SCHOOL OF SCIENCE AND TECHNOLOGY

CSD 3997

DIET BASED ON USER STRESS FEEDBACK

DATE	20TH APRIL 2018
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CAMPUS	MIDDLESEX UNIVERSITY MALTA

A THESIS SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF BACHELOR OF SCIENCE (HONS) IN COMPUTER SCIENCE (SYSTEMS ENGINEERING)

SCHOOL OF SCIENCE AND TECHNOLOGY

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MODULE NUMBER CSD 3997

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Abstract

Stress eating is a disorder where users eat food to supress negative emotions. This can result in a high-calorie diet which could sabotage any weight loss efforts. The solution proposed in this project is a stress eating health management application which identifies stressful periods and provides an incentive to reduce the habit as a whole. The application analyses the RR and GSR of a user when they start eating and provides a daily score based on the following stress eating factors: calorie count, outside factors including stress factors and time the food is consumed. The stress detection was evaluated in 12 people and had an accuracy of 70%.

Acknowledgements

I would like to thank my supervisors Omar Zammit, Mark Borg and Clifford de Raffaele for guidance and inputs throughout the process. I would also like to thank my family for their valuable support.

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School of Science & Technology,
Department of Computer Science Ethics Committee

Middlesex University Malta

Form D: Declaration Form

This form should be given to your supervisor along with your project proposal. It must also be included in your Project Report.

Student Project: Ethical Approval Request

Name:	Student ID:	Date:
Gabriel Stellini	M00598900	9/04/18

Supervisor:
Omar Zammit

Title
Diet based on stress feedback

Ethical Approval Statement:

Declaration A

(i) I have studied the Ethical Approval section.
(ii) I have established that my study does not require additional human participation.
(iii) I agree to re-apply for approval if the nature or goals of my project change.

Declaration B

Project Goals involving human participation:

Gather non - stress data (through MS band)
Gather stress data (through MS band)

(i) I have studied the Ethical Approval section.
(ii) My study involves human participation through
- observation
- questioning.

(iii) Participants will be selected without coercion (see Chart 1).
(iv) I will obtain informed consent (see Chart 2) from each participant using Form C.
(v) I have arrangements in place for the protection of personal data (see Chart 3).
(vi) I agree to re-apply for approval if the nature or goals of my project change.

☑

Declaration C

My project does not fulfil the conditions for fast track Ethical Approval and I am applying separately to the Ethics Committee

☐

Note: to make an application to the Ethics Committee, you need to complete **Form E** - Application for Ethical Approval & **Form C** – Informed Consent Form (Download from: **http://tinyurl.com/mdx-ethics**)

Student Signature........ Date 9/04/18

Supervisor's Signature........ Date 9/04/18

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Keywords

- Multiple signal classification
- Time-Domain analysis
- RR/RR interval/HRV – heart rate variation –time between heart beats
- Galvanic skin response / Skin conductance / Electro-dermal activity - GSR
- FFT – fast fourier transform
- Poincaré plot
- Tackychardia
- Breadychardia
- Hyper hidrosis
- LF – low frequency
- MF – middle frequency
- HF – high frequency

Introduction

The central nervous system has evolved to react to primal dangers using the fight or flight response (Dhabhar, 2009). Although the primal dangers have subsided, the body reacts similarly to stress - the heart beat speeds up, the heart rate variation changes drastically and the body tries to cool down using sweat (Dhabhar, 2009). In order to mitigate the side effects and reduce overall negativity, subjects might resort to eating high calorie based foods such as chocolates and ice cream. This is known as stress eating and results in a weight gain when it is not managed correctly.

The aim of this project is increasing awareness and identifying stress associated eating and binging., It provides a program which guides users unobtrusively.

Background and Literature review

Requirement in the industry

A study has identified that 69.75% of the Maltese population is either obese or overweight (Cuschieri *et al.*, 2016). A number of studies also linked stress to obesity and diabetes (Adam and Epel, 2007; Nanri *et al.*, 2010; Heraclides *et al.*, 2012)

In "Stress in America - Paying with our health" (Adam and Epel, 2007; Jääskeläinen *et al.*, 2011; Anderson, N.B., Belar, C. D., Breckler, S. J., Nordal, K.C., Ballard, D. W., Bufka, L. F., Bossolo, L., 2015) it was concluded that 33% of people eat too much as a result of stress.

The current solution to stress and obesity was found to be stress management through meetings, changes in lifestyle, medication or meditation (Cox *et al.*, 2013)(Greco and Hayes, 2008; Cox *et al.*, 2013; Mantzios and Giannou, 2014; Hanley *et al.*, 2016; Sampaio, Lima and Ladeia, 2016; Sanchez *et al.*, 2017)

A paper published in 2016 (Ueda *et al.*, 2016) made use of keywords to find recipes which match a user's mood. Although the result was deployed successfully, the site is not available today. The paper does not mention how the system was tested – so there are no statistics on how successful the system was in matching up recipes with user's moods. Based on the implementation, it is also not a "good" diet. This assumption is based on the mechanism of the system – the proposed system matches up keywords in recipes with user mood as opposed to healthy eating.

Stress management

(Anderson, N.B., Belar, C. D., Breckler, S. J., Nordal, K.C., Ballard, D. W., Bufka, L. F., Bossolo, L., 2015) found that the 3 main ways to deal with stress in the average American parent is to Watch TV, Surf the internet, nap/sleep, drink or smoke. This is in stark contrast to millennials who prefer to surf the internet, watch TV, nap, eat drink and smoke respectively.

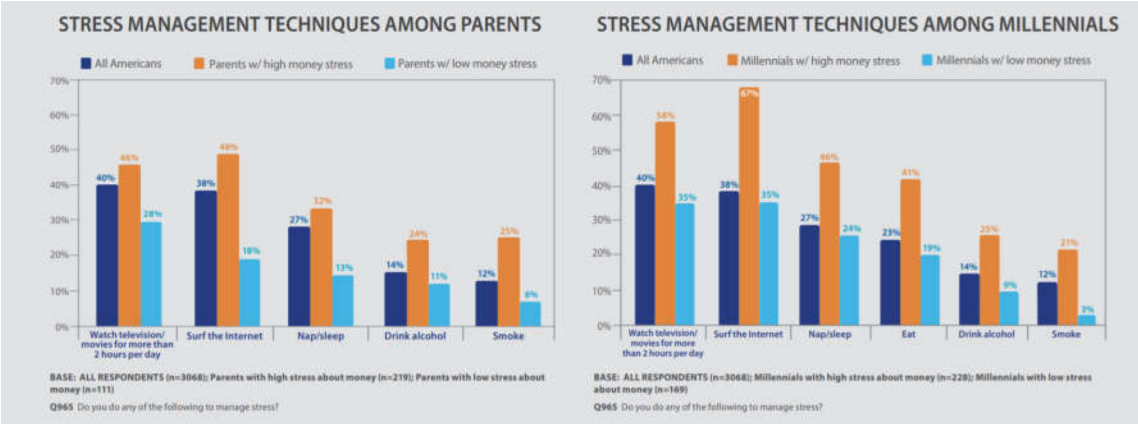


Figure 1: Stress management techniques

Stress factors

Financial pressure

(Anderson, N.B., Belar, C. D., Breckler, S. J., Nordal, K.C., Ballard, D. W., Bufka, L. F., Bossolo, L., 2015) used a scale of 1 to 10 for identifying stress levels. One of the most influential factors was average income – those in the lower income bracket suffer from dramatically more stress when compared to those in higher income brackets. This ultimately results in unhealthy behaviour. This factor effected 26% of all adults. It also resulted in nearly 1 in 5 Americans to have skipped or considered skipping going to the doctor due to financial concerns.

It was also found that those in lower-income households are almost twice as likely to say that lack of money prevents them from living a healthy lifestyle.

Emotional support

Using the aforementioned scale of 1 to 10, people with no emotional support had an average stress level of 6.2, while those who had emotional support had an average stress level of 4.8 (Anderson, N.B., Belar, C. D., Breckler, S. J., Nordal, K.C., Ballard, D. W., Bufka, L. F., Bossolo, L., 2015).

Gender

The Stress in America survey found that women report higher stress levels than men and are more likely than men to say they experience symptoms of stress. They are also more likely to indulge in unhealthy/sedentary behaviours. (Anderson, N.B., Belar, C. D., Breckler, S. J., Nordal, K.C., Ballard, D. W., Bufka, L. F., Bossolo, L., 2015). Using the 1 to 10 scale, women had an average stress level of 5.2 and men had an average stress level of 4.5 in 2014.

Weather and the relationship to mood

A number of studies agree that climate, rather than weather has a link to stress (Page, Hajat and Kovats, 2007; Huibers *et al.*, 2010; Li, Wang and Hovy, 2014). This meant that extended periods of bad weather, or very large spikes in temperature were associated with higher levels of stress. Snow also seemed to cause stress, although it is not clear if the depression results from the snow itself or other factors effected by snow (such as traffic jams, accidents and other unforeseen accidents)

Blood pressure - Heart rate variation

The two main types of stress are chronic stress and acute stress. Chronic stress is long term stress while the latter consists of stress suffered in a short period of time – e.g. a traffic jam or an argument. (Dimsdale, 2008) considers stress that lasts less than a week to be acute. In a study observing stress related to earthquakes, (Dimsdale, 2008) observed a spike in the heart rate, as well as an increase in the low frequency heart rate variation after the earthquake.

Heart rate variation (also known as RR-interval/RRI/HRV interval) is the distance between two beats. This is better shown in the following diagram:

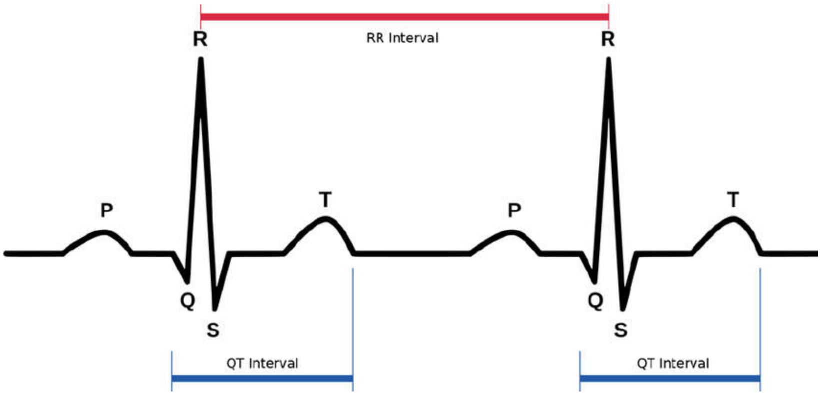


Figure 2: RR-interval (Image based on SinusRhythmLabels.png by Anthony Atkielski)

Usually a higher low frequency HRV means that a subject is experiencing a withdrawal from parasympathetic nervous system activity and an increase in sympathetic nervous system activity (Huang *et al.*, 2001). In other words, the patient would be experiencing a “fight or flight” response when there is a higher low frequency of HRV. This data agrees with data found from other stress related studies (Blanchard *et al.*, 1982; Huang *et al.*, 2001; Choi and Ricardo, 2009; Thayer *et al.*, 2012).

Blood pressure can prove to contain noisy data due to respiratory influences. One paper tried to mitigate this by modelling the effects of breathing on HRV through an autoregressive moving average model (ARMAX), and then subtracting respiratory-driven predictions from the HRV signal (Choi and Gutierrez-Osuna, 2011). Some people have other possible stress triggers; Clinical emulations performed on war veterans with PTSD made use of sudden sounds, hypnotic imagery or combat experiences. Responses to these stimuli included tachycardia, increased blood pressure, tachypnoea, tremor, and excessive sweating. (Kolb, 1987)

It was also found that short term factors have a heavy influence on HRV(Choi and Gutierrez-Osuna, 2011). Such factors include “public speaking, mental arithmetic, or reaction-time tests”. Body posture also influences the HRV. The study also found that a decrease in respiration rate induced an increase in the low frequency power of heart rate variation in all subject groups. Unfortunately, this paper had a small sample size of 4 people, so the results from the paper were not thoroughly verified.

There are 3 main competing categories for analysing HRV:

- Time-Domain analysis
- Frequency Domain analysis
- Non-linear analysis

A few examples of time-domain analysis methodologies are:

- Mean RR
- STD RR or SDNN (Standard Deviation of Normal to Normal (heart rate))
- STD HR (standard deviation of the heart-rate in bpm)
- RMSSD
- NN50
- pNN50

Frequency Domain analysis has 2 main methods used in the following papers:

- FFT spectrum (Fast fourier transform)
- AR spectrum (Auto regressive spectrum)

Non-linear intervals are used to plot the RR intervals against itself. These in turn results in 2 main readings, an "SD1" and an "SD2". The width (SD1) represents short term HRV, while SD2 represents long term HRV. Usually, these values are used in neural networks. This would allow classification and learning of what the values are when a user is stressed.

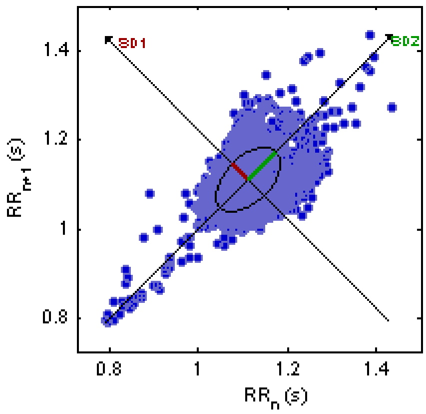


Figure 3: Non-linear example of RR-interval analysis

Many papers make use of power spectrum analysis (PSA) to analyse stress. (Cohen *et al.*, 2000; Healey and Picard, 2005; Choi and Ricardo, 2009). More specifically, they make use of Fourier transforms to determine the HRV bands. A Fourier transform is defined as a function derived from a given function and representing it by a series of sinusoidal functions. This can be used to determine the 3 main bands of HRV – the low, medium and high frequency bands.

A study which analyses stress levels while driving (Healey and Picard, 2005) normalised the data then found the parasympathetic frequencies to be between 0 and 0.5Hz. When subjects were stressed (and experiencing a sympathetic system response) – the paper found significant gain below 0.1Hz – the very low band frequency. These numbers were calculated by using a Lomb periodogram to calculate the power spectrum. They then divided the low-frequency band (LF) in the high frequency band (HF)

$$LF/HF$$

The result was used to determine whether a user was stressed or not. They also made use of another formula when they had a smaller test window:

$$\frac{LF + MF}{HF}$$

The paper then used a Fisher projection matrix and a linear discriminant to identify and train the algorithm. The training vectors were used to create a Fisher projection matrix and a linear discriminant. This is another way one can find the stress levels.

The following table shows the highlights of the HRV time-domain algorithms. This table was taken from (Stein and Pu, 2012).

Table 1
Time-domain HRV measures.

AVNN (ms)	Average of NN intervals for period of interest	Can convert to average HR of NN intervals (HR = 60,000/AVNN)
SDNN (ms)	Standard deviation of NN intervals for period of interest	Reflects total HRV
SDANN (ms)	Standard deviation of AVNN for 5-min intervals for period of interest	Reflects primarily circadian HRV
SDNNIDX (ms)	Average of 5-min standard deviations of N–N intervals for period of interest	Reflects average short-term HRV and combined SNS and PNS influences
pNN50 (%)	Percent of NN intervals > 50 ms different from previous (NN) for period of interest	With normal sinus rhythm reflects vagal activity
pNN625 (%)	Percent of NN intervals different from previous by 6.25% or more of local AVNN (NN) for period of interest	With normal sinus rhythm reflects vagal activity normalized by HR
rMSSD (ms)	Root mean square of successive differences of NN intervals for period of interest	With normal sinus rhythm reflects vagal activity
CV	Average coefficient of variance (SD/Mean) for 5-min intervals for period of interest	Reflects average short-term HRV normalized by HR

Figure 4: Table with summary of how Time-domain HRV measures work

The study compared the different algorithms on sleeping subjects (due to resting HRV). The study concluded that each algorithm was greatly dependent on the positioning, and noise in the data.

Another comparative study (S Tsakiraki, Riegler and Mahbod, 2015) found the best methods are wavelet denoising, the Pan-Tompkins method for detecting the R-peaks and Welch method for spectrum estimation. However, this study had a small sample size of 4 people.

Another paper suggested making use of a classifier based on the Poincaré Plot measures and on the Approximate Entropy. This enabled the detection of stress due to university examination with a total classification accuracy, a sensitivity and a specificity rate of 90%, 86%, and 95%.

Another study analysed the same data by making use of KNN, SVM, SVM-RBF and RBF classification methods. Linear SVM combined with STFT-analysis resulted in a 83.33% accuracy for the stress classification (Munla *et al.*, 2015). This is lower than the fisher projection matrix, which had an accuracy of 97.4% (Healey and Picard, 2005)

Other factors that can be used are STD RR (or SDNN). This is used to determine the range of RR-intervals over time. A higher SDNN is associated with parasympathetic behaviour, while a lower SDNN is associated with sympathetic behaviour. A study compared different algorithms together, namely:

- E–I difference (also known as E/I ratio)
- RMSSD
- SDNN
- Power LF

The comparison was done using Bland–Altman plots.(Weinschenk, Beise and Lorenz, 2016). It found that when performing a deep breathing test, HR, E/I ratio and SDNN were superior to Power LF and RMSSD. (Weinschenk, Beise and Lorenz, 2016). An E/I ratio is the ratio between the highest and the lowest heart rate within a breathing cycle.

It is important to note that studies seem to agree that low frequency consists of 0–0.115 Hz +-0.03 and high frequency consists of 0.15 to 0.5Hz. (Healey and Picard, 2005; Weinschenk, Beise and Lorenz, 2016)

Other papers made use of “R-Waves” and Least squares frequency analysis. (Healey and Picard, 2005; S Tsakiraki, Riegler and Mahbod, 2015)

In order to measure the HRV, Electrocardiogram (EKG - electrical and muscular functions of the heart) and Electromyography (EMG - electrical activity of muscles) were used. (Healey and Picard, 2005)

Skin conductance/ galvanic skin response/electro-dermal activity

In the following research paper, (Villarejo, Zapirain and Zorrilla, 2012) Galvanic skin response was measured with the use of a ZigBee and correlations were made to the stress level of users. Although the sample size of the paper is a bit small (only 15 people tested the system) – the GSR was able to detect different states of each user with a success rate of 76.56%. The paper made use of the following formula to determine whether a user was stressed:

$$Limit = \frac{stress\ average \times 0.6 + relax\ average \times 0.4}{2}$$

(Bakker, Pechenizkiy and Sidorova, 2011) identified several issues with measuring stress based on GSR. They identified several other factors which resulted in peaks for the GSR, such as poor contact with the skin as well as local disturbances in the skin (such as bumping the device into something). The study identified that when a user is stressed there is usually a spike and the GSR reading does not go down to its initial value (Figure 5: Effect of stress on GSR).

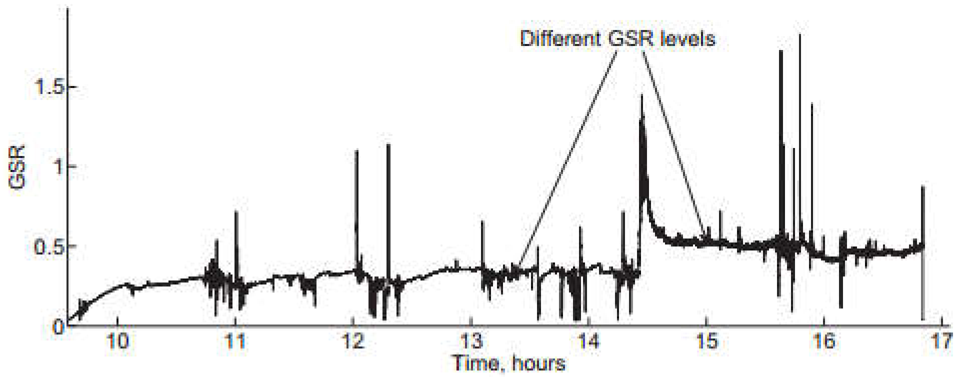


Figure 5: Effect of stress on GSR

Physical exercise also results in a higher GSR reading as can be seen here:

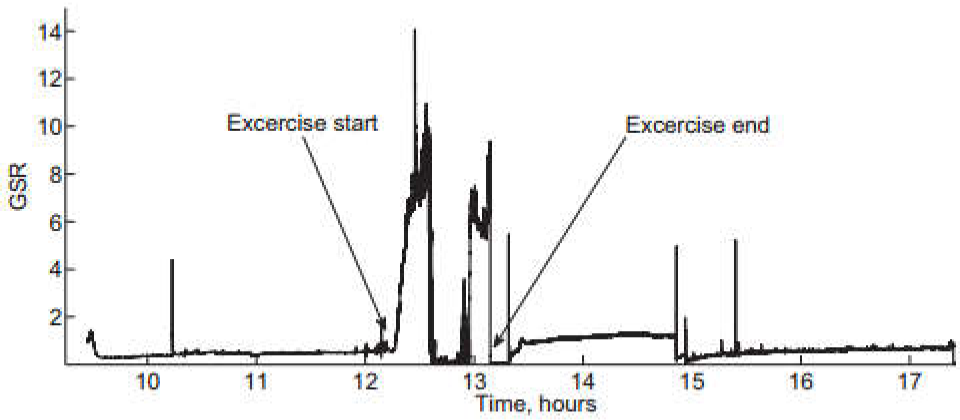
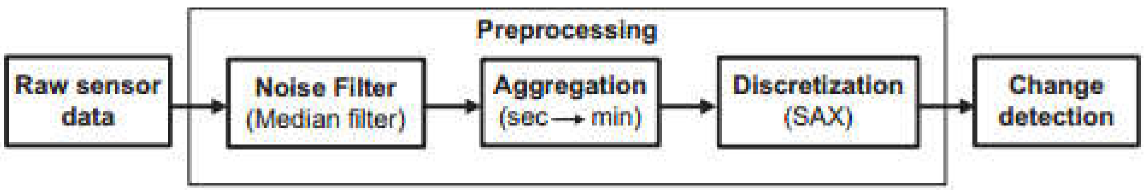


Figure 6: Effect of exercise on GSR

In the above diagram Figure 6: Effect of exercise on GSR, one can differentiate between exercise and stress with the amplitude of the GSR wave (seen at 13:15).

The paper made use of the following algorithms to filter the signal and detect stress:



The change detection mechanism was Cumulative Sum (CUSUM) which monitors the mean input data and gives an alarm when it is significantly different from 0. When more processing power is available, Auto-regression functions and neural networks were used– in particular the paper used ADWIN (adaptive windowing) and another approach based on monitoring model error. The study concluded that ADWIN detected less points, but the other approach had more false positives.

ADWIN works by performing change detection on raw data. It checks for significant differences between the means of each possible split in the sequence. When a significant difference is found, the oldest data is dropped, and the splitting procedure starts over.

The ADWIN algorithm was also used in another paper (Bakker *et al.*, 2012)

(Liu *et al.*, 2016) suggested making use of Wavelet de-noising as well as covariance. The data was then passed to a SVN classifier which identified the mood. This can be seen in the following image:

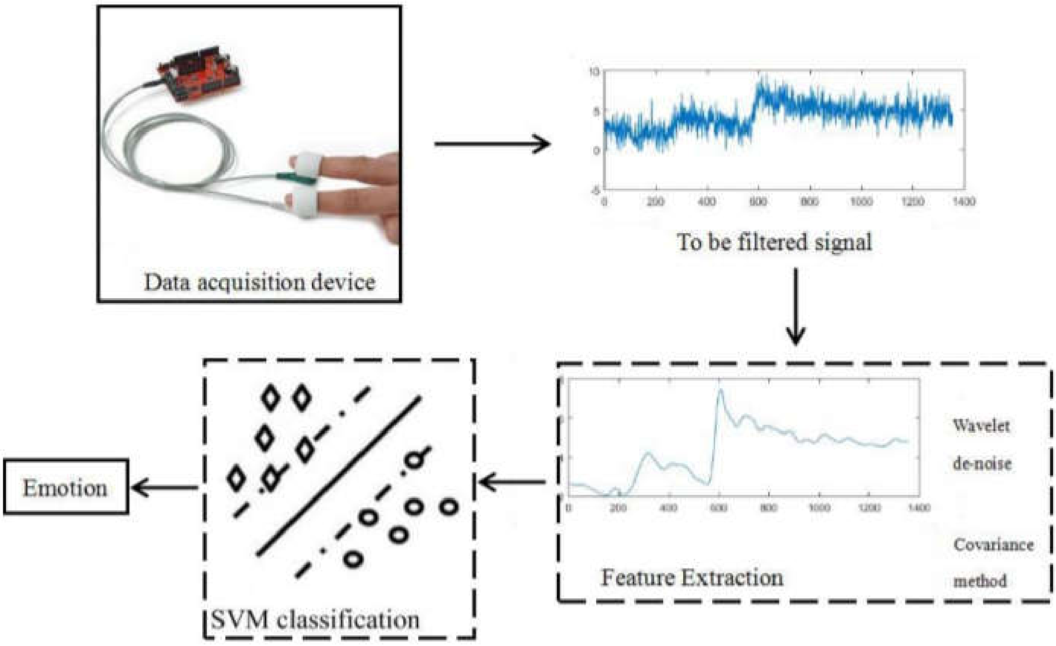


Figure 7: Image from "Human Emotion Recognition Based on Galvanic Skin Response Signal Feature Selection and SVM" explaining methodology

This paper made use of test and training data and found the accuracy to be 66.67% when a SVM was used. They recommended using cross-validation to check the result.

Another solution is through the use of Weka software.(Villarejo, Zapirain and Zorrilla, 2012) The paper made use of an EKA learning machine for testing the following methods: Bayesian Network, J48 and Sequential Minimal Optimization (SMO). The accuracy achieved in this study was of 90.87%, however the algorithm could not differentiate between stress and effort.

Respiration

Papers gathered respiratory data by making use of a chest strap (Choi and Gutierrez-Osuna, 2011) or a temperature sensor on the nostril to acquire the necessary data. (Emil Jovanov, Dejan Raskovic, no date).

The paper used a Hanning window and an implementation of Welch's averaged. A modified periodogram method was used to calculate the normalized power spectrum. The paper found Four spectral power density features were calculated by summing the energy in the bands 0–0.1, 0.1–0.2, 0.2–0.3, and 0.3–0.4 Hz. (Healey and Picard, 2005).

Music analysis

Background music is used in commercial settings and has been found to impact the sales per minute based on the category and tempo (Turley and Milliman, 2000).

However as stated in (Napiorkowski, 2015)'s paper, emotions are difficult to monitor quantitatively, with no standardised model to examine emotion. He also found that some music might produce more than one emotion, and is difficult to classify. Thus many papers resort to classification of mood with genre – which may not represent the mood experienced by the user effectively.

Native Bayes Classifiers were found to be the most effective way to extract emotion, with multi-layer perceptron networks displaying the most erratic behaviour of the 3 classifiers examined. (Nikolaou, 2011). The results from this study seem mixed however, as it had to discard sample data to increase the accuracy of the classifiers. It also required a large amount of data from the users themselves – a user would need to manually classify a song as “good” or “bad” and this might be too unintuitive/intrusive due to the high level of intervention required in the system proposed. It is also highly opinionated. Different genres also pose issues, and lyrics were not found to accurately represent the mood of the users.

Current implementations and similarities with other systems

A study (Poels and Dewitte, 2006) tried to analyse human emotion in advertising. Based on previous studies, it classified emotion as a spectrum, ranging from lower order emotions such as pleasure, to basic emotions such as fear, anger and happiness, to higher order emotions which are complex. These need to be continuously labelled as a specific emotion. It then compared two main sets of emotion measurements; automatic and self-reporting.

The self-reporting aspect was further slit into 2: verbal self-reporting and written self-reporting. They finally concluded with the following illustration:

	Self-Report Measures			Autonomic Measures		
	Verbal	Visual	Moment-to-Moment	Facial EMG	Skin Conductance	Heart Rate
Cognitive bias: Yes (Y) or No (N)	Y	Y	Y	N	N	N
Pleasure (P) or arousal (A)	P/A	P/A	P/A	P	A	P/A
One (O) or multiple emotions (M)	M	M	O	O	O	O
Continuous (C) or static (S)	S	S	C	C	C	C
Individual (I) or group assessment (G)	G	G	I	I	I	I
Cheap (C) or expensive (E)	C	C	C	E	E	E
Noise	N	N	N	Y	Y	Y

In "A Recipe Recommendation System that Considers User's Mood" (Ueda *et al.*, 2016) recipe is generated using factors like nutritional value, taste, time to create the food and price. The following are contrasts between the latter and the system proposed:

- The user is asked to manually input the mood, and there is no system in place to detect the user's mood
- The paper is not designed to help with weight loss, but it suggests what the user might want to eat at that point in time

Requirements specification

Introduction

The proposed system's scope is to reduce stress eating habits of participants. The final result should thus be able to detect stress, as well as motivate the users to reduce stress eating habits through gamification.

Problem definition

Studies have shown that stress drastically effects food consumption (Alberts *et al.*, 2010). A study on mice (Pyndt Jørgensen *et al.*, 2014) has found that changes in food choice based on the mood, contributed to depression-like behaviour. Other negative effects noted included differences in the immune system. A similar study was performed on university students and had similar results, where students who had poor diet quality also had a higher chance of depression (Quehl *et al.*, 2017) . Another study found that 33% of people suffer from eating too much as a result of stress (Anderson, N.B., Belar, C. D., Breckler, S. J., Nordal, K.C., Ballard, D. W., Bufka, L. F., Bossolo, L., 2015).

Applications in this domain usually focus on the user group controlling themselves or their emotions by use of meditation (Mantzios and Giannou, 2014; Victorson *et al.*, 2015; Sampaio, Lima and Ladeia, 2016) , and group meetings (Alberts *et al.*, 2010; Mantzios and Giannou, 2014). By performing an analysis on each user's mood and dietary patterns, approaches can be implemented to control dietary intake.

Requirements

Functional requirements

The application should be able to differentiate between different users; thus it must make use of some form of authentication and allow new users to register with the system. The new users should input their relevant information; this includes emotional support financial pressure as well as any possible medications they are taking. Statistically, these factors all effected stress as can be seen in “stress in America” - (Anderson, N.B., Belar, C. D., Breckler, S. J., Nordal, K.C., Ballard, D. W., Bufka, L. F., Bossolo, L., 2015).

The application must also be able to take readings of heart rate, as well as galvanic skin resistance. These factors were chosen as they were found to be the most reliable differentiators (Healey and Picard, 2005), and they are also the least intrusive to the end user - as opposed to temperature sensors in front of the nose. A smartwatch was deemed as less intrusive and more usable in day-to-day usage.

The aim of the system is to perform stress analysis with as little intervention from the user as possible. This means that non-linear analysis is not practical, as it would require very frequent intervention from the user to calibrate correctly and/or direct analysis to identify starting/ending points for stress periods. This might cause frustration and reduce the overall appeal of the application.

Due to the computational intensity of the alternatives as well as its popularity in the researched papers, power spectrum analysis (PSA) was used to analyse heart data and determine the stress levels of a user. Other classifiers were also found to be successful, however the fast fourier transform seems to be the most documented and frequently tested algorithm. The main advantage of this algorithm is lack of user data entry, as well as high reliability of 97.4% using 5-min intervals of data (Healey and Picard, 2005). Other papers were also fairly successful with accuracies of 90%, 86%, and 95% using a variety of algorithms. (Weinschenk, Beise and Lorenz, 2016).

The other solution with the SVN classifier was not to be implemented as it would require too much intervention from the user to calibrate it correctly.

For similar reasons, WEKA was not deemed appropriate as it requires direct training as opposed to using a FFT. Since FFT seems to be reliable without the use of training data, it would reduce the computational intensity of the program itself if WEKA is avoided.

The system should also try to motivate users by making use of gamification which has been found effective in other studies (da Rocha Seixas, Gomes and de Melo Filho, 2016). This should include a point system which is based on both the calorie intake as well as the stress level at the time of consumption. This means that the application should allow users to enter food consumed at a particular point in time.

The system should make use of factors provided in the sign up stage such as gender to dictate the calorie intake, and take into consideration the other factors provided. Some of the factors described above were dropped, as they did not have a significant impact on the minute to minute stress, or had no clear correlation to stress detection. These factors included weather and music preferences.

Non-functional requirements

The system must motivate the users to continue reducing their stress eating habits. It should also be performant – thus the mobile device should do as little as possible and processing should be offloaded to a remote server. The system must also be non-intrusive, requiring minimal input from the user and not getting in the way of daily tasks. The application must also be easy to use and navigate.

To summarise, the application should make use of most of the identified factors with a few minor exceptions, and will not try to suggest a diet, but rather the calorie intake. It will make use of FFT to analyse the data, and will offload the heavy processing to a server. The application must also have a form of gamification for user motivation.

Analysis and design

Design

The following section will show the structure of the application with the help of UML diagrams and mock-ups.

UML diagrams

Use case diagram

The design is made up of 3 main components. These consist of the user, who will interact with the application as well as a server which will handle the heavy processing and security. The system was built to allow the user to interact with the server in both a direct and indirect manner. This can be seen in the diagram below; (Figure 8: Overall use case diagram)

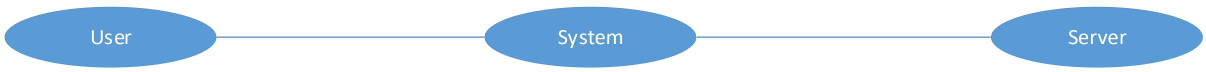


Figure 8: Overall use case diagram

The finalised system (Figure 9: Use case diagram) will allow individual users to view their own score as well as the score of competing peers. This means that a user should be able to add friends from within the application. The user interface should also let users view their own calorie count. This in turn means whilst using the UI, one can add a food eaten during a specific time as well as search for foods in order to calculate the calories. The application should also allow logging in, logging out, signing up and exiting the app.

In order to calculate the score, the user application should register HRV (heart rate variation) and GSR (galvanic skin resistance) with the server in the background. Thus the server should be capable of receiving raw sensor data, as well as processing the respective sensor data and food data into scores for each user. The backend should also store all this information – namely each sensor data point, stress/scores for each user, friends of each user and other user related information.

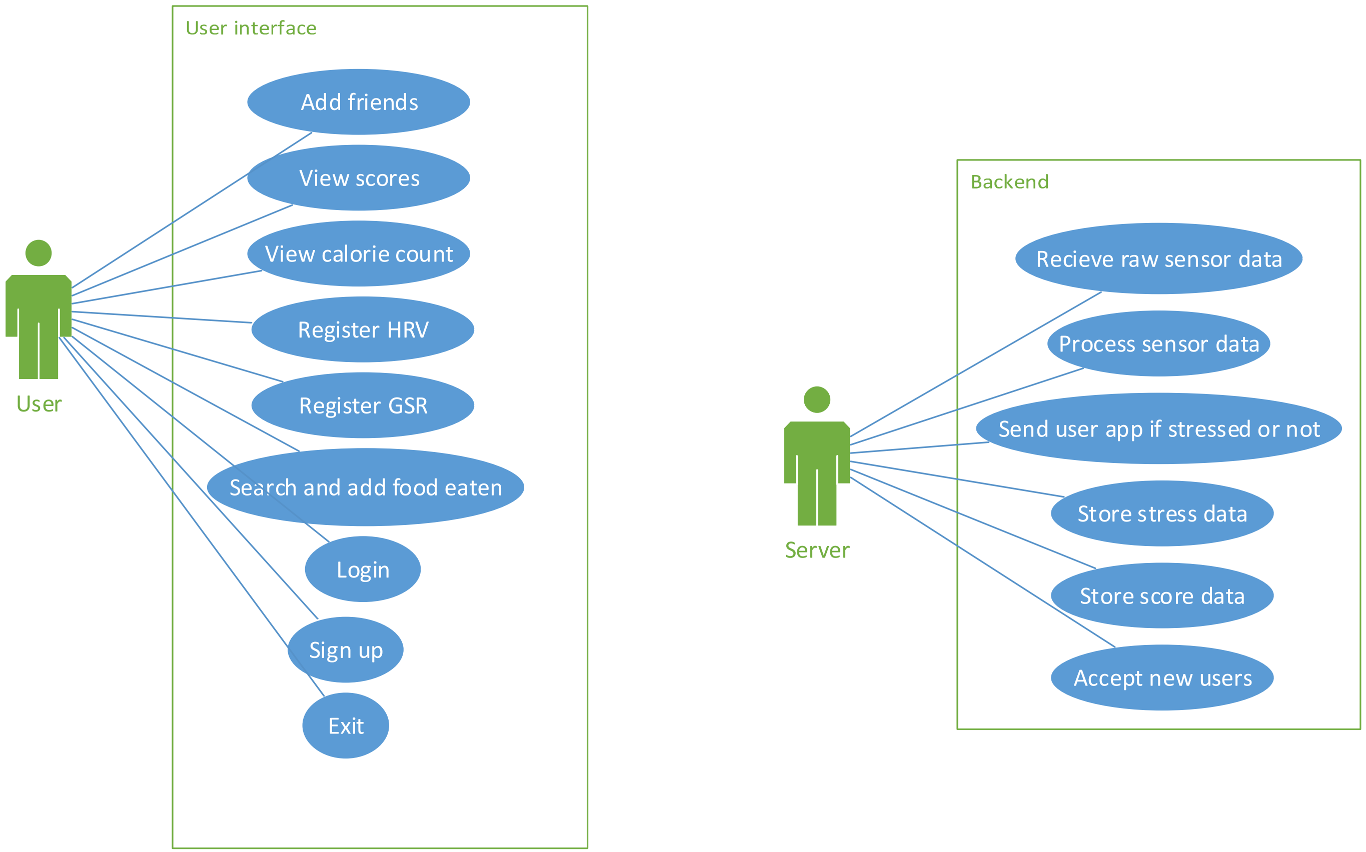


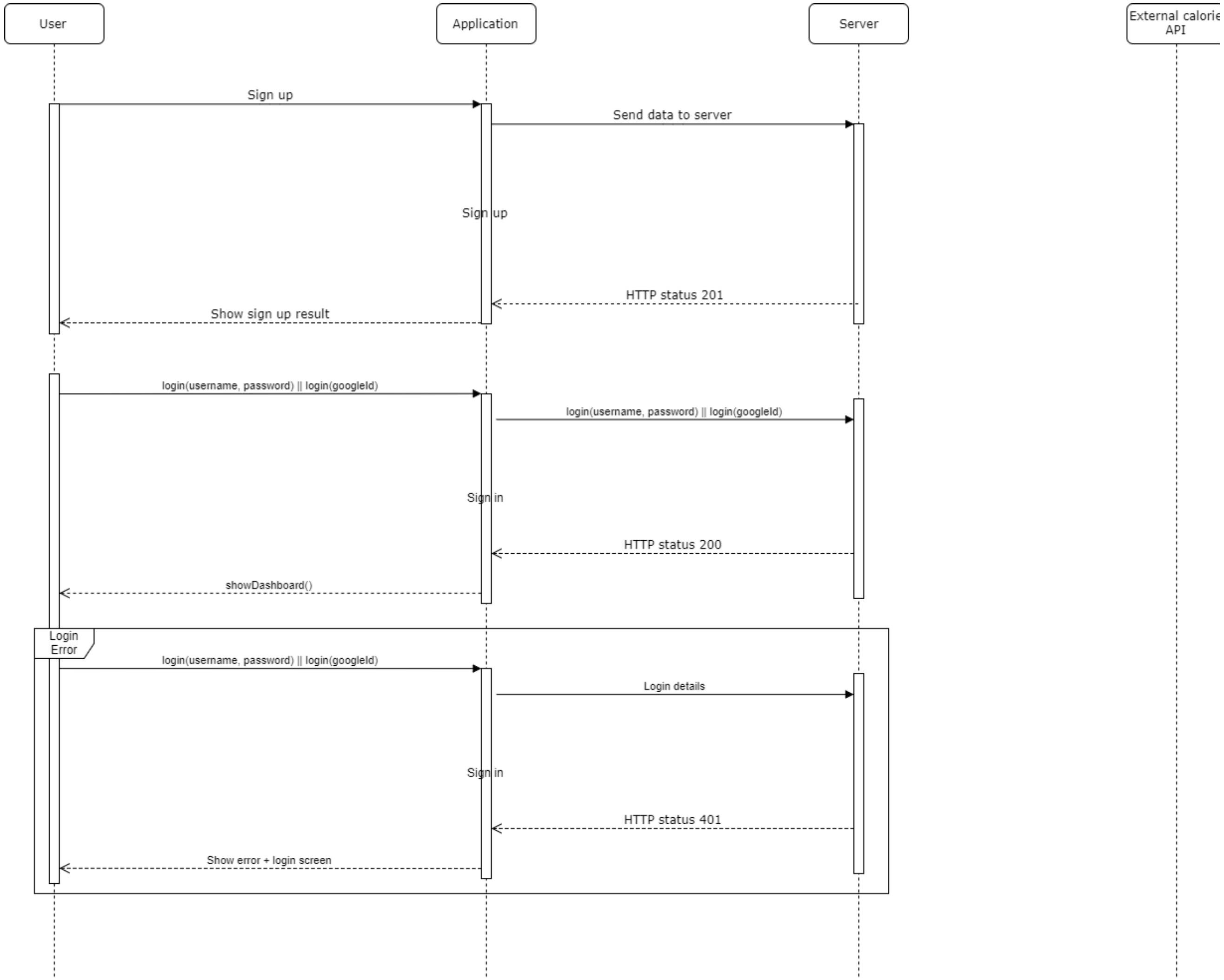
Figure 9: Use case diagram

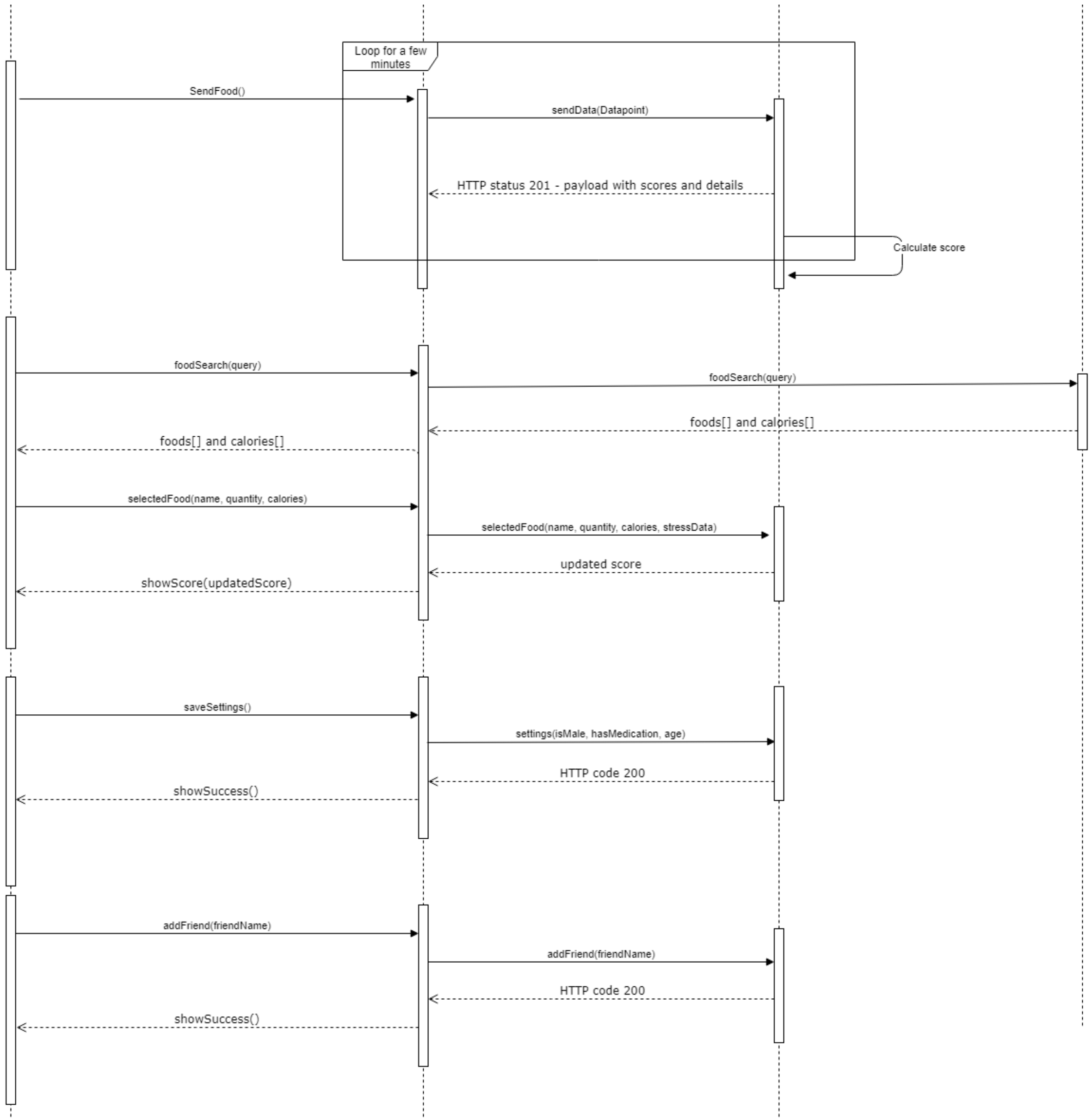
Sequence diagram

As can be seen in the sequence diagram below (Figure 10: Sequence diagram), the user should be able to signup and login to the service. The API should respond accordingly to each of the above API calls with status codes 201 and 200 respectively.

The user should also be able to call the appropriate APIs to view scores for the day (showDashboard). Food, settings, personal scores and friends' scores should also be present between the server and the client. An important item to note is that when a user posts a food, the app would send datapoints to the server. These would contain heartrate and skin resistance and this data would be used to calculate the stress levels of a user. They would also be used to update the user score.

Another important aspect highlighted in the diagram is the addition of food. This is used to add food eaten and should be added before eating something. In order to support most food sources, the user app will query external APIs to find the matching food item. This would reduce user input as they would not need to manually calculate the calories for a particular food item.


User
Application
Server
External calorie API
Sign up
Send data to server
Sign up
HTTP status 201
Show sign up result
login(username, password) || login(googleId)
login(username, password) || login(googleId)
Sign in
HTTP status 200
showDashboard()
Login Error
login(username, password) || login(googleId)
Login details
Sign in
HTTP status 401
Show error + login screen



Loop for a few minutes
SendFood()
sendData(Datapoint)
HTTP status 201 - payload with scores and details
Calculate score
foodSearch(query)
foodSearch(query)
foods[] and calories[]
foods[] and calories[]
selectedFood(name, quantity, calories)
selectedFood(name, quantity, calories, stressData)
updated score
showScore(updatedScore)
saveSettings()
settings(isMale, hasMedication, age)
HTTP code 200
showSuccess()
addFriend(friendName)
addFriend(friendName)
HTTP code 200
showSuccess()

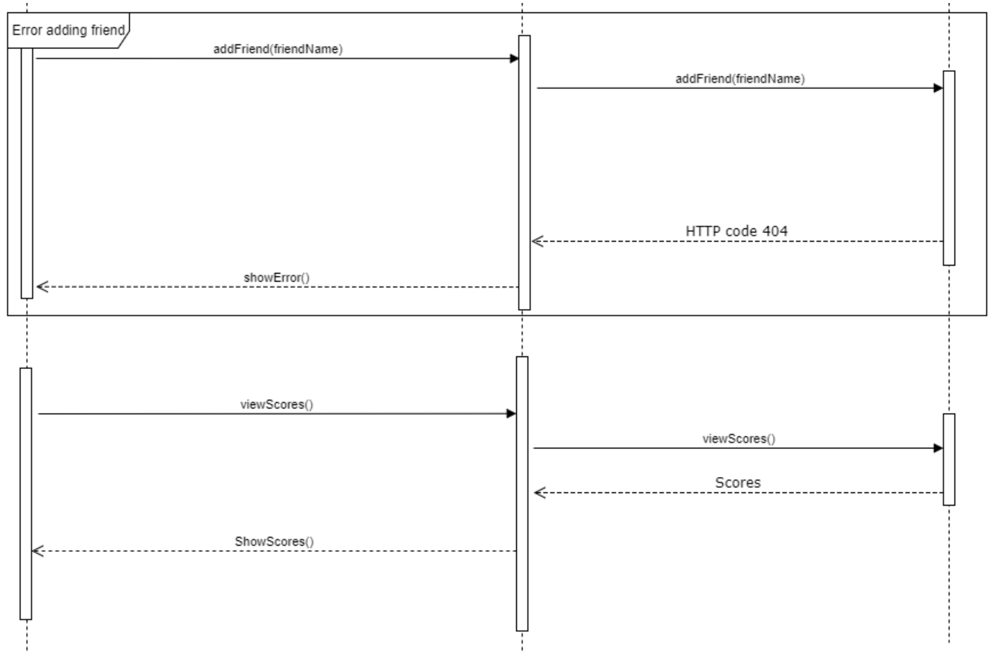


Figure 10: Sequence diagram

Class diagram

The server Controller classes consist of the UserController, FriendController, DataPointController, FoodController, ScoreController classes. These handle the API calls from the android app using the REST architecture. The controllers in turn make use of services which use repositories to get their data. The services handle any filtering and processing while the repositories handle getting the data from the database. The classes can be seen in Figure 11: Server class diagram.

As can be seen in the diagram, most services extend the UserService. This was done as most data is stored in relation to a User (as seen in the ERD diagram).

The DatabaseEntities package contains all the Entities used in the project. These are mapped to MySql using the Spring framework. These contain all the details on each user, preferences, and data on skin resistance, heart rate and relevant scores. In order to add security to the app, RequestResponse package was created which reduces the fields sent back. A use case example of this is searching for a user. If the user receives the age of each user in the query response, it would be a breach of data privacy. These classes extend EntityToRequestResponse which allows easy conversion from their respective Entity values.

The Server code also makes use of a StressEngine package. This contains the necessary classes required to process the data collected from the Microsoft band 2 – GSRStressEngine, HRStressEngine, RRStressEngine. These all extend Engine, which has common functions between classes including the visualisation of the data and cleaning up the data itself. The code used to visualise the algorithms was left unused in the final implementation; however, it was left as a potential future development utility on the server.

The client also contains a RequestResponse package similar to the one in the Server. This is used to correctly parse objects to and from JSON.

In order to send and receive data from the server, the android client has an APIServiceCallback. This service was extended by most fragments throughout the android app in order to connect with the server endpoints. The classes which extend it include: LoginActivity, FoodFragment, EatingTimesFragment, DashboardFragment, PreferencesFragment and FriendsFragment. The client makes use of 2 main activities: The DashboardActivity and the LoginActivity. Content is dynamically loaded into the two activities respectively whenever a user completes an action with the use of fragments.

The model on the client is the same found on the server's requestResponse classes. This allows easy parsing of the data using the GSON library. The LoginActivity makes use of callbacks to switch between fragments. The main thing of interest found on the client is the Utils package. This contains the Microsoft band 2 connector logic – it asks for the band 2 permissions if necessary, collects data into a global object and allows the code to dynamically stop and resume recording of the data – all as a background service so as to not hog the UI.

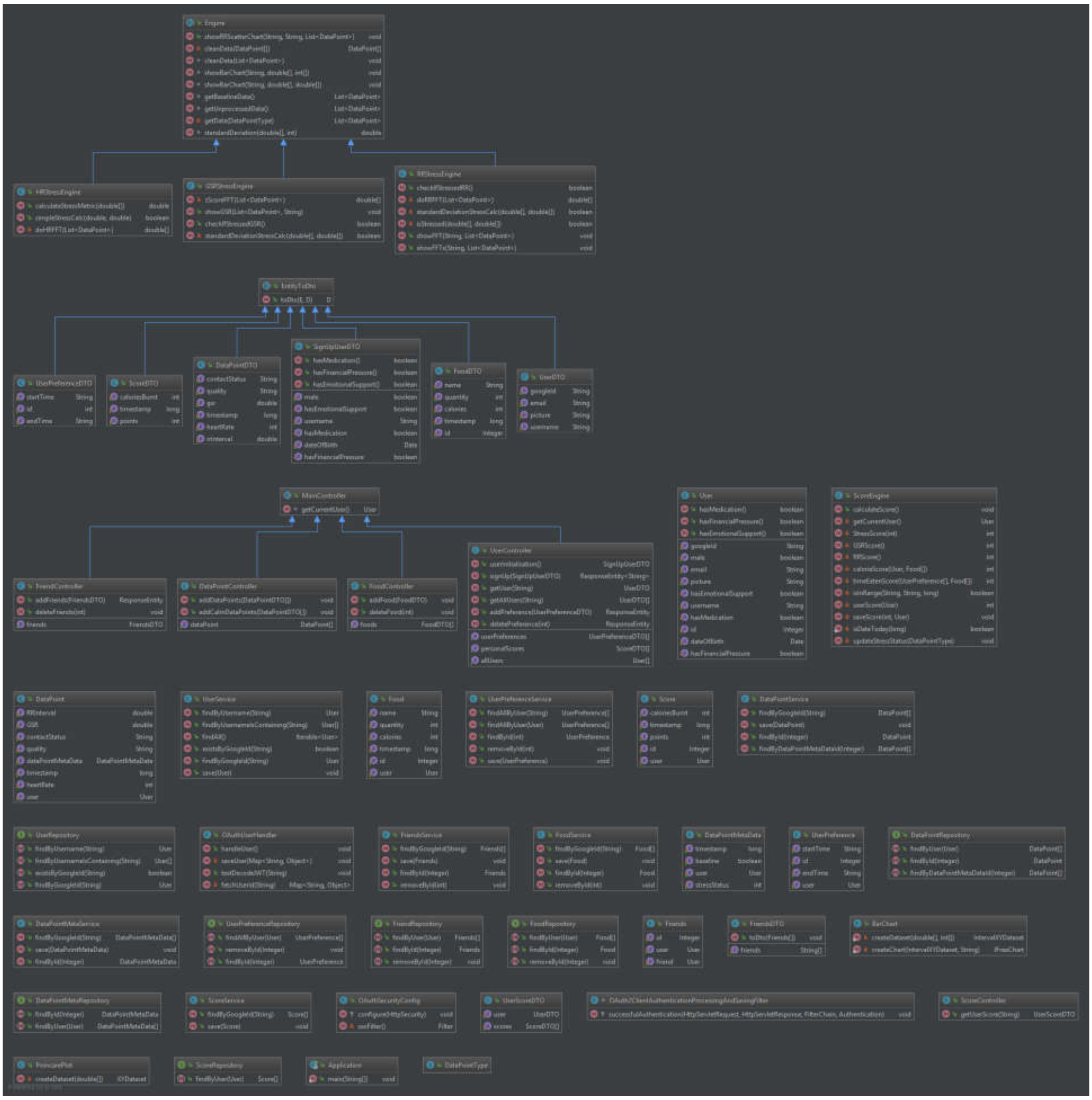


Figure 11: Server class diagram

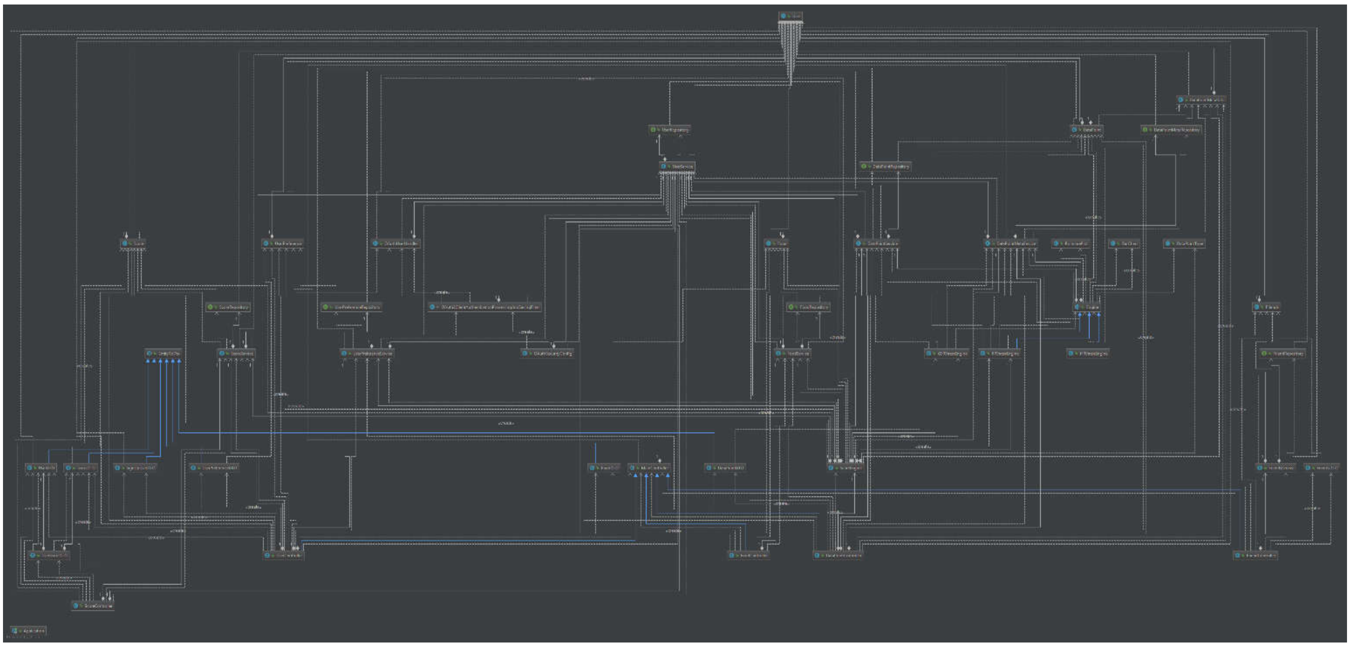
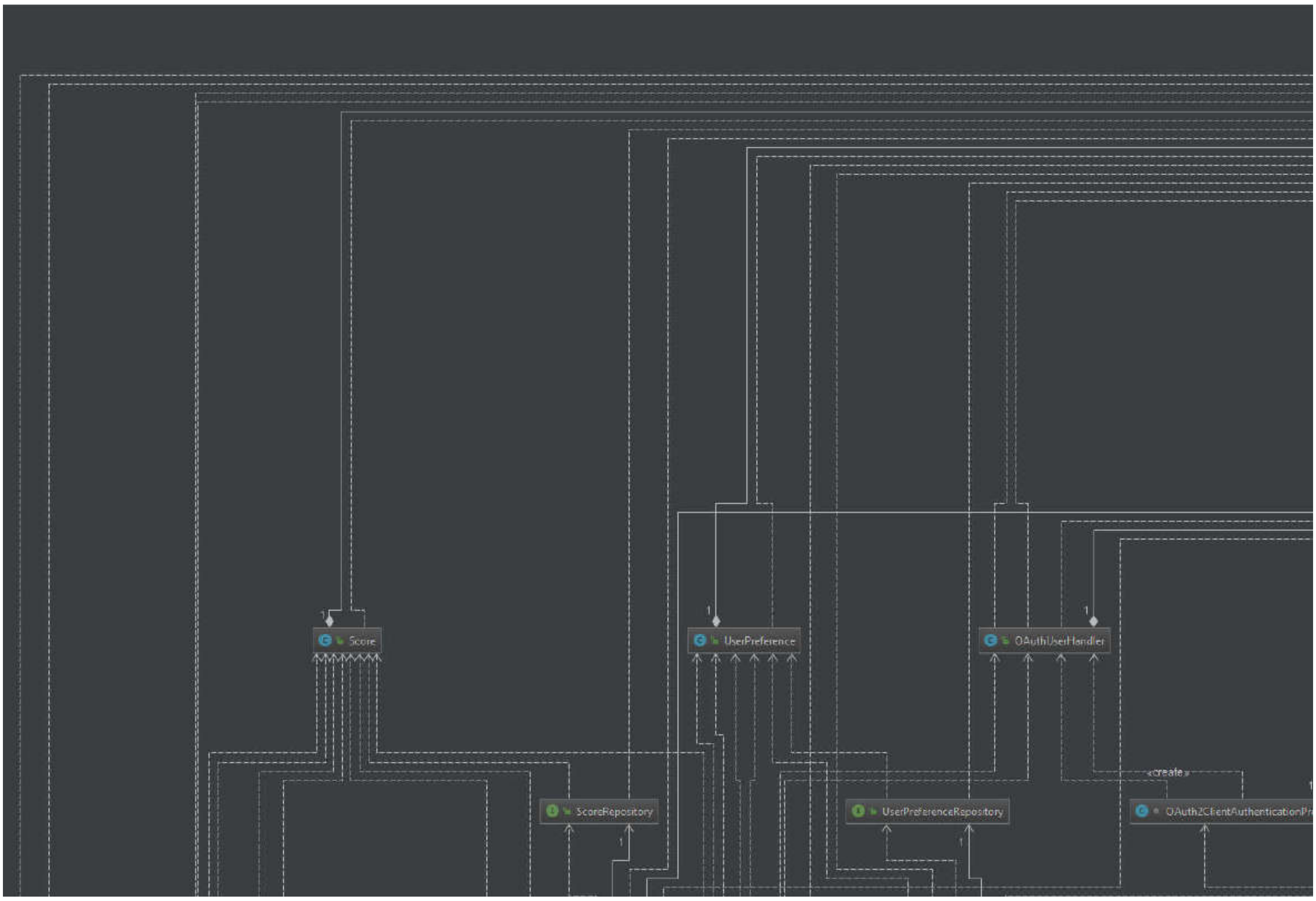
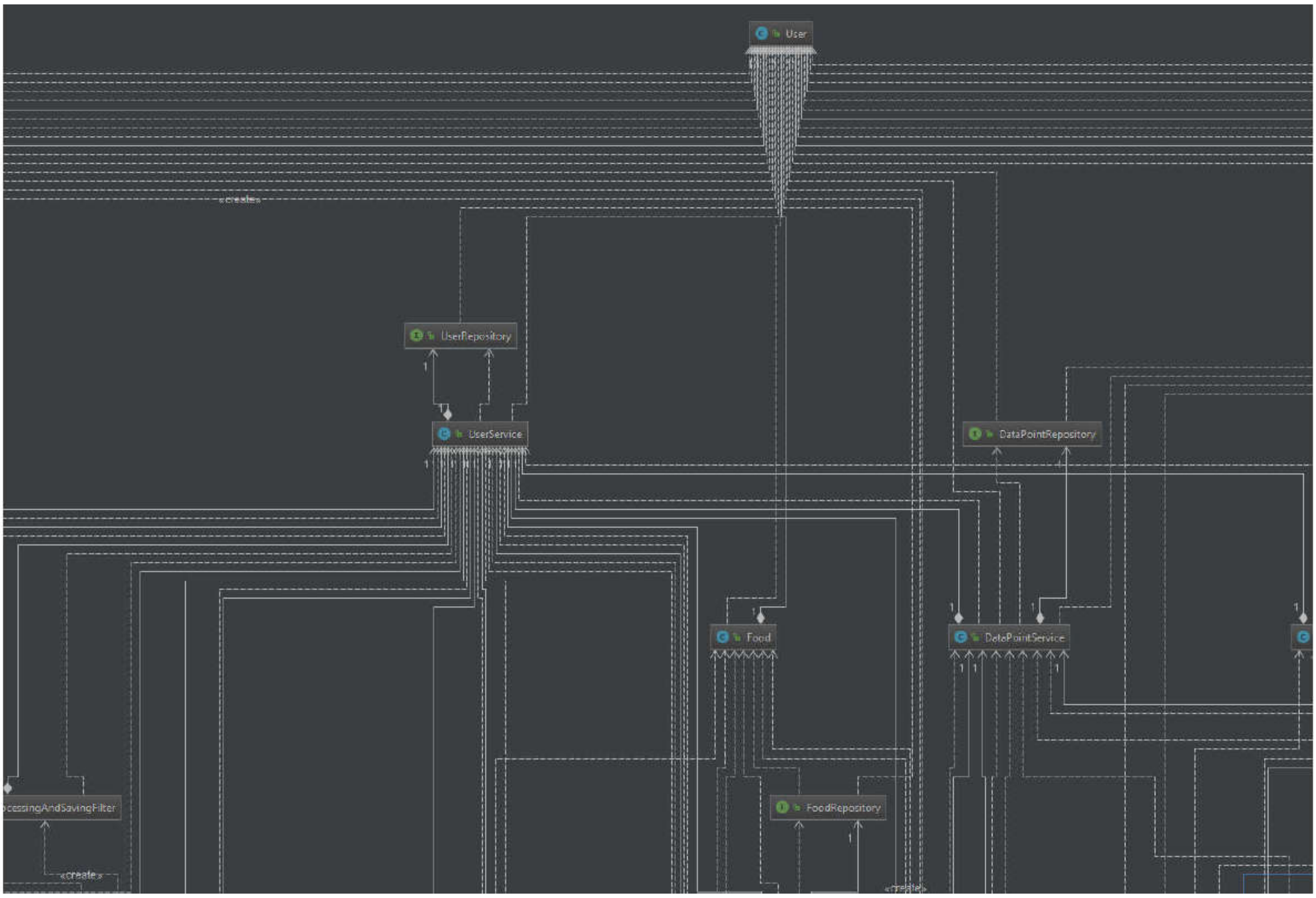
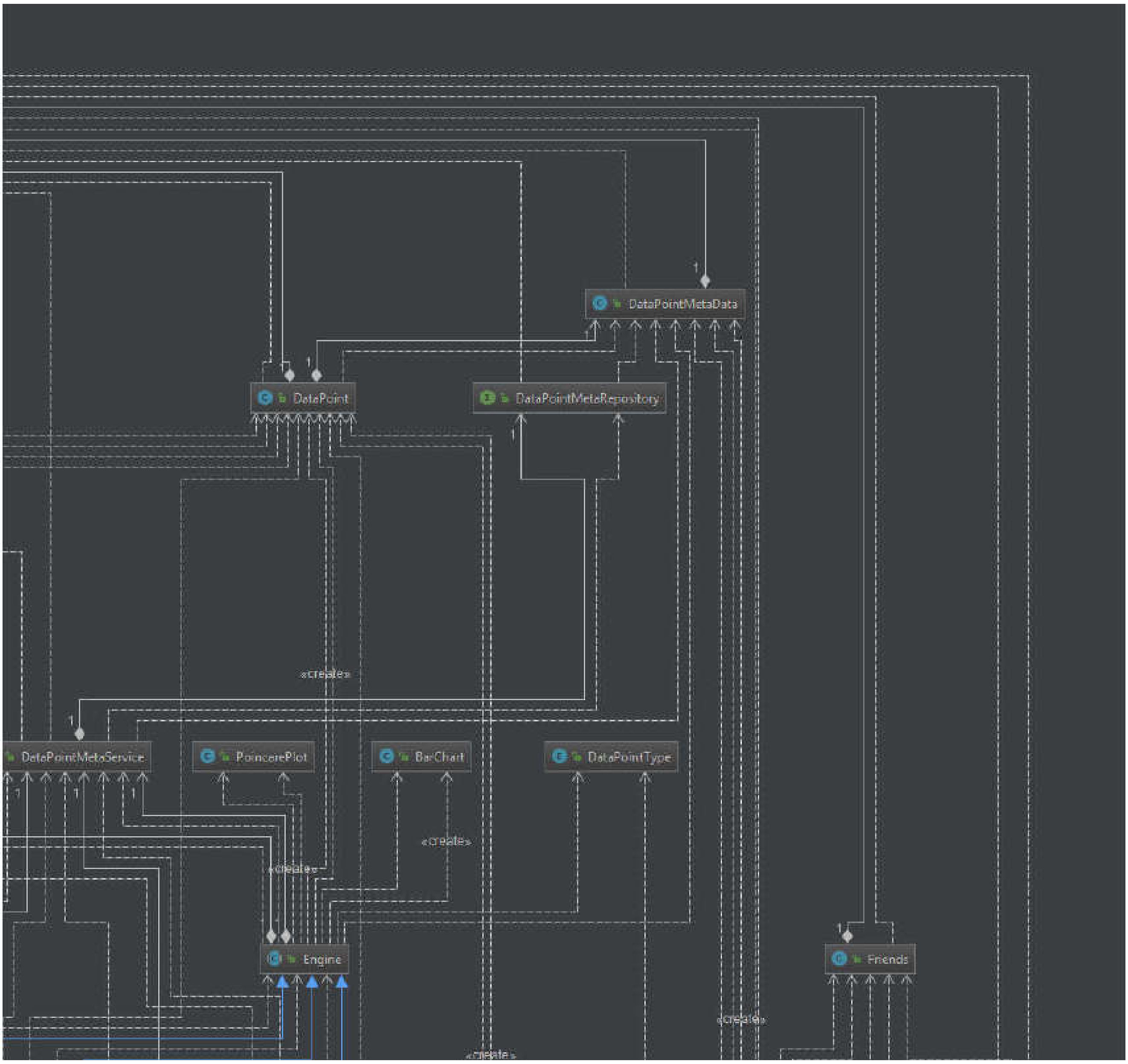


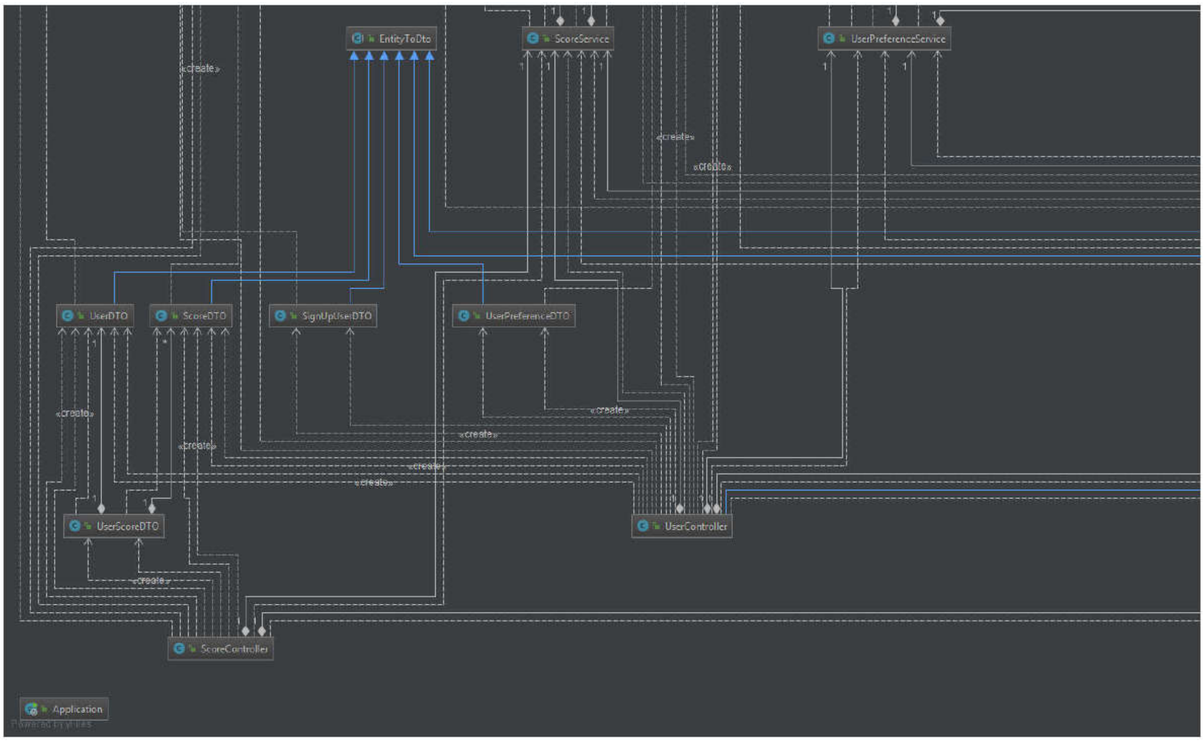
Figure 12: Class diagram dependencies

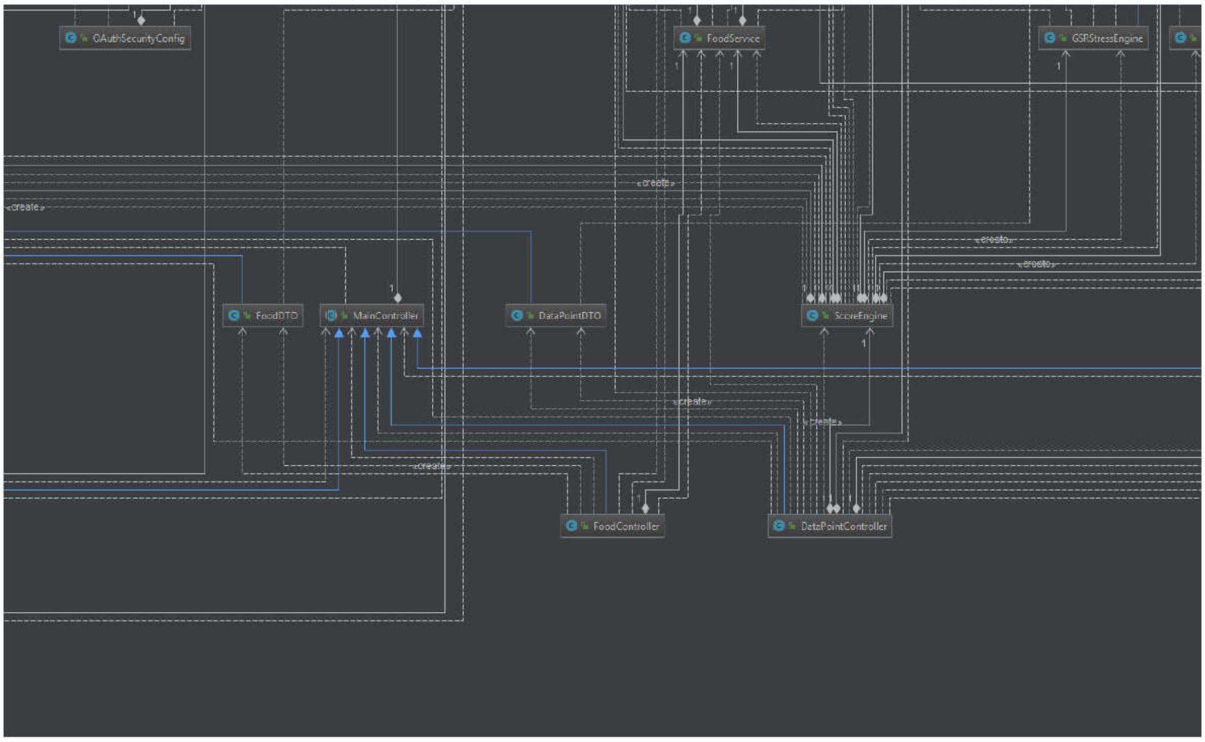
The following is an expanded class diagram for easier viewing:




User
«create»
UserRepository
UserService
DataPointRepository
Food
DataPointService
FoodRepository


DataPointMetaData
DataPoint
DataPointMetaRepository
«create»
DataPointMetaService
PoincarePlot
BarChart
DataPointType
«create»
«create»
Engine
Friends
«create»
«create»


EntityToDto
ScoreService
UserPreferenceService
UserDTO
ScoreDTO
SignUpUserDTO
UserPreferenceDTO
UserScoreDTO
UserController
ScoreController
Application


OAuthSecurityConfig
FoodService
GSRStressEngine
FoodDTO
MainController
DataPointDTO
ScoreEngine
FoodController
DataPointController

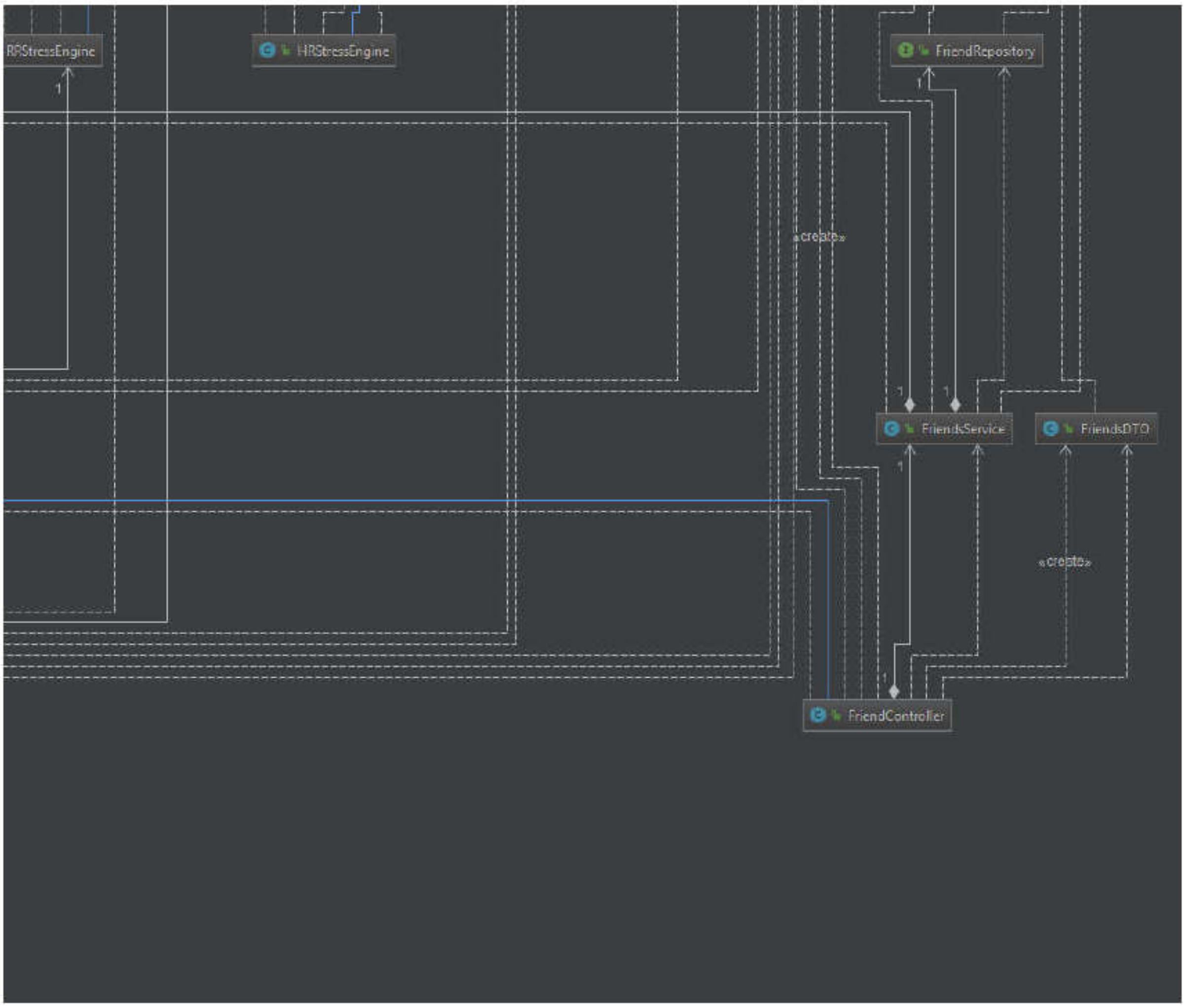


Figure 13: Client class diagram

ERD diagram

In the ERD diagram (Figure 14: ERD diagram) the “user” entity is used to store all the details on a user – namely the date of birth, email, googleId, picture URL, username, hasEmotionalSupport, hasFinancialPressure and hasMedication. The googleId is a unique user Id given in the OAuth2 API. The picture value will store the URL for user images. hasEmotionalSupport, hasFinancialPressure and hasMedication are used to store related stress factors.

The Friends entity links 2 users together as friends.

The “data_point” entity stores sensor readings for each user as well as the time of reading and the relevant userId. These are used to calculate stress for a particular time period. The “data_point_meta_data" contains information on a particular set of datapoints. This allows the code to distinguish between datapoints used as a calm baseline, unclassified datapoints, stressful data points and calm datapoints.

The “user_preference” stores the preferred eating times of each user.

The score entity stores the final score of the day. The food entity stores food eaten during a particular day, as well as calories of said foods.

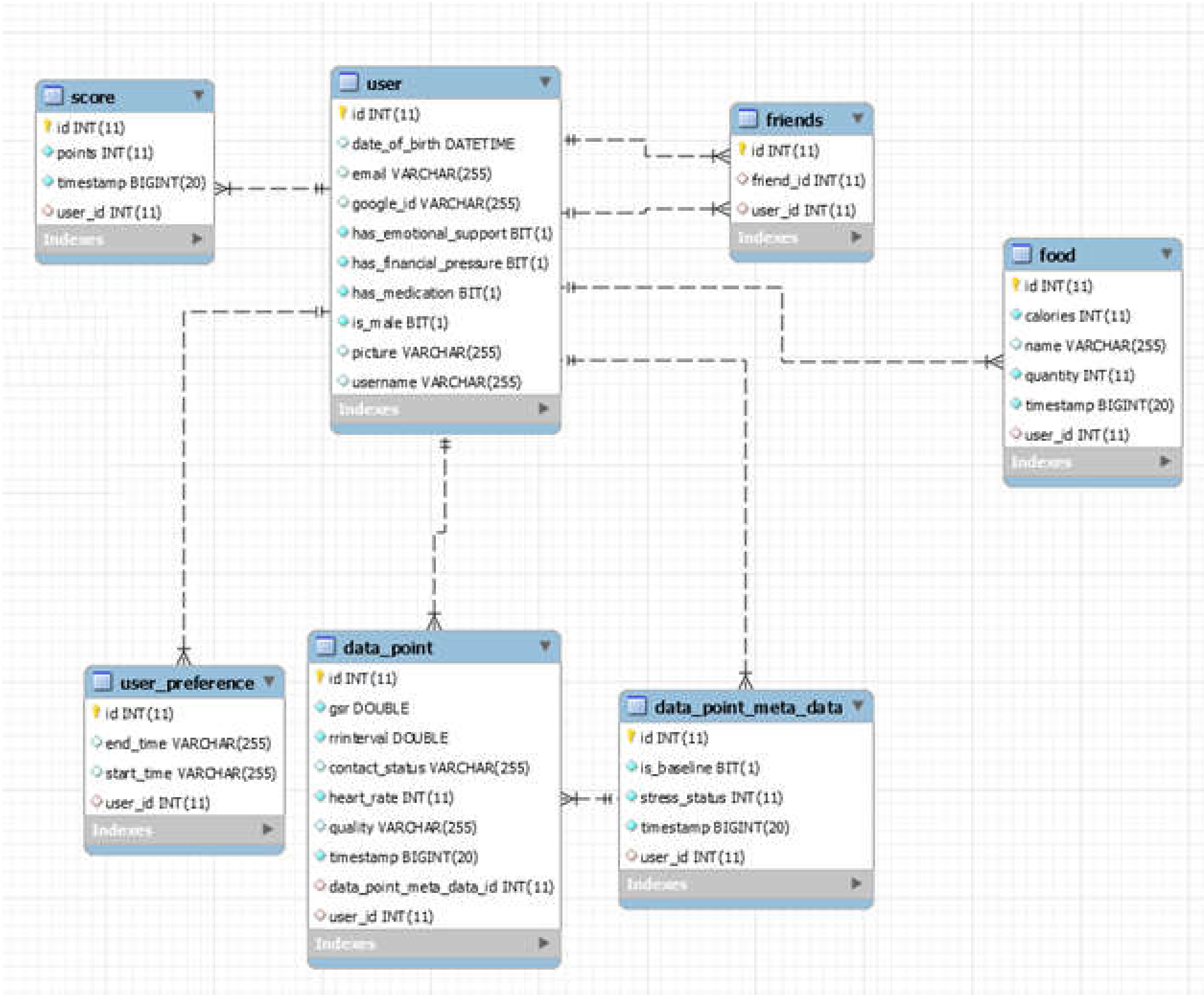


Figure 14: ERD diagram

Deployment diagram

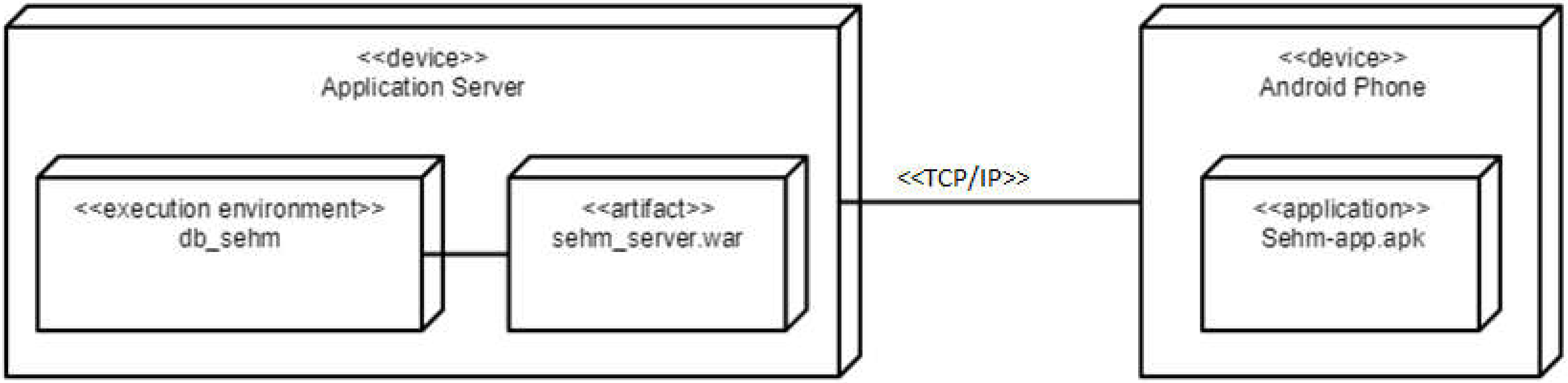


Figure 15: Deployment diagram

The deployment diagram featured in Figure 15: Deployment diagram shows that the system is made up of 2 main nodes – the server and the client. The server has a mySql execution environment with “db_sehm” database on it. This is handled with the “sehm_server.war” application deployed to the node itself.

The android device will have an apk installed which will communicate with the server using TCP/IP.

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Components diagram

The component diagram in (Figure 16: Component diagram) was used to define the boundary and make-up of course-grained software components. The server needs to have an API endpoint so as to communicate with the client. This should be secured using authentication filters. The server should also have a data processing module which processes the necessary data points into scores, as well as retrieve any data required by the API. This should make use of a database to store and retrieve the data.

Similarly, the client should have the ability to authenticate and connect to the server. It should also be capable of collecting the necessary data by connecting to the watch, as well as show the user both personal scores and friends' scores. The segregation in functionalities performed on the server and client allows the score algorithm to be modified without updating the client application. It also means that it is less easy to cheat, and battery on mobile devices is conserved as the score is not calculated client-side.

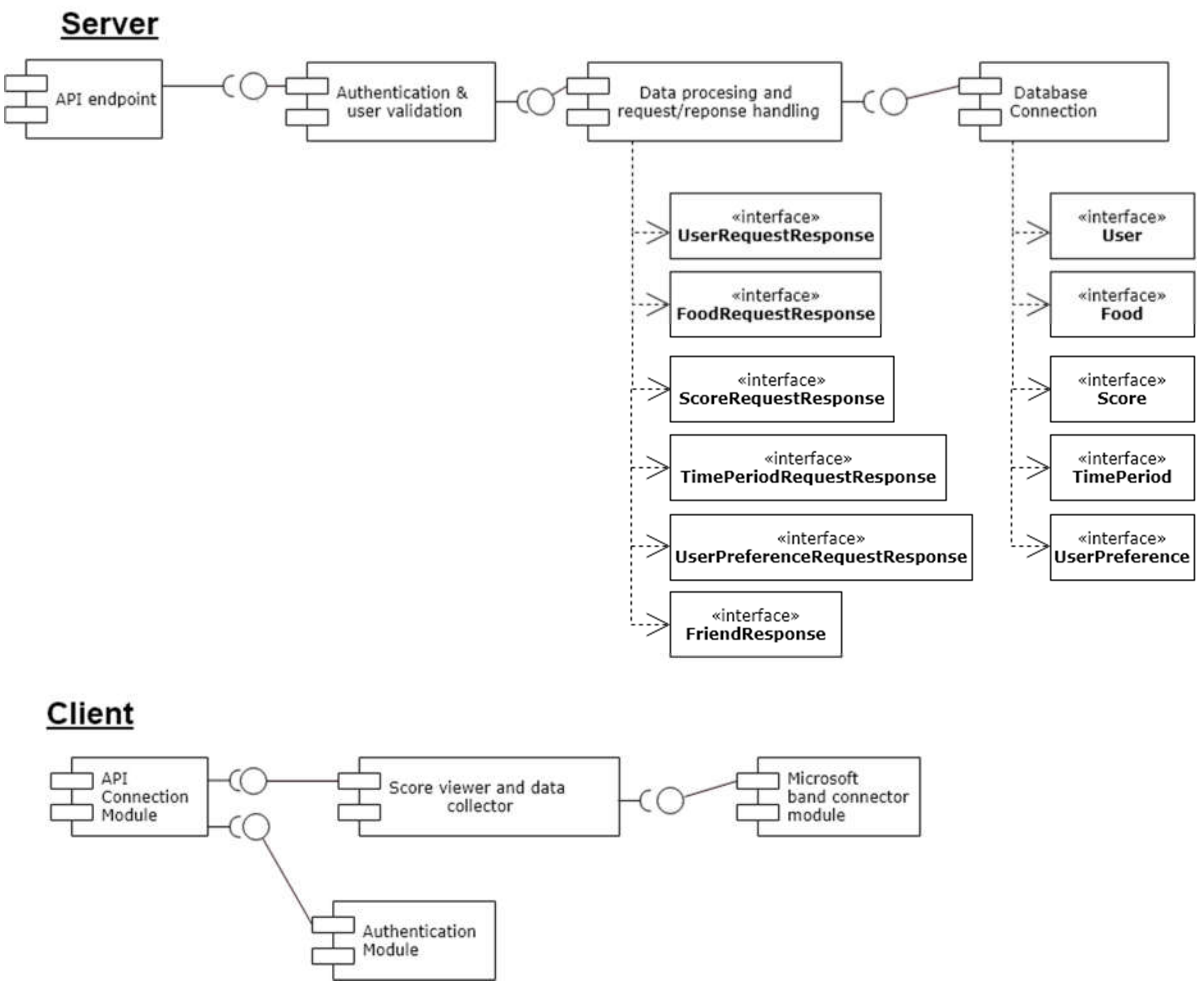
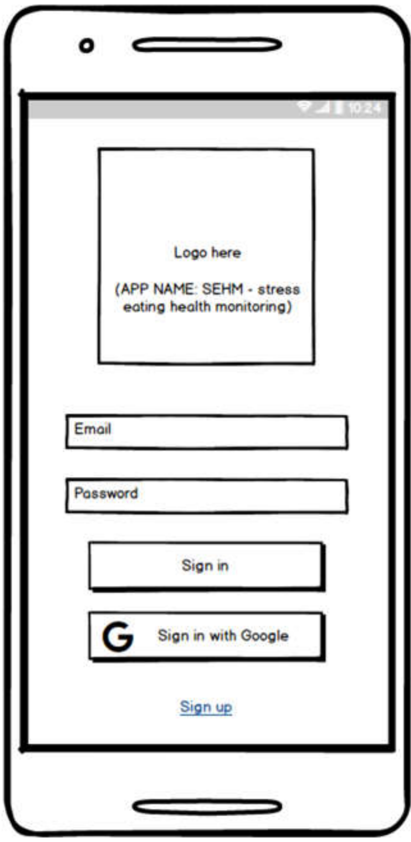


Figure 16: Component diagram

Mock-ups

In the first stage, a user signs in using other a major social network sign in (Figure 17: Mock-up – login Figure 18: Mock-up - Sign up. The user then provides the application with external stress factors (Figure 19: outside factors Figure 20: calibration - 1. The user then calibrates the app with calm and stress data respectively Figure 19: outside factors Figure 20: calibration - 1). The can then proceed with browsing their own scores/calories, add friends, view scores of their friends and add foods eaten. (Figures 23-27)



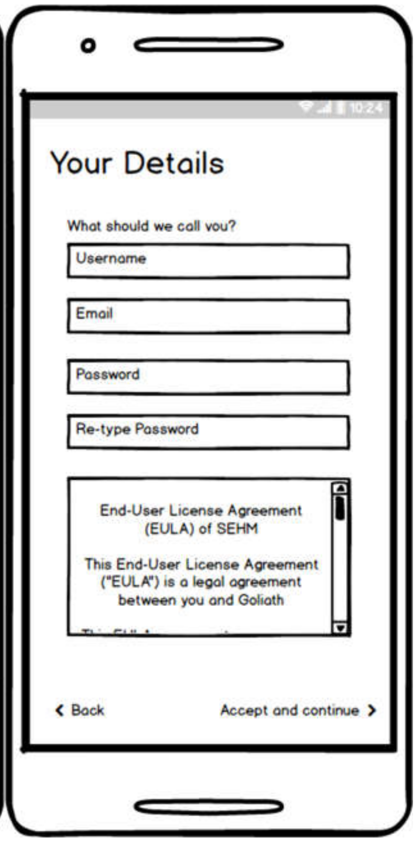


Figure 17: Mock-up – login

Figure 18: Mock-up - Sign up

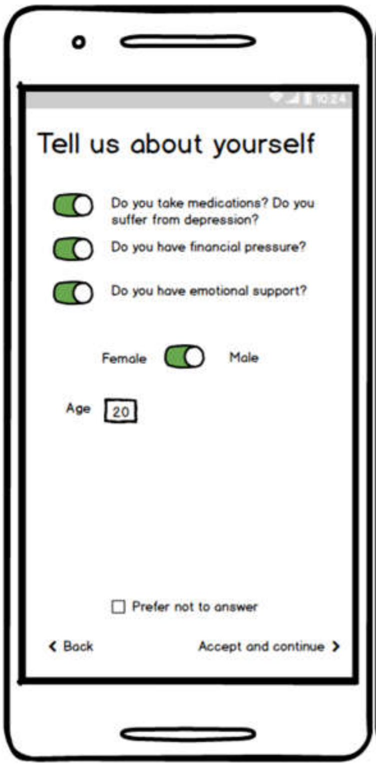


Figure 19: outside factors

Figure 20: calibration - 1

Figure 21: Calibration – 2

Figure 22 - Calibration - 3

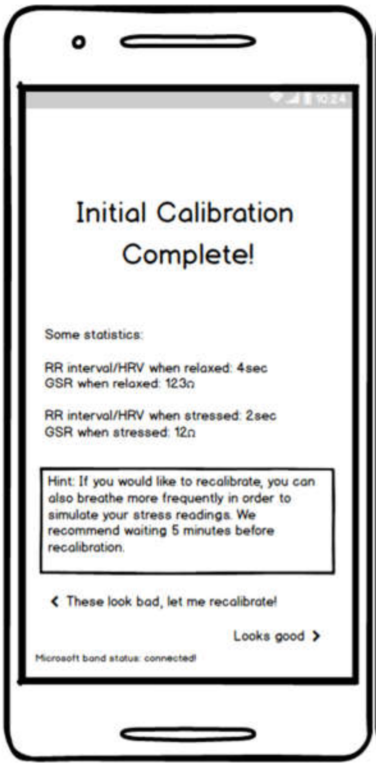


Figure 23 - Calibration – 4

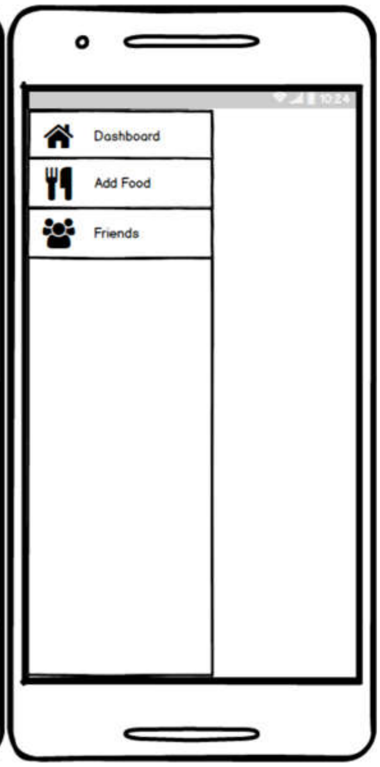


Figure 24: Sidebar navigation

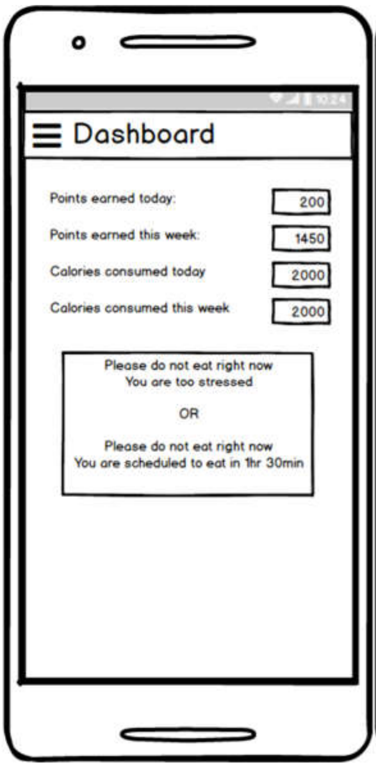


Figure 25: dashboard

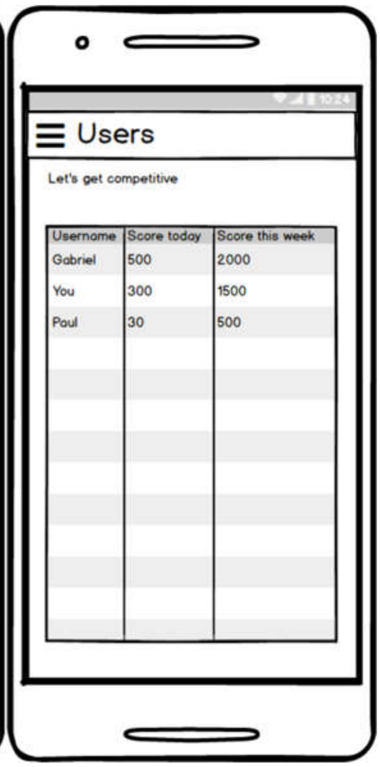


Figure 26 Scores of other users

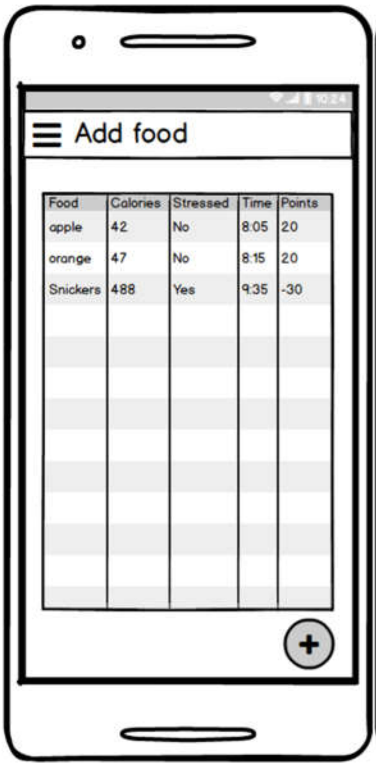


Figure 27: View foods eaten

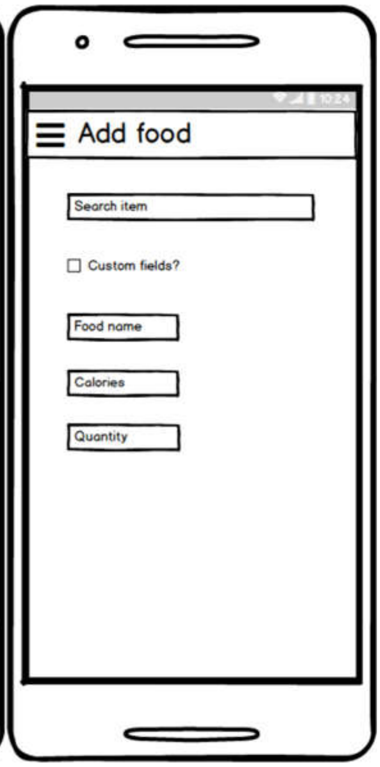


Figure 28: Add food eaten

To conclude, UML diagrams were found useful in the initial stages of the project for modelling the data structure, application flow and deployment of the application. The above diagrams helped highlight some potential issues in the data flow before the implementation. It also allowed for discussions on the system as a whole, resulting in time savings in the long run. The design decisions performed here were also helpful in keeping the project on track.

Implementation and Testing

Screenshots

The following are screenshots of the final application:

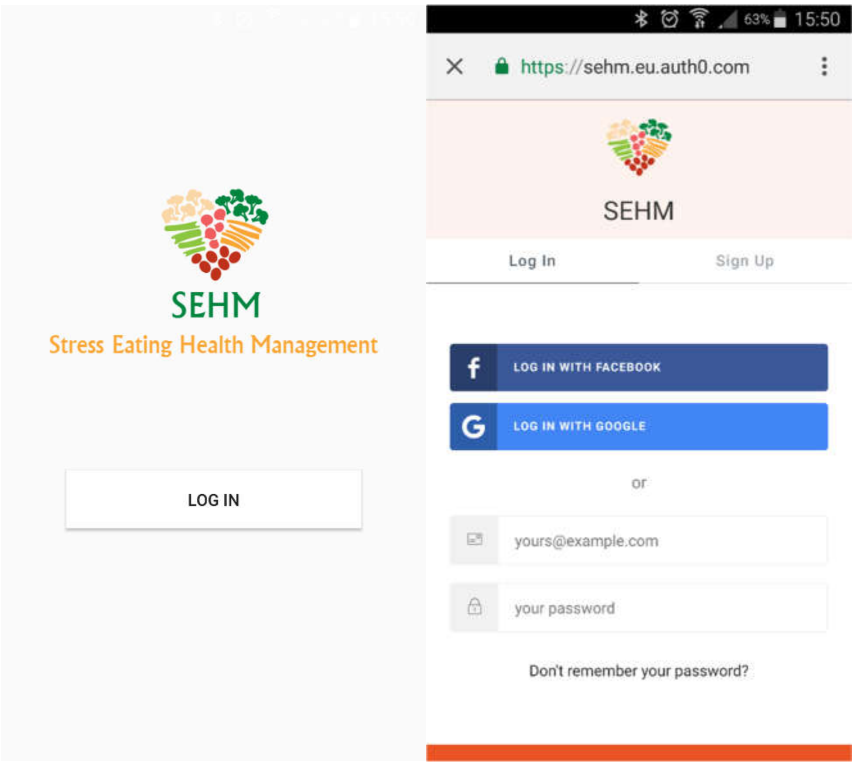


Figure 29: sign up/log in

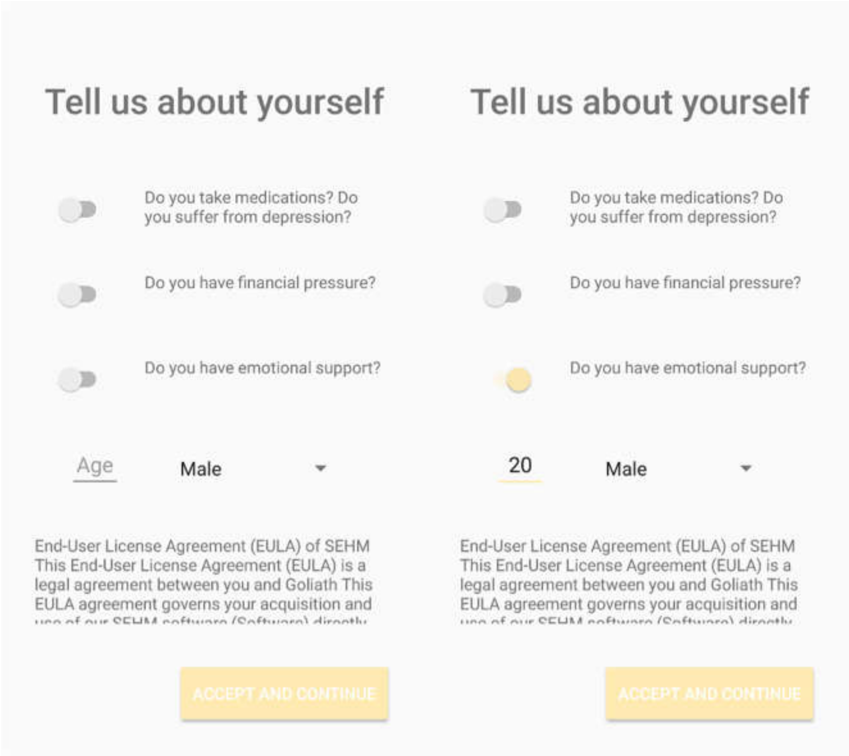


Figure 30: external factors

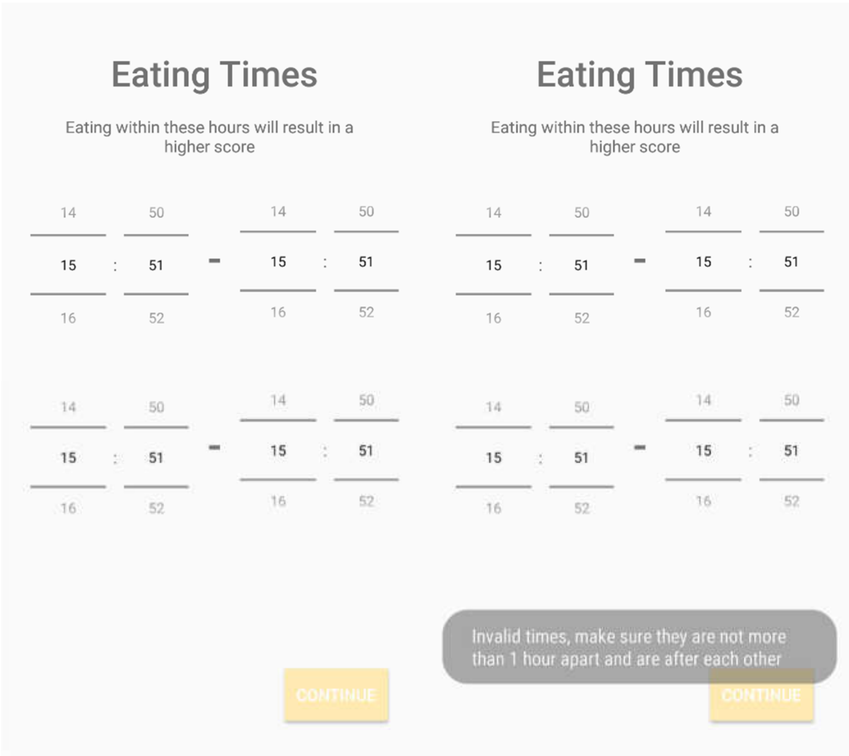


Figure 31: Eating times with validation

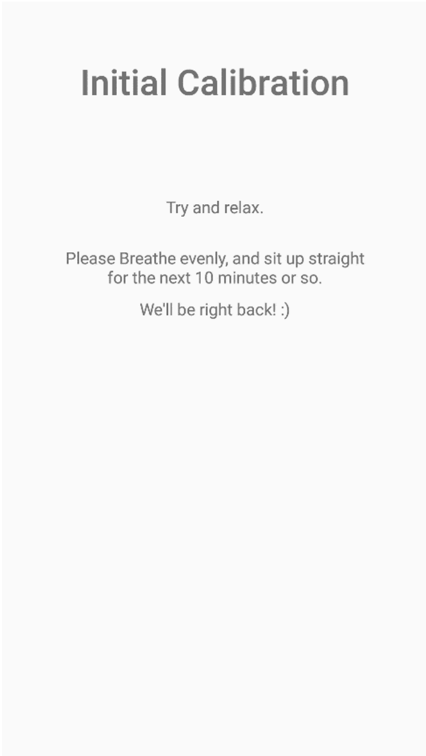


Figure 32: Calibration

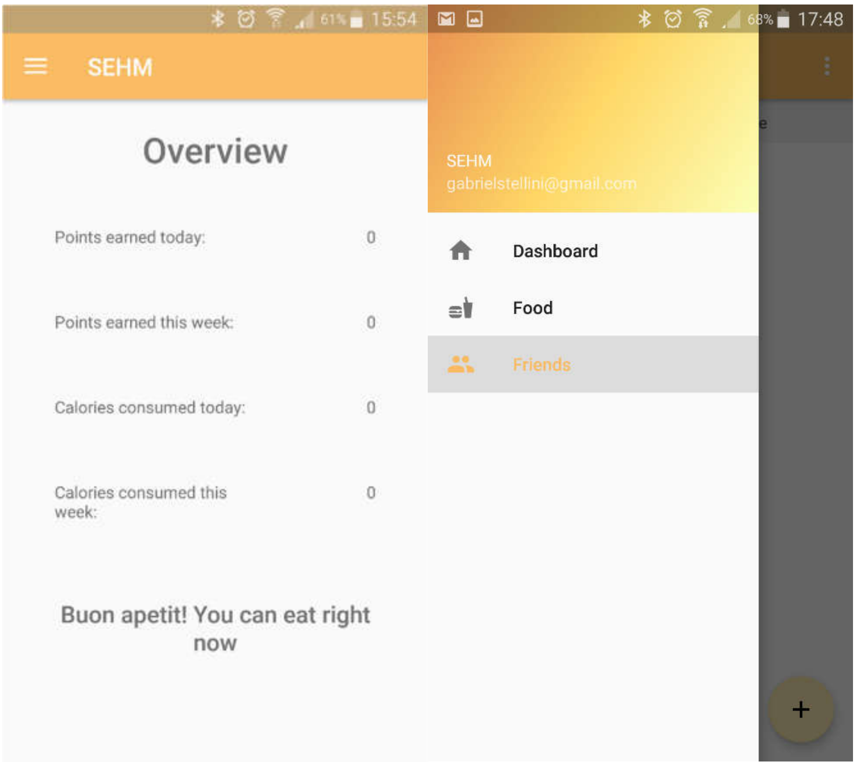


Figure 33: Dashboard

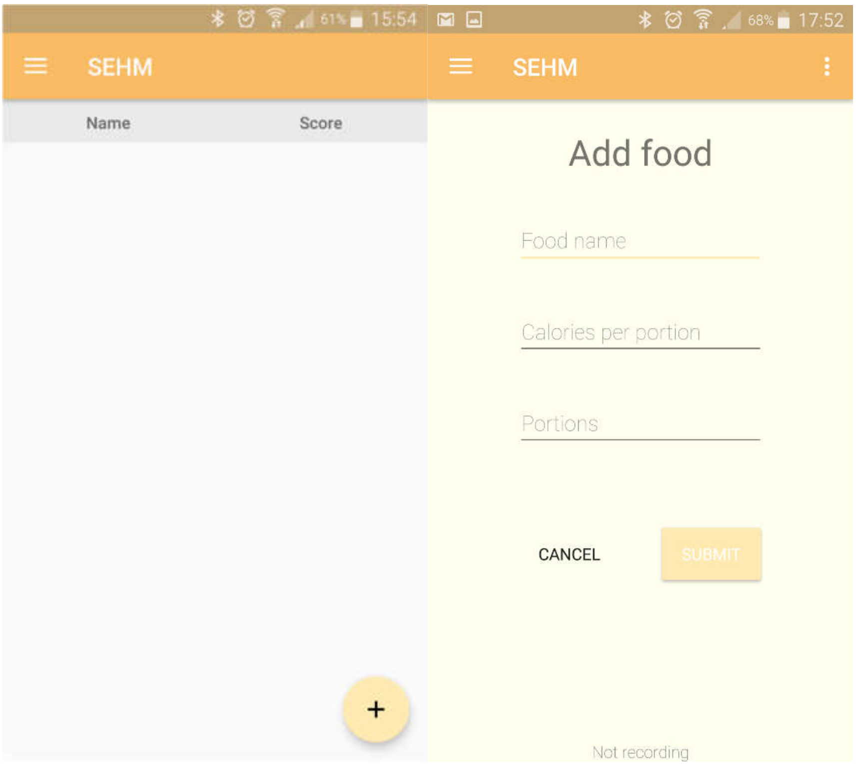


Figure 34: Food panels

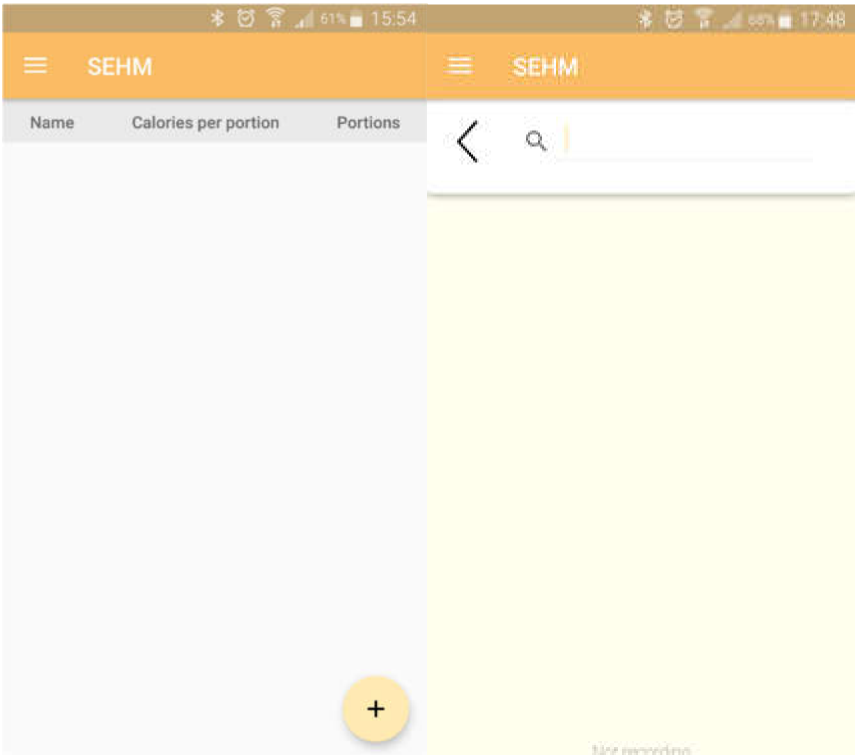


Figure 35: Friends dashboard

As can be seen in the screenshots, the final application looks similar to the initial mock-ups – barring a few key changes. The friends screen has a plus button to add friends – similar to how one adds food eaten. This adds consistency to the application as a whole. The application also makes use of additional social media login including Google, Facebook and a classical sign up form. The stressful calibration was removed from the final implementation as it was not deemed necessary – the calm dataset was enough. The add food search was also removed as inputting the food calories manually could be seen as a potential motivator – similar to how paying in cash makes users more aware of their spending than paying with a debit card (Shah *et al.*, 2016).

Crucially, the application does not recommend a diet, rather it calculates scores based on calorie intake. Due to the complexities involved in recommending a healthy diet, this idea was dropped. Such an implementation would need to take into consideration foods eaten previously, calories, nutritional values in the food as well as variations/preferences by the user such as vegan/vegetarian/gluten free and food which they dislike. An ideal, healthy diet is also not clear cut as many papers suggest vastly different “ideal” diets (Bray *et al.*, 2018; Sofi *et al.*, 2018).

Algorithms

A main functional requirement for the application was to be unobtrusive. This meant that notifications were not a good idea, as that would interrupt the user to the point of removing the application.

A non-intrusive application also meant that in order to “learn” what calm and stressed datapoints look like for a user, a time domain algorithm was necessary. This differed to alternatives like a neural network, as unsupervised learning had to be utilised. After viewing a Poincaré plot of the collected data, the idea was dropped as the data was indistinguishable between stress and non-stressed participants. Similarly, an SDNN was also attempted, but it was also unsuccessful in distinguishing between stressed and calm datasets for each person. A FFT was also tested and used successfully.

The following are screenshots of the FFT algorithm when run on the RR interval and the GSR:

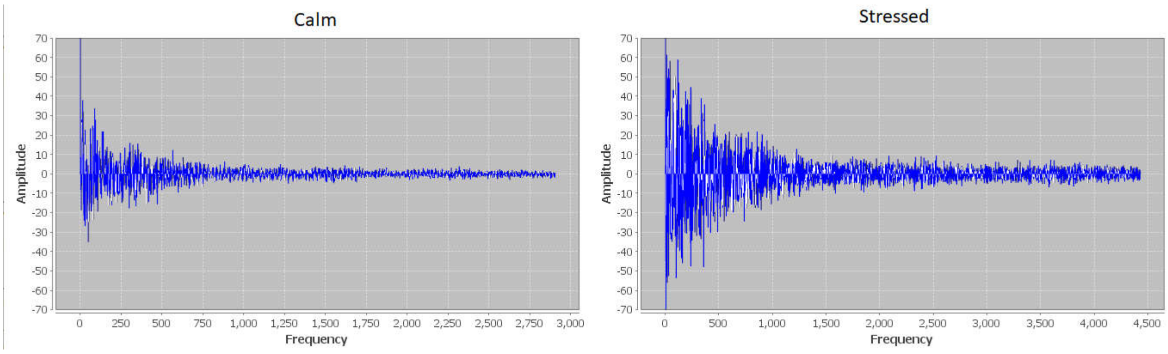


Figure 36: FFT visualisation of RR interval

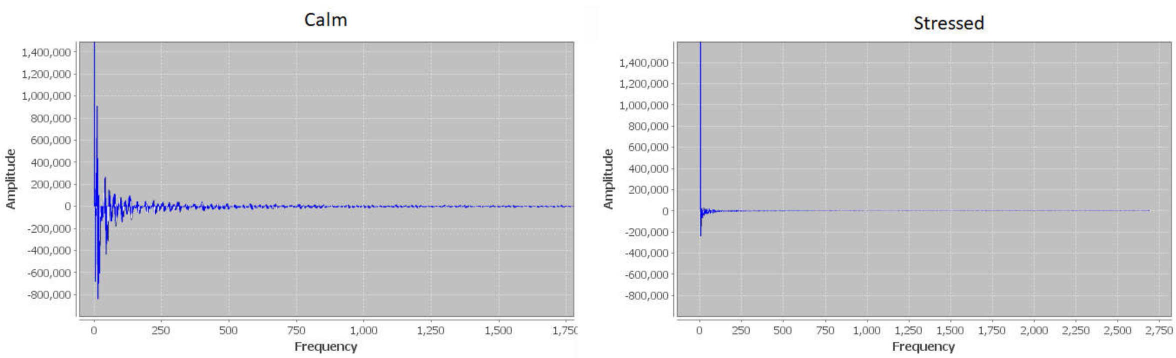
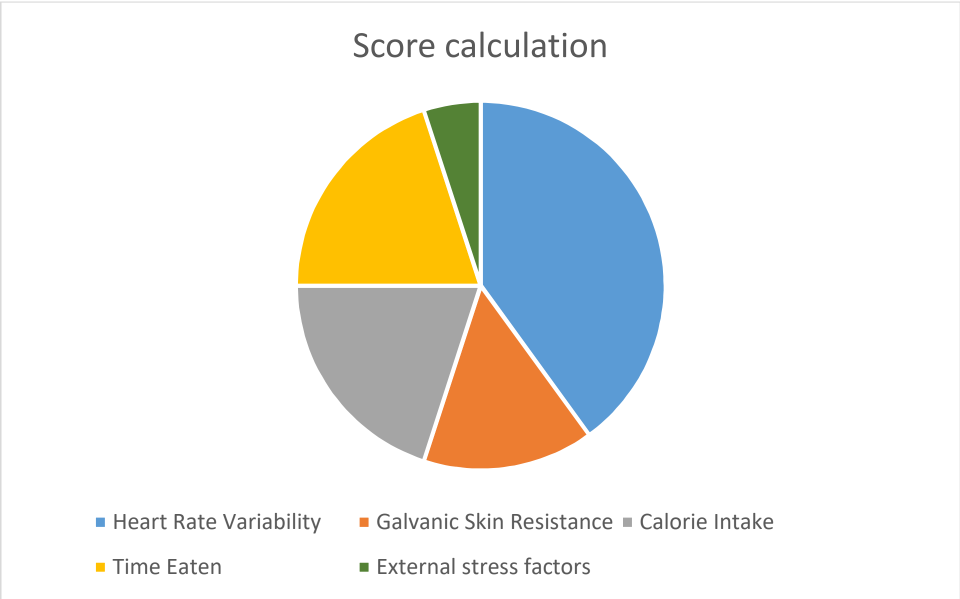


Figure 37: FFT visualisation of GSR

Several de-noising techniques were performed on the data, such as band pass filters and z-score, however the results were marginally better when these were left unused.

A score of 1 to 10 for each of the main factors; these factors being HRV, GSR, time eaten, calorie intake, and external stress factors. These were then weighted to give a final score out of 100 for a particular day.

Based on the papers and the weight of each factor implied from the literature review, a score is generated using the data available on the user. This can be seen here:



The heart rate was given a high weighting due to the high accuracy achieved in the papers found in the literature review. This means that a user with a healthy RR interval will achieve a higher score. Similarly, the GSR was also given a high weighting, as it was an accurate predictor of the stress levels of the user. In most papers, it was found to be slightly inferior to the RR interval, so it was given less weighting overall. The other characteristics, such as calorie intake were given equal priority – barring the external factors. Although external factors are important in evaluating overall stress, they do not heavily impact minute-to-minute stress, hence the implementation.

Testing

Test cases

Test ID	Action	Expected result	Actual result	Result pass/fail	Comments
1	As a new user, attempt to log in	Should initialise sign up sequence	Initialised sign up sequence	Pass	
2	Initialise sign up sequence	Should check for external stress factors and get calibration data	Checks for external stress factors and gets calibration data	Pass	
3	Exit sign up sequence mid-way	Should continue where user left off	Either starts from the beginning, or skips calibration collection entirely	Fail	
4	User takes off band while data is being collected	Ignore data while band is off	Invalid data was ignored	Pass	
5	Band is not worn correctly	Wait till band is worn correctly	App waits until user wears it correctly to collect data	Pass	
6	User tries to add themselves as a friend	Should not be allowed	App does not allow user to add themselves	Pass	Users can still search for themselves
7	As an existing user, I should be able to search for current users	Should allow searching by name	App searches by username	Pass	
8	As an existing user, I should be able to add a friend	Add friend button shold work	Add friend button works	Pass	

9	As an existing user, I expect to have an updated score after I eat something	Score should update based on factors	Score updates	Pass	
10	As a new user, I entered a huge time period	Should not allow time periods more than 2 hours and less than 15min	User cannot continue to next stage until time periods are correct	Pass	
11	As a new user, I entered overlapping time periods	Should not be allowed to continue	Blocked from continuing to next stage if time configuration is incorrect	Pass	
12	As an unauthenticated user, I try to perform API calls	Responses should be 403 (unauthorised)	Responses were 403 (unauthorised)	Pass	
13	As a authenticated user, I add food to the items	App should start recording data	App started recording data	Pass	
14	User enters invalid credentials	Should stay on the login screen and show an error	Stays on the login screen and shows an error	Pass	
15	As a user, I navigate to the friend panel	Should view scores	Scores were viewed	Pass	
16	As a user, I navigate to the Food panel	Should view foods eaten	Foods eaten were viewed	Pass	
17	As a new user, I don't wear the band	Wait for user to wear band	Waits for user	Pass	
18	As a user, I add a food after I have eaten it	The application should notify the user and let them know they should record before eating	The application thinks the user is going to start eating the food at the time the data is entered	Fail	

Evaluation

Methodology

In order to test the accuracy of the data analysis, both calm and stress data points were needed. A data collector app was built which collects data and marks individual time periods for later analysis. Another app was created to analyse the data itself. Twelve Participants were asked to sign the consent forms (refer to attached forms) and were informed on what the evaluation involved. The participants were asked to sit down and perform any leisurely activity of their own choice (provided it was not exciting). The data collected during this period was then classified as “calm”. The second phase of the evaluation involved making use of a game called “Super Meat Boy”. Participants were first left to practice the controls and get a feel for the game, and after 5 minutes were told that they had 3 lives left and would have a 5ml of ice cold water was put down their backs when they lose all their lives. The idea behind the game was to have participants engrossed in the game and forget that they were being monitored. Due to the gradual difficulty curve of the game, most participants experienced a gradual increase in heart rate (and a lower respective RR interval) with large downwards spikes in the GSR when they died or got close to dying. After the small amount of water (5ml) was dispensed, participants were allowed to calm down again to capture the “peaks” in the data correctly.

The apparatus used in this experiment involved a small syringe connected to a miniature hose and was used to dispense small amounts of ice cold water down the participants back. The evaluation also made use of a Microsoft band 2, a PC and an Xbox controller.

Results of algorithms

The FFT implementation discussed in the implementation achieved an accuracy of 75% for the RR interval, and 75% for the GSR. Upon further inspection, the 75% does not seem to be made up of overlapping participants – some participants were not detected as being stressed through the RR but were detected through the GSR (and Vice versa). This was deemed sufficient as it is over 50% accuracy which would be a random algorithm.

Issues with the data collected

There were some issues with the data collected as a whole. One of these was that some people were not apprehensive of the water in the experiment. This was seen in the “stress” data and the “calm” as they were similar after running the algorithm. Another issue encountered was that some participants took medication which had direct impacts on the heart rate. Even when the user was stressed, the HRV and heart rate remained calm and non-stressed. Another issue is that the wide variety of medication has different effects on heart rate – some would speed it up more, others would slow it down, and others would change the characteristics of the heart rate. Medication was also not generic enough, as one can use alternative substances like cigarettes which would not be categorised as medication – however these have a drastic effect on the heart rate itself. Lastly, the data would have been much more reliable if the band was worn for longer periods of time. 25 minutes of data was collected per participant due to time constraints – this included stress and non-stress data. Had the data been collected for longer periods, the data would have been more accurate.

Positive aspects of the evaluation

The increases in difficulty increases of the game ensured that everyone lost within a 10-minute period at least 3 times. As a person cannot lose in the first few levels, the game proved ideal. The “3 tries and then water” strategy also worked well as participants had steady increases of HR and RR as they approached their third life in-game. This is representative of real life stress. Using a visually distracting game proved to be useful as participants forgot about the watch during the study itself. The HR stress detection was tested by passing both calm and stress data to the stress engine. The calm data was passed as a “calibration” while the stress data was passed as an “uncategorised” set of data. The very low frequency was analysed using a fast fourier transform and an accuracy of 75% was achieved. The HR stress detection was tested by passing both calm and stress data to the stress engine. The calm data was passed as a “calibration” while the stress data was passed as an “uncategorised” set of data. The data was passed through a zscore algorithm to get the “spikes” in the graph. The resulting graph was passed through an FFT and the result was 66.66%

accuracy. Keep in mind that only 15min of data was gathered, and most participants were still adjusting to the watch itself (Figure 38: GSR consistently going down).

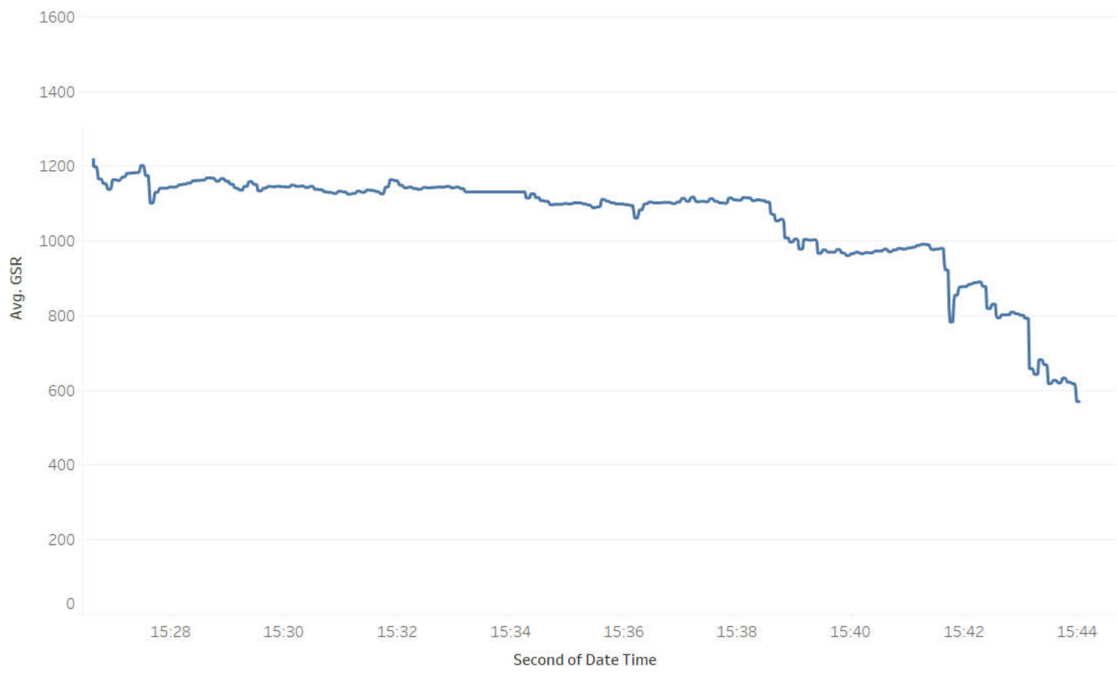


Figure 38: GSR consistently going down

As can be seen in the sample graph, the data never truly stabilised in most participants. As both RR and the heart beat are measures from heart readings, it was decided that only RR will be used in the score calculation. Another positive aspect of the application was that some metadata on the fields gathered were available through the SDK. An example of this is the "quality" field. This is generated by the band, where "locked" means that the data is correct and "acquiring" means the band is still unsure whether the band is being worn correctly. This was used to filter out invalid data points before passing them through the application. Although this data is not currently being used, it was still stored in the database, as it could potentially be used for deep learning in a future application. An example of a possible application is to turn on the watch before food data is written to the app. Another positive aspect of the SDK is that it had built in de-noising techniques, as the data was very accurate with no unreasonable jumps.

In the analysed data it was found that with a confidence level of 75% correlation between the predicted stress level and the actual stress level ($P<0.01$)

Conclusions and Suggestions for further work

With the use of social motivators and a points system, one could potentially reduce bad eating habits and motivate users to a healthier living.

The accuracy of the algorithms achieved was 75% ($P<0.01$), and has the potential to achieve a higher accuracy as more users make use of the application. The application was found to be easy to use, as it follows Google's guidelines for material design concepts.

Further work could test the implementation on more users. An alternative implementation could also make use of additional sensors such as an EKG sensor as suggested by other papers in the domain. The idea could also be improved if the application recommends a diet based on the user's preferences. A future version could also set calorie goals, with a slow decrease in calories until they are at optimal physique. It could also be integrated with exercise and provide users with positive reinforcement on both eating and exercise. One could also check for stress during the day and try to calm the user. One could also analyse the psychology behind entering the calorie count manually – checking if the awareness provided when inputting a food outweighs the advantage of convenience.

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Appendices

Technical details

Libraries and frameworks and architectures used

The following are a list of libraries and frameworks and why they were chosen over other alternatives:

Frameworks:

- Spring – spring is a library which allows easy implementation of restful endpoints. Combined with a token based security system, it was used as a backend framework. It was chosen over alternatives like node as it contains additional libraries which help automate the java to SQL connection.
- Android SDK – Android was chosen over alternatives due to the similarity to java. There was also no iOS hardware available for development.
- Maven was used for the server, and Gradle was used for client. These were used to inject libraries into the project.

Architecture

- Restful architecture – a restful architecture was chosen as it allows easy modification and manipulation of the endpoints.
- Layered architecture/3 tier architecture

Server libraries:

- Auth0 – this was used to generate the JWT tokens sent and received with each request.
- Jtransforms – this was used to perform the FFT operations on the data
- JFreeChart – used to view and debug the FFT

Client libraries

- Microsoft band SDK – used to connect the phone to the Microsoft band 2
- Okhttp – library for sending/receiving raw data

- Auth0 – this was used to generate the JWT tokens sent and received with each request.
- Gson – Used to parse the JSON to and from each request
- Picasso – used to load images into the application – specifically the jpgs used when searching for a user
- Revealator – used for the circular animations when adding a food item or a friend.

Running the code

Setting up mySql

```
1. Install mySql

2. sudo mysql -password -- Login

3. mysql> create database db_sehm; -- Create the new database

4. mysql> create user 'springuser'@'localhost' identified by
   'ThePassword'; -- Creates the user to be used by the server

5. mysql> grant all on db_sehm.* to 'springuser'@'localhost'; --
   Gives all the privileges to the new user on the newly created
   database
```

Running the server

1. Install java
2. Open the location in command prompt

```
cd /Builded code
```

3. Run the server

```
4. java -jar sehm-server-0.1.0.jar
```

Running the client

1. Buy and pair a Microsoft band 2 to an android device
2. Install the Microsoft band application from the playstore (required by SDK)
   https://play.google.com/store/apps/details?id=com.microsoft.kapp
3. Enable "install from unknown sources" from your android device (different steps depending on version of android and manufacturer)
4. Copy the apk to the device and install
   (different steps depending on version of android and manufacturer – android 5.0 minimum and supports up to android 8.0)

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Middlesex University Malta

SCHOOL OF SCIENCE AND TECHNOLOGY
CSD 3997

DIET BASED ON USER STRESS FEEDBACK

DATE	20TH APRIL 2018
SUPERVISOR	OMAR ZAMMIT
STUDENT NAME	GABRIEL STELLINI
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CAMPUS	MIDDLESEX UNIVERSITY MALTA

A THESIS SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF BACHELOR OF SCIENCE (HONS) IN COMPUTER SCIENCE (SYSTEMS ENGINEERING)

1

Middlesex University, Malta

Appendix C – Ethics Form D

School of Science & Technology,
Department of Computer Science Ethics Committee

Middlesex University Malta

Form D: Declaration Form

This form should be given to your supervisor along with your project proposal. It must also be included in your Project Report.

Student Project: Ethical Approval Request

Name: Gabriel Stellini	Student ID: M00598900	Date: 9/04/18

Supervisor: Omar Zammit

Title

Diet based on stress feedback

Ethical Approval Statement:

Declaration A

(i) I have studied the Ethical Approval section.
(ii) I have established that my study does not require additional human participation.
(iii) I agree to re-apply for approval if the nature or goals of my project change.

Declaration B

Project Goals involving human participation:

Gather non - stress data (through MS band)
Gather stress data (through MS band)

(i) I have studied the Ethical Approval section.
(ii) My study involves human participation through
- observation
- questioning.

(iii) Participants will be selected without coercion (see Chart 1).
(iv) I will obtain informed consent (see Chart 2) from each participant using Form C.
(v) I have arrangements in place for the protection of personal data (see Chart 3).
(vi) I agree to re-apply for approval if the nature or goals of my project change.

☑

Declaration C

My project does not fulfil the conditions for fast track Ethical Approval and I am applying separately to the Ethics Committee

☐

Note: to make an application to the Ethics Committee, you need to complete **Form E** - Application for Ethical Approval & **Form** C – Informed Consent Form (Download from: **http://tinyurl.com/mdx-ethics**)

Student Signature............ Date 9/04/18

Supervisor's Signature............ Date 9/04/18