome includes diseases such as heart disease, lipid problems, dementia, cancer, type II diabetes, and several other health risks. The human body needs regular exercise of the heart and lungs, blood circulation, and exercise of muscles. With exercise, health risks of cardiovascular and metabolic diseases are known to be greatly reduced.

The Limitations and Barriers of SCI

Individuals with SCI do not have the ability to get up and decide to go out for a quick run. Exercising for some can be a quick decision to go to the local gym, while individuals who use wheelchairs rarely have this luxury. SCI individuals are limited by transportation and mobility and the need for specialized equipment and often health instructors to ensure safety while working out. In most circumstances, there are multiple health instructors required to monitor a single individual - one to monitor safety, one to monitor heart rate, and another to facilitate movement and encourage the individual to continue working out. These types of facilities and health instructors are not cheap and require a considerable investment. SCI individuals also have to overcome social stigmas associated with being a wheelchair in order to go out in public and work out in front of others. Due to these limitations and barriers, it is understandable why they eventually lose motivation and willpower for exercising regularly.

Improving Cardiovascular Fitness for Spinal Cord Injury (SCI) Patients

Our Goal

Our project is a part of a larger scope project, consisting of kinesiology, counseling, and engineering departments. The kinesiology department is contributing the exercise workout protocol specially designed for SCI individuals to achieve cardiovascular fitness safely. During the summer, the engineering team known as “The Dream Team” created a mobile platform integrated with wireless sensors to monitor activity and provide feedback to user. With their work, an app was created with basic functionality to interface with EMG (electromyography) the detection of muscle contraction, heart rate, and IMU which is accelerometry sensors.

The senior design team's goal is to design an exergaming system that will facilitate exercise at home and motivate patients to exercise regularly. A gaming system will be designed which implements the exercise workout protocol established by the kinesiology department and make it fun for the user. The objective is for the user to focus on winning the game rather than on the actual workout. The below figures show a user that has the sensors placed on muscle that are detecting output values and inputting in app. Figure 1 shows user that is using workout exercise protocol that require resistance bands. Figure 2 shows a close up of EMG sensors and IMU on wrist. Figure 3 shows the phone suspended in front of user on portable stand attached to wheelchair.

Figure 1: User Performing Exercise with Resistance Bands

Figure 2: EMG Sensor Worn on Arm and IMU On Wrist

Figure 3: Phone Suspended in Front of User on Portable Stand Attached to Wheelchair

As seen in Figure 4, our project advisory/review authority is Dr. Won. Omar Ochoa is student lead and in charge of Racing game development. Isaac Bowser is in charge of sensor, testing, and metrics verification. James Enciso oversees Metric Research and verification. Boxing game development for app is Christine Ong.

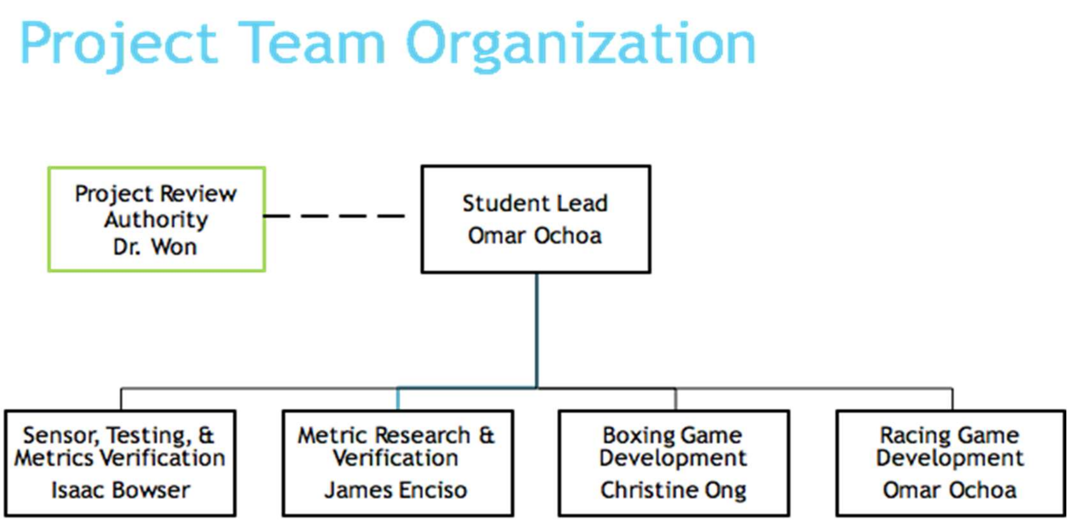


Figure 4: Project Organization Chart

Project Requirements and Capabilities

Our project requirements and capabilities are outlined in Table 1. The project requires the mobile application to support a minimum version of Android version 6.0. Our design is compliant in this requirement allowing our application to run on most phones manufactured in the past 2 years. The sensors' connectivity protocol is uses Bluetooth and ANT+. These allow data to be communicated with the app. The sensors being used include heart rate, Electromyography, Inertial Measurement Unit, and RPM sensors. We expect the preparation and calibration setup time to take less than 3 minutes. So far, this time takes between 5-10 minutes, making the project non-compliant in this area. The accuracy of cardiometabolic fitness metric is still be analyzed. We expect estimation errors not to exceed 10 kcal. The heart range alerts are still be tested to find the min and max that can be set for safety of wheelchair individuals.

Table 1: Project Requirements and Capabilities

No.	Requirement Name	Performance Objective	Capability	Compliance	Method of Verification
1	Operating System	Android v. 6.0 or newer	Android v.6.0	Compliant	Design
2	Sensor Connectivity Protocol	Bluetooth, ANT+	Bluetooth, ANT+	Compliant	Design
3	Sensors Used	Heart rate, Electromyography, Inertial Measurement Unit, RPM	Heart Rate, EMG, Custom IMU	Compliant	Design
5	Preparation and calibration setup time	< 3 minutes	5-10 minutes	Non-Compliant	Testing
6	Accuracy of cardiometabolic fitness metric	+/- 10 kcal	In Progress	TBD	Testing
7	Heart rate range alert	Alert Users if: Heart Rate < min Heart Rate > max (monitor malfunction)	In Progress	Compliant	Testing

Deliverables

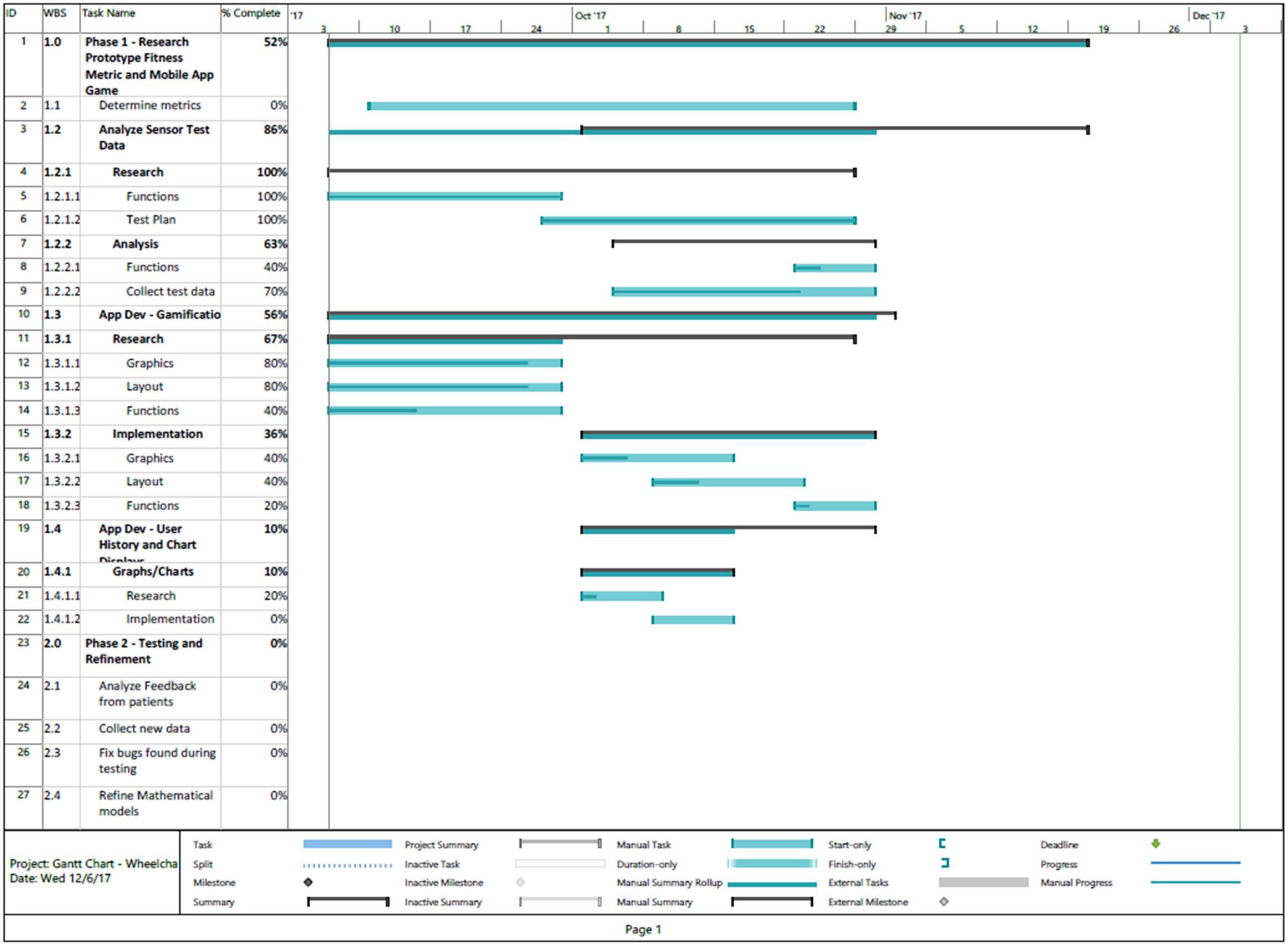
At the end of December, we intend to deliver a app prototype that will include the gaming system. Over the break, we will analyze metrics needed to drive app games. When we come back from the winter break, we will use feedback from SCI subjects to analyze for implementing changes in the app. Before the end of the following semester, we will have fixed changes needed for the app prototype and fitness metrics to have a final product. Finally, once final app is completed we will create a user manual to explain how to operate the app and sensors. The following table lists our project deliverables and deadlines for delivery.

Table 2: List of Project Deliverables

Item	Quantity	Deliverables Description	Date of Delivery
1	1	App prototype (including games and user data/charts)	12/9/2017
2	1	Drivers for app games (metrics)	12/9/2017
3	1	Data collected from SCI subjects while using DREAM app prototype	1/20/2018
4	1	Refined app prototype	5/11/2018
5	1	Refined fitness metric	5/11/2018
6	1	Documentation – e.g., user manual	5/11/2018

Project Schedule

As seen in Figure, we are currently working on making a gaming prototype using only Bluetooth EMG sensors. Over the winter break, our goal will be to be able to implement proper coding for EMG signal processing to operate the game's functionality. Before the new semester, we hope to have a rough draft gaming system that we can give to wheelchair individuals to test and receive feedback. For the next semester, we will use the user feedback and analyze the changes needed and implement them to make a final gaming product. The metrics correlation analysis is slightly behind schedule due to technical difficulties encountered during data collection. Issues resulted from sensors not transmitting data or detaching from the skin due to sweat.



ID	WBS	Task Name	% Complete
1	**1.0**	**Phase 1 - Research Prototype Fitness Metric and Mobile App Game**	**52%**
2	1.1	Determine metrics	0%
3	**1.2**	**Analyze Sensor Test Data**	**86%**
4	**1.2.1**	**Research**	**100%**
5	1.2.1.1	Functions	100%
6	1.2.1.2	Test Plan	100%
7	**1.2.2**	**Analysis**	**63%**
8	1.2.2.1	Functions	40%
9	1.2.2.2	Collect test data	70%
10	**1.3**	**App Dev - Gamificatio**	**56%**
11	**1.3.1**	**Research**	**67%**
12	1.3.1.1	Graphics	80%
13	1.3.1.2	Layout	80%
14	1.3.1.3	Functions	40%
15	**1.3.2**	**Implementation**	**36%**
16	1.3.2.1	Graphics	40%
17	1.3.2.2	Layout	40%
18	1.3.2.3	Functions	20%
19	**1.4**	**App Dev - User History and Chart Displays**	**10%**
20	**1.4.1**	**Graphs/Charts**	**10%**
21	1.4.1.1	Research	20%
22	1.4.1.2	Implementation	0%
23	**2.0**	**Phase 2 - Testing and Refinement**	**0%**
24	2.1	Analyze Feedback from patients	0%
25	2.2	Collect new data	0%
26	2.3	Fix bugs found during testing	0%
27	2.4	Refine Mathematical models	0%

Figure 5: Project Schedule

Exercise Protocol

Table 3 outlines the exercise protocol that we will gamify in our exergaming system, and which we used during our testing for Objective 2. For the cardiovascular spin, each subject stationed their wheelchair onto a stationary roller called an Invictus® Roller which permitted the wheelchair to roll without moving forward. Subjects would continuously roll their wheelchair forward whilst maintaining the heart rate zone for a specified duration. For the exchange exercise routine, subjects were instructed to pass a medicine ball back and forth to a trainer standing in front of them for 4 minutes. Then, the medicine ball was held in front of the subject to be punched at a rate that maintained their heart rate within the heart rate zone. Resistance category exercises consisted of subjects using a resistance band oriented in various ways to target specific muscle groups. Subjects performed five reps of each resistance band position as consistently as possible.

Table 3: Exercise Protocol Used During Data Collection

Exercise Category	Heart Rate Zone	Activity	Duration
1: Spin	65-70%	Wheelchair Roll	4 min.
	75-80%		1 min.
	55-60%		3 min.
2: Exchange	65-70%	Ball Toss	4 min.
	75-80%	Punches	1 min.
	55-60%	Uppercuts	3 min.
3. Resistance	N/A	Military Press	5 reps
		Horizontal Row	
		Chest Fly	
		Lateral Pulldown	
		Modified Dip	
		Bicep Curl	

Objective 1: Energy Expenditure Metrics Modelling

Energy expenditure as a measure of cardiovascular fitness and barriers to measuring it

The gold standard used for quantifying cardiovascular fitness is energy expenditure, or calories burned. In order to implement a game which is driven by the user’s actual achievement in cardiovascular fitness, we need to develop a method for reliably quantifying the amount of energy expended in Calories (kcal) from the physiological sensors we have at our disposal. Calories burned will serve as relevant, motivational feedback to present to users about their progress during a workout. Caloric expenditure is most directly measured through whole-body calorimetry, which is not feasible during real-time exercises at home. Therefore, we first researched sensors that would most likely carry information related to energy expenditure: heart rate, electromyography (EMG), and acceleration sensors.

Based on previous research performed by other institutions, including the American College of Sports Medicine[1], there are published equations that relate various cardiometabolic metrics. Among these existing metrics, two relevant cardiometabolic metrics are VO_2 (instantaneous volume of oxygen uptake) and METs (metabolic equivalent). VO_2 represents the volume of oxygen consumed in liters per minute. VO_2 is a direct measurement of metabolic activity occurring in respiration, and energy expenditure can be relatively directly calculated from VO_2. However, measuring VO_2 requires wearing a respiratory mask attached to specialized equipment, often in a controlled, clinical setting. This imposes a limitation of directly recording energy expenditure in a portable manner; therefore, a method must be derived to indirectly estimate absolute VO_2 from easily accessible sensors.

Heart rate monitors are commonly used in fitness tracking devices. However, there are two main limitations in relying on heart rate monitors for our exergaming system. One is that the monitors worn on a chest strap provide the most accurate measures of heart rate, but because exercises in a wheelchair tend to move the torso more and require more bending at the waist or with arms moving across the chest, the chest strap tends to move and motion artifact is detrimental to accurate heart rate monitoring. We also hypothesized that due to a condition in SCI patients called autonomic dysreflexia, excessive physical exertion may lead to aberrant heart rate activity, namely random spikes in heart rate, making heart rate an unreliable metric to use.

Deriving Caloric Expenditure from VO_2 Measurements

VO_2 can be represented in two forms: absolute and relative. Absolute VO_2 [L/min] is a measurement of the rate of gas flowing (or being breathed in) per unit time. Relative VO_2 [mL/kg/min] is absolute VO_2 normalized by body mass. The relative VO_2 value can be converted to another metabolic metric called METs which represents a magnitude of the physical exertion according to the following equation 1.

$$1\, METS = 3.5\, mL\, O2 \bullet kg^{-1} \bullet min^{-1} \quad (1)$$ [2]

Using the relationships between VO_2 and METS, an algorithm was produced to accurately calculate energy expenditure, shown in Figure 6. This prediction model involves a series of steps beginning with absolute VO_2 [L/min]. The intermediary steps require absolute VO_2 [L/min] to be converted to relative VO_2 [mL/kg/min]. Then, relative VO_2 is converted to METs from which energy expenditure is derived. The unknown input to this algorithm is the metric obtained from one or more sensors that can best estimate absolute VO_2. Equations 2 and 3 outlines how this can be achieved.

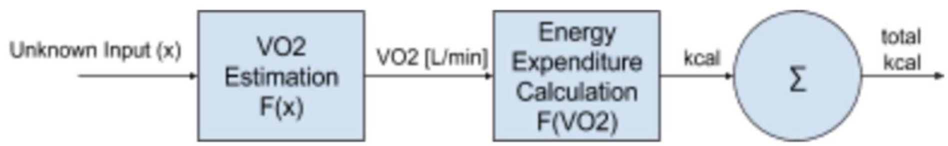


Figure 6: Energy Expenditure Algorithm Model

For 1 sample interval,

$$Energy\ Expenditure\ [kcal] = 5x10^{-6} \bullet Mass^2 \bullet VO_2 \bullet dt, \text{ (2)}$$

where dt is the time difference between samples in minutes.

$$Total\ Energy\ Expenditure\ [kcal] = \Sigma\ EE_{1\ sample\ interval} \text{ (3)}$$

Test data was obtained from a total of six subjects, four of which were able-bodied control subjects and the remaining two were spinal cord injury subjects, each varying in mass and fitness levels. The testing protocol involved each subject performing a series of exercises whilst seated in a wheelchair. Each subject wore a respiratory mask attached to a MET Cart data acquisition apparatus for capturing VO_2 data and a chest strap heart rate monitor to acquire heart rate.

The exercise protocol was broken into three sections, separating exercise routines into three exercise categories - spin, exchange, and resistance. A new data set was collected at the beginning of an exercise category routine. During the cardiovascular spin and exchange exercises, subjects were instructed to roll their wheelchairs at a pace that maintained their heart rate within a given range called a heart rate zone, calculated based on a percentage of their estimated maximum heart rate. The following equation was used to calculate each subject’s estimated maximum heart rate based on their age.

$$HR_{max} = 208.0 - (0.685 \bullet Age) \text{ (4)}$$

Estimating VO_2 Using Heart Rate and Linear Regression Methods

Linear regression estimates of VO_2 from heart rate already exist in the literature. However, no one has purported that it is sufficiently reliable for fitness trackers, particularly in the SCI population. Therefore, we wanted to test our hypothesis that heart rate alone would be inadequate to reliably monitor fitness and measure caloric expenditure in real-time while our target user population (individuals with SCI) exercise. For purposes of simplicity in this discussion, the term “VO_2” will refer to absolute VO_2, measured in liters per minute, unless specified otherwise.

Thus, to determine how well we could estimate VO_2 from heart rate, we collected heart rate and VO_2 data simultaneously from SCI subjects and non-injured control subjects during the prescribed exercises from the kinesiology protocol outlined in Table 3. Figure [##] shows a plot of heart rate and VO_2 data obtained throughout an SCI subject's spin exercise. By plotting heart rate vs. VO_2, it became evident that a linear correlation exists between heart rate and VO_2.

We calculated the linear regression coefficients, m and b, from each heart rate vs. VO_2 plot. These coefficients would be used to model VO_2 using the following linear equation which will be referred to as the VO_2-Heart Rate model.

$$VO_2 = f(HR) = m \bullet HR + b \quad (5)$$

Drawing a regression line through the heart rate vs. VO_2 plots yielded R-squared values within a range of 0.02 - 0.75 depending on the type of exercise performed. In this case, the R-squared value for the plot in Figure [##] was 0.6943.

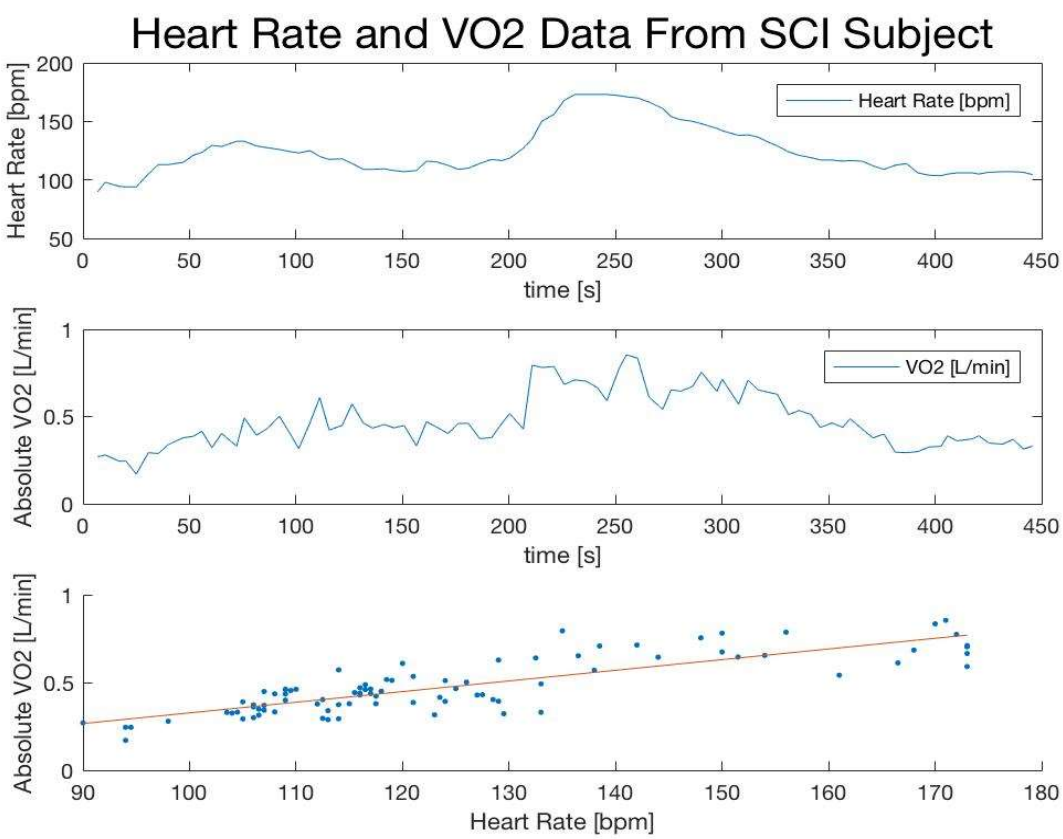


Figure 7: Heart Rate and Corresponding VO_2 Data of SCI Subject Performing Spin Exercise

Table 4 below shows the average R-squared values for each exercise category for spinal cord injury subjects and non-spinal cord injury subjects. Heart rate data from the cardiovascular spin yielded the highest correlation and resistance exercises appeared to be the least correlated. Furthermore, data from SCI participants surprisingly produced higher R-squared values than non-SCI participants in each exercise category.

Table 4: Comparison of Average R-squared Values for Each Exercise Among SCI and Non-SCI Participants

Exercise Category	SCI	Non-SCI
Spin	0.60895	0.31567
Exchange	0.47495	0.30125
Resistance	0.20005	0.18305

These results lead us to believe our hypothesis was wrong in one respect, and correct in another – namely, that heart rate alone is not sufficient to fully capture the variation in energy expenditure, but it is actually more accurate in SCI individuals than in non-SCI. An interesting finding from these results is that we may need to use a different model/metric for each exercise. Heart rate may be a better metric to use for some exercises, but we should incorporate other sensors at least for the exchange and resistance exercises. Therefore, we have a new problem of needing to determine when to use which metric. It appears that we could use a particular metric based on the intensity level, and this intensity level may be able to be measured with the accelerometer or EMG sensors.

The VO_2-Heart Rate model produced will serve as the input to the energy expenditure algorithm depicted previously in Figure 6 to become the completed following algorithm shown below in Figure 8.

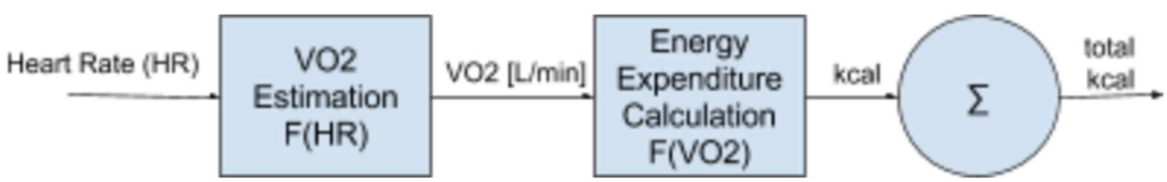


Figure 8: Energy Expenditure Algorithm with Heart Rate as Input

By applying the VO_2-Heart Rate model to each data set from which it was produced, a comparison between the calculated total energy expenditure estimation and that measured by the MET Cart could be performed. For each data set collected, a VO_2-Heart Rate model was derived and verified against its own data to determine how well the VO_2-Heart Rate model estimated energy expenditure fit that particular data set. Upon doing so, energy expenditure estimates were fairly close with a maximum error of 3 kcal and a standard deviation of 0.688, therefore confirming energy expenditure can be estimated using a linear regression using heart rate. The VO_2 estimations, as seen in Figure 9, however only follow the general trend, similar to a moving average and not the high frequency variations in VO_2.

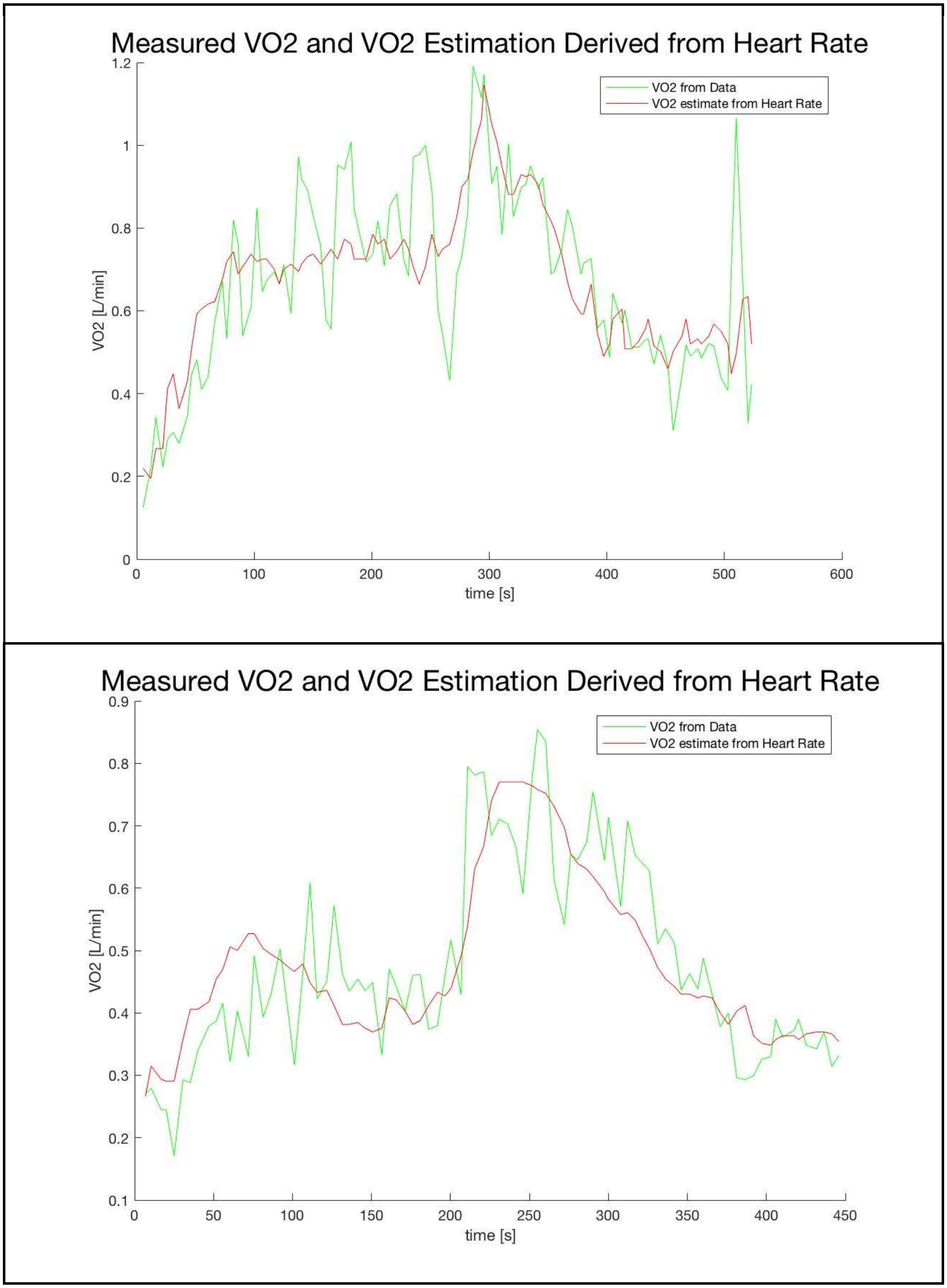


Figure 9: Comparison of Measured VO_2 and VO_2 Estimation Based On Applying the VO_2-Heart Rate Model On Spin Exercise Data From A Control Subject (top) and SCI Subject (bottom)

In order to apply the VO_2-Heart Rate model to fit multiple data sets of any given exercise, an average must be taken. To reduce the error of the model, a threshold was imposed to only include VO_2-HR correlation coefficients with R-squared values >0.5. The m and b values of the data sets satisfying the condition were averaged. By doing so, a new model was produced given by the following equation:

$$VO_2 = f(HR)_{avg} = 01335090 \bullet HR - 0.71259315 \quad (7)$$

This new model was then applied across all data sets collected to determine the accuracy of energy expenditure estimates produced by this new model. Based on this model, the maximum error was +/- 20 kcal with a standard deviation of 8.949. As shown below in Figure 10, there are cases where the linear regression model fits well and other times where it overestimates.

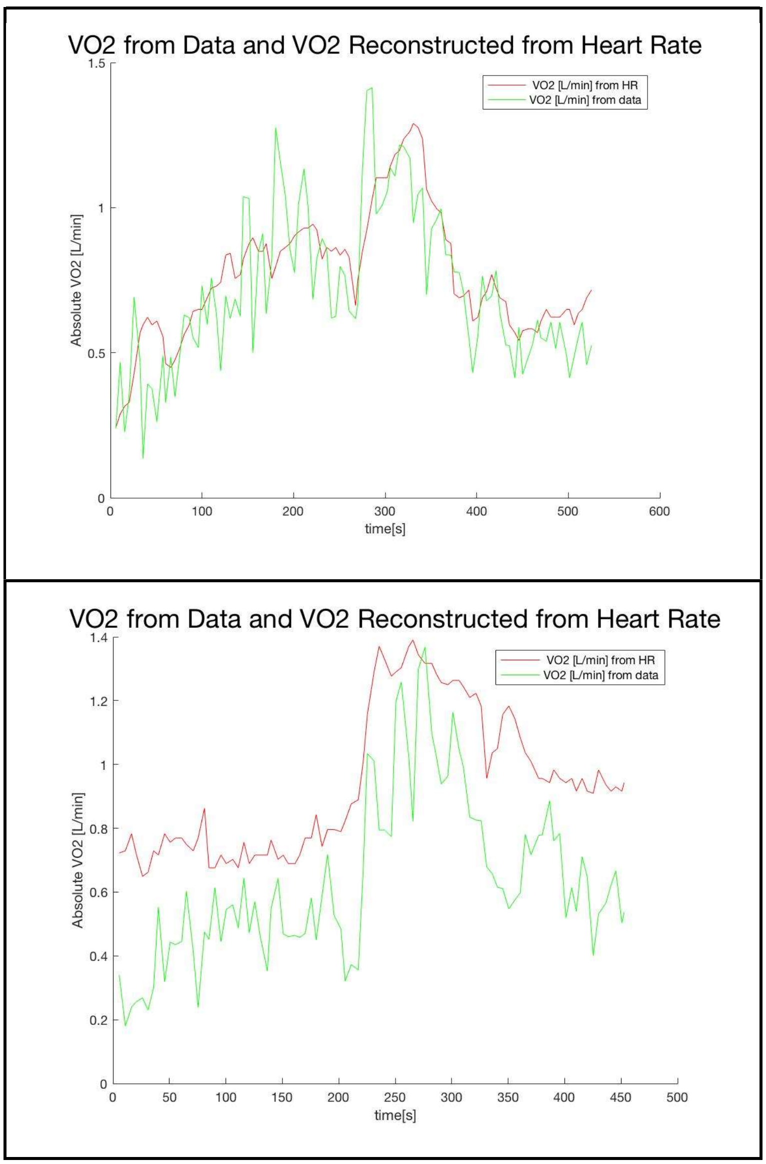


Figure 10: A Comparison Between VO_2 Estimates Produced by Average VO_2-Heart Rate Model for Exchange Exercises on Non-SCI Subject (top) and SCI Subject (bottom)

Table 5 shows a comparison of the statistics produced when validating both models. The error margins are significantly higher when an average linear regression is applied to multiple data sets, concluding that heart rate and VO_2 are somewhat linearly correlated but do not provide consistent results across different data sets. As a result, other metrics must be explored to produce a more robust model capable of yielding higher accuracies when applied to larger data sets.

Table 5: Energy Expenditure Calculation Validation Statistics

	VO_2-HR derived from single data set and validated against itself	VO_2-HR model derived from data sets with R-squared >0.5 and validated against all data sets
Maximum Error	+/- 3 kcal	+/- 20 kcal
Standard Deviation	0.688	8.949

Incorporating EMG

We have been obtaining some good correlations between Heart Rate and VO_2, but occasionally the correlation is poor, and more generally speaking, we would like to capture more of the variability (or "AC" signal) and not just the linear "DC" trend. To understand why, please refer to the top chart of Figure 9. At ~130s and 170s, based on VO_2, purportedly the subject was exercising very intensely and had some peaks in energy expenditure. At ~150s, the energy expenditure dipped to a low. If the game score was based on heart rate, the player's score would hardly vary from ~80s all the way to ~280s; thus, when the player's actual energy expenditure is low, they would have no incentive to work as hard as they would if the estimates were more accurate. Their score would be no different at the two peaks or large valley that occur between approximately 130s and 170s. As mentioned earlier, one of the main goals of our testing is to determine whether we can increase the accuracy of energy expenditure calculations by incorporating other measurements such as muscle activity and arm motion.

Sensor Overview

During testing, we have been using two separate types of EMG sensors. Delsys Trigno sensors are accurate, customizable, and come with software that can perform a lot of filtering and data analysis, however they require a proprietary wireless base and the system is very costly. The Dynofit Flexdot sensors are simple to use, automatically filter and process electrical muscle signals and easily connect to an android phone using Bluetooth. Their downside is that they do not record a raw EMG signal and the sampling rate is much lower than the Trigno sensors. For this reason, we are using the Trigno system for testing, analysis, and algorithm development, but will use the Flexdot sensors for the final product.

We also have an IMU wristband which can be used to determine the motion of a subject's arms. We do not have much hope that this will help us determine how much energy is being consumed, but we may be able to use the information in order to differentiate between different types of activities or exercise. This might be helpful if we can determine that different muscles have better correlation during specific types of activities.

Current Results of Testing

Table 6 and 7 below show how our R-squared values improve when we added EMG. Table 6 is a duplicate of the previous table 4 except that it was modified to ignore one SCI individual's spin results and another control subject's spin results due to incomplete or incorrect EMG readings. As you can see from table 7, the R-squared values increased across the board when we included EMG values and applied multiple linear regression to correlate VO2 with both heart rate and muscle activity instead of just heart rate alone. The increase in SCI individuals was 0.098, and in non-SCI individuals it was 0.119 giving us an average increase of 0.108. This is a significant amount showing that we are correct in our assumption that muscle activity can give us more accurate estimates, but unfortunately it is not as large an increase as we would hope to see.

Table 6: R-squared Values for Correlation Between Heart Rate and VO_2

Exercise Category	SCI	Non-SCI
Spin	0.6943	0.3888
Exchange	0.47495	0.30125
Resistance	0.20005	0.18305

Table 7: R-squared Values for Correlation of VO_2 With Both Heart Rate and EMG

Exercise Category	SCI	Non-SCI
Spin	0.7427	0.51303
Exchange	0.5541	0.371975
Resistance	0.3666	0.3442

Objective 2: Gamifying Cardiovascular Fitness

Overview

After calculating a formula that accurately measures cardiovascular fitness, the metric will be used within the mobile application to motivate users to exercise consistently. The sensors will transmit information about the user to the app by using a Bluetooth connection to provide the convenience of wireless technology. The app records the information in sessions to track users' fitness progress. Users will be able to sign into the app after creating a username and password. To provide further motivation, exercise routines will incorporate *exergaming*, which is the gamification of fitness, with two games being currently developed: the boxing game and racing game.

The games will incorporate single-player and multiplayer modes to promote the idea of exercising independently in one's home while also having the option to play against other users if they are interested in competitive gameplay. To create this competitive edge, the app will allow people to play against each other live, or one can replay their opponent's recording of their fitness and play against the replay. A point system will eventually be developed to rank the players onto a leaderboard (see Figure 11). The significance of exergaming is to provide motivation through entertainment to those in wheelchairs so that they do not feel the burden of exercise.

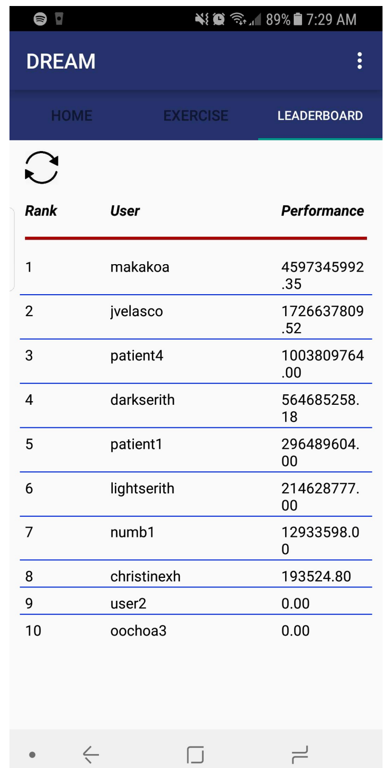


Figure 11: Leaderboard Sample for Multiplayer Mode

Game Features

Additional game features will be designed in extension to the objective of the exergaming development. In the midst of entertaining the players, a health indicator must notify them if they exert too much energy and their heart rate triggers autonomic dysreflexia. Therefore, the sensors must be calibrated for each user to develop the appropriate heart rate target zone and [muscle activity] target zone so that players stay within their own limits. Other features include adding game levels and informing the player how many calories they have burned. There will simply be three game levels, easy, medium, and hard and these levels will be completed based on the number of burned calories, which is dependent on the metric being researched. At the end of each level, a message will appear, telling the player that they have completed the level and also inform them about the number of calories they have burned. However, some users may not be able to understand whether or not those number of calories is a sufficient amount that allows them to conclude that they have exercised productively. Due to this probability of obscurity, another message will be included with the number of calories, providing a food equivalent to said number of calories.

Boxing Game Development

The boxing game will consist of different types of punches, such as a hook, uppercut, and jab. Each punch has a different range of EMG values that are also based on the muscle the sensors are placed at. Tables 8, 9, and 10 are examples of what the EMG ranges might look like for each punch and each muscle.

Table 8: EMG Values for Hook

Muscle Name	EMG Range
Tricep	2 – 4 mV
Bicep	15 – 18 mV
Deltoid (shoulder)	12 – 15 mV

Table 9: EMG Values for Uppercut

Muscle Name	EMG Range
Tricep	~ 3 mV
Bicep	~ 16 mV
Deltoid (shoulder)	9 – 12 mV

Table 10: EMG Values for Jab

Muscle Name	EMG Range
Tricep	14 - 16 mV
Bicep	12 - 15 mV
Deltoid (shoulder)	10 – 12 mV

The purpose of the EMG target zones is to not only be a health indicator, but to also make sure the players are actually doing the exercises instead of performing random movements to gain points and pass the levels. If a player does not perform a punch within their calibrated EMG target zone, a red message will appear during the game indicating a “miss” (see Figure 11).

Figure 11: Red Message Indicating "Miss"

Figure 12: Blue Message Indicating "Good!"

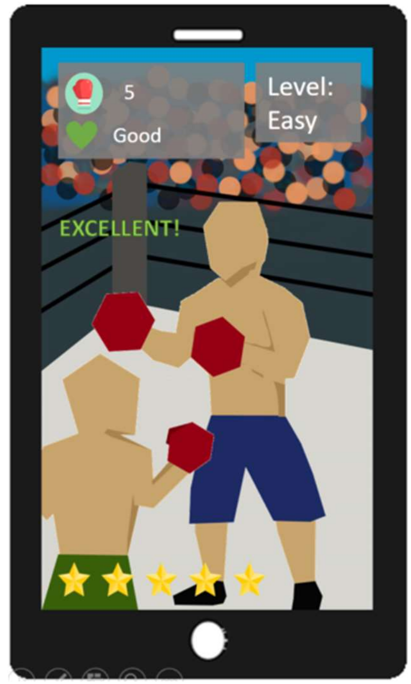


Figure 13: Green Message Indicating "Excellent!"

If they player performs within their target zone, a blue message will appear, stating, "Good!" (see Figure 12). On the chance that the player performs above their expected maximum EMG value for a certain punch by about 1 mV, a green message will appear, stating, "Excellent!" (see Figure 13). To clarify, the EMG target zone is not to be confused with the heart rate target zone. The EMG target zone focuses on muscle performance and is an independent reflection of the user's health condition. The heart rate target zone focuses on the user's heart condition and its main purpose is to alert the user if their heart rate may trigger autonomic dysreflexia.

Therefore, the game will also include a heart rate indicator to alert the player about the current condition of their heart. As seen in Figure 14, the green heart shown on the top-left side of the screen indicates that the user is within the heart rate target zone, thus stating that it is in "good" condition. If they are nearing towards their maximum heart rate, the heart will turn yellow to warn the player the "slow down" (see Figure 15). If they have reached beyond their maximum heart rate, then a red heart will appear, alerting the player that they have reached a dangerous heart rate level (see Figure 16).

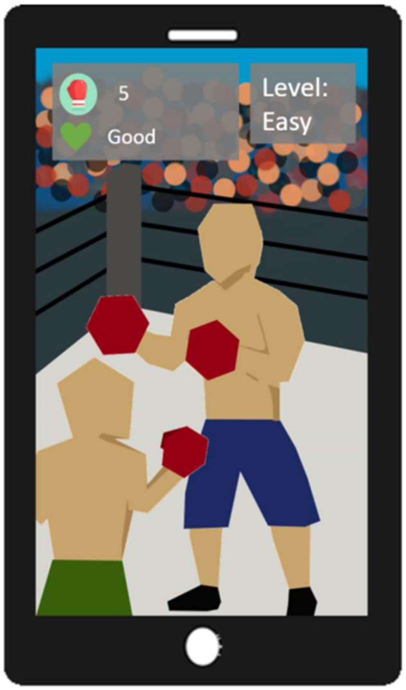


Figure 12: Green Heart Indicates Heart Is In "Good" Condition

Figure 15: Yellow Heart Indicates Heart To "Slow Down"

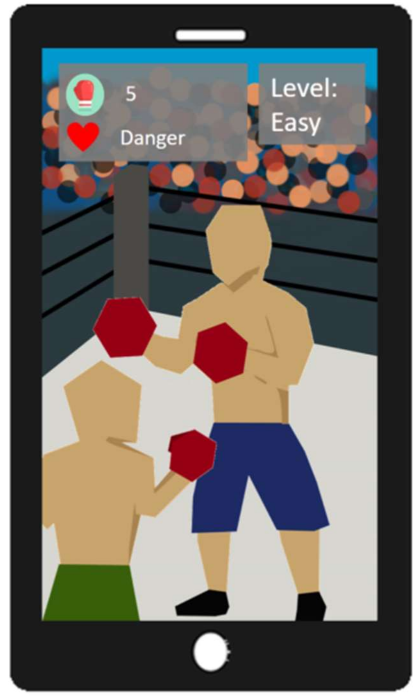


Figure 16: Red Heart Indicates Heart Is In "Danger"

To progress through the game, the developed energy expenditure metric will be used to create checkpoints during the level, which will be demonstrated using stars and can be seen in Figures 11, 12, and 13 at the bottom of the game interface. For example, each star is worth about 5 Calories and each level needs five stars to pass the level. Every time the player burns 5 Calories, a star (the checkpoint) will appear until five stars have been reached, which will be a total of burning 25 Calories. After reaching five stars, the player advances to the next level and if they have finished the "hard" level, then they have completed the game.

Racing Game Development

The objective of this game will be to complete a set distance in a certain amount of time. The game is designed for the user to use an Invictus roller for spin exercises. When the user begins to work out and the EMG wireless sensors have been placed on either biceps, triceps and shoulder muscles, the app will be able to correspond and receive the output values. As long as the app receives input from the sensors, the game character will continue moving forward and will stop when no activity is detected. The game user will be set in predetermined heart rate values to monitor the safety of user. If a user's heart rate gets too high to the predetermined maximum heart rate value, the game will display a message reading "Slow Down". At this point, if the user slows down too much and the heart rate falls too low, then the game will display the text "Speed Up" to the user. Each lap will be set to burn a certain number of Calories. For example, if one lap is set for 25 calories, the user will lose 100 Calories after the first mile and will be given a star at bottom of screen. Each lap/round will be set so that it is motivational for user to continue working out and go faster. The harder the user works out, the faster the character will move on the screen to complete the game. The game graphics will show a background of track, running character, heart rate, laps completed, time and calories burned.

Risk Assessment

Our risk assessment tables demonstrate which aspects of our project may hinder the project's completion and prevent us from accomplishing our goals. These aspects are called our risk items and are determined by the probability of them occurring and how it will impact the entire project. They are ranked from a scale of 1 to 5, with 1 defined as a low risk and 5 defined as a high risk. On Table 11, our mitigation approach explains how we will manage these risks.

The exergaming system will require animations, which will affect the memory usage of the mobile app. We may minimize the memory usage by using Java code to move the characters more than XML layouts and to minimize the usage of frame animations. Since one of our objectives for the project involves research to accurately measure energy expenditure, we will have to find methods to minimize motion artifact, which occurs when the friction between the sensors and the skin introduce additional noise to the original signal during data collection. Data accuracy is also dependent on the sensors' placement on the muscles as different muscles are affected by the exercises performed. A control group is necessary according to the scientific method. Bluetooth connection is a main feature of our project since it communicates the sensors' data to the mobile app. To mitigate its potential to fail, we will work with members of the DREAM team. An exercise protocol is used during testing and its effects on the test subjects depends on its intensity due to the subjects' likelihood to experience autonomic dysreflexia.

Table 11: Risk Assessment Table

Risk #	Risk Item	Mitigation Approach	Impact	Probability
1	Memory Usage	minimize usage on animation (implement animation through Java more than XML)	3	4
2	Data Collection (accuracy)	minimize motion artifact, research correct muscle placement, create control group	4	4
3	Bluetooth Connection	work with DREAM team about the code	4	3
4	Exercise Protocol (effects on test subjects)	work with kinesiology department, subject feedback	3	3

An overview of how the impacts and probability affect the overall risk of each risk item is shown in the diagram, Table 12. The risk item numbers from Table 11 are used to show where these risk items are mapped in the diagram. Data collection (Risk 2) and Bluetooth connection

(Risk 3) are shown to display a med-high risk with some disruption likely to affect the project. Memory usage (Risk 1) and Exercise protocol (Risk 4) have a medium risk with some disruption possible to affect the project.

Table 12: Overview of Risk Assessment

			Risk Impact				
			Low 1	Minor 2	Moderate 3	Substantial 4	Severe 5
Probability of Occurrence	Very Likely 5	>70%					
	Likely 4	30-70%			1	2	
	Possible 3	10-30%			4	3	
	Unlikely 2	1-10%					
	Very Unlikely 1	<1%					

Table 13: Risk Assessment Legend

High		Major disruption Likely
Med-High		Some disruption likely
Medium		Some disruption possible
Med-Low		Minor disruption possible
Low		Minimal disruption

Conclusion

We are currently analyzing collected data from the control group and from spinal cord individuals. We will continue creating more functions to the boxing and racing game to complete a working prototype. We have recently come to a decision that accelerometers will not be used as user input for gameplay. We are still in the process researching energy expenditure modelling with EMG. We have determined that including EMG sensors do improve the accuracy of our energy expenditure estimate, but seemingly not enough to be useful to the end user. Therefore, we will begin to explore alternatives such as including IMU data (hand/arm motion) in the hopes of accurately modeling the peaks and valleys found in VO_2 graphs in addition to the general trends we can model with heart rate alone. If we are successful with our project, we will hopefully help wheelchair individuals decrease risk of heart disease, improve immune system, gain a sense of autonomy and social integration. With all these hopeful health attribute goals, our main goal is to provide these individuals generally an improved quality of life.

Works Cited

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