A Smartphone-based Wellness Assessment Using Mobile Environmental Sensors

by

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ABSTRACT

A SMARTPHONE-BASED WELLNESS ASSESSMENT USING MOBILE ENVIRONMENTAL SENSORS

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This thesis presents the results and correlation analysis of experiments on a system designed to assess an individual’s wellness using mobile environmental sensors. The system uses Bluetooth Low Energy to communicate sensor data from an Internet of Things device to a mobile application designed for this system. Participants were given a smartphone application presenting a psychological survey three times per day. A device in their possession reads environmental data for five variables: temperature, humidity, air pressure, luminosity, and noise. The first experiment, with eight participants over five days, saw statistically significant moderate correlation between several variables and stress/distress. The second experiment had 20 participants for 10 days. While no moderate-high correlation was determined, the highest of the statistically significant correlations were for light, noise, and number of people present. A third experiment of 34 people over 5 days saw similarly weak coefficients, but statistical significance for the noise variable.
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<tbody>
<tr>
<td>BLE</td>
<td>Bluetooth Low Energy</td>
</tr>
<tr>
<td>CMHA</td>
<td>Canadian Mental Health Association</td>
</tr>
<tr>
<td>CSV</td>
<td>Comma Separated Value</td>
</tr>
<tr>
<td>IoT</td>
<td>Internet of Things</td>
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<tr>
<td>K10</td>
<td>Kessler Psychological Distress Scale</td>
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<tr>
<td>PSQI</td>
<td>Pittsburgh Sleep Quality Index</td>
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<tr>
<td>PSS</td>
<td>Perceived Stress Scale</td>
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<tr>
<td>PTSD</td>
<td>Post-traumatic Stress Disorder</td>
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<tr>
<td>SI</td>
<td>International System of Units</td>
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<tr>
<td>UN</td>
<td>United Nations</td>
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<tr>
<td>WHO</td>
<td>World Health Organization</td>
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<td>WLAN</td>
<td>Wireless Local Area Network</td>
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Chapter 1

Introduction

Mental health and general wellness are becoming a growing concern as research in the field increases. While the cost of mental health care continues to increase worldwide, the economic drain caused by mental health issues increases in kind. The Canadian Mental Health Association (CMHA) reports that 50% of the Canada’s population will have or have had a mental illness by the age of 40 [5], a contributing factor to the cost of mental health care in the country. In recent years there has been a strong concern for the student demographic. Suicide ranks as the leading cause of death among Canadians aged 15-24 as reported by the CMHA [5]. This degree of research and attention to the issue incents a health care system such as Canada’s to increase spending in the area. The cost of health care relating to mental illness in Canada was estimated to be $42.3 billion in 2011 [6]. As noted, the research methods and approaches to mental health vary by country. Similar
statistics exist in the United States, a country of similar economic standing and demography. In the US, the leading cause of disability among people aged 15-44 is a depressed mood [7]. Additional research determined that this particular subset of disability accounts for over a $31 billion loss for the economy in terms of annual loss of productivity. Mental health is becoming increasingly expensive in first world countries due to both cost of care and productivity loss.

This thesis presents the experimental results for a system designed to evaluate the relationship between individual wellness and one’s environment. The system makes use of an Internet of Thing (IoT) device communicating via Bluetooth Low Energy (BLE) communication protocol. IoT is a growing network of intercommunicating devices. The network enables the machine-to-machine collection and exchange of data [3]. It is estimated that the network will contain 26 billion connected devices by 2020 [8]. BLE is a communication standard which is advantageous for low-cost and low-power-consumption design. For that reason, it is useful in applications of small scale data transfer such as the one presented here.

The system consists of two main components: a mobile application and a SensorTag device. The SensorTag is an IoT device which communicates with the mobile application via BLE and contains ten sensors, five of which are used in this system. The mobile application connects to the SensorTag via BLE and asks the participant to complete a brief psychological survey three times per day. During the time the participant is answering questions, the
SensorTag is reading data from five environmental variables: temperature, humidity, air pressure, luminosity, and noise level. Upon submission of the survey by the participant, the survey results and the raw data of the five environmental variables are sent to the researchers’ server via a secure WiFi network. Our system serves no diagnostic purpose, and is designed only to provide a wellness assessment.

1.1 Motivation

There is a growing desire for wellness assessment worldwide across many demographics. This is due to an increased concern for mental health, particularly in certain underrepresented populations. There are several global issues pertaining to mental health care that can be helped by an individualized wellness assessment: growing cost of mental health care, the stigma associated with seeking help, and lack of access to proper care in certain populations.

First, the cost of mental health care is growing as it becomes a larger concern worldwide. The costs related to mental health care in Canada were estimated at $42.3 billion in 2011 [6]. In the United States, a country of similar demographics, a depressed mood is the leading cause of disability about people aged 15-44 [7]. Additionally, the cost of lack of mental health care can be expensive. Disability related to a depressed mood in the United States is estimated to account for a $31 billion loss annually in terms of
productivity [7].

The stigma of mental health concerns is another reason why individualized assessment systems are advantageous. A small, discrete mobile solution such as the one presented in this thesis is a good solution for those hesitant to seek care in person.

Finally, some populations face a lack of access to care. One example is the refugee population [9], who are at a greater risk of mental illnesses including anxiety and depression. The United Nations (UN) estimates that there are currently five million Syrian refugees worldwide, many of whom are staying in refugee camps where they face additional life stresses [9]. Mobile access to support has been proposed as a solution, in part based on a study that counted 90% of refugees in a camp as having access to a smartphone [9].

1.2 Problem Statement

Wellness in student populations is a growing and costly concern worldwide. There is a desire for solutions that have the ability to reach a diverse group of people with minimal cost. There has been a recent rise in individualized mobile solutions in health care. Individualized, low-cost care would be essential to mental health care as there is a need to cut both cost and stigma. It is desirable for an individual to be able to associate a change in their wellness with their surroundings.
1.3 Research Objectives

The research objectives of this thesis are as follows:

• Design a low-cost, low-power system to wirelessly assess wellness using appropriate technology.

• Perform several experiments to assess wellness in the student population in varying seasonal conditions.

• Perform a correlation analysis on the experimental results to determine any correlation between the five selected variables and the wellness assessment.

1.4 Methodology

This thesis designs a system to assess wellness using a mobile application utilizing IoT and various communication standards. Subsequently, several experiments were performed with over 30 participants and the results were used to provide a correlation analysis between individual wellness and environmental variables. The design, results, and analysis are all provided in this thesis.

Specifically, the design is interested in five environmental variables (temperature, humidity, air pressure, light, and noise) and seeks to correlate them with wellness as assessed by questions from three surveys (PSQI, PSS, and K10). The surveys are completed on a mobile application, and the variables
measured by a SensorTag IoT device which communicates to the application via BLE technology. Following initial testing, three experiments have been performed to test the design. Following the experiments, a correlation analysis was performed using a variety of appropriate correlation coefficients.

1.5 Contributions

The contributions of this thesis are as follows:

- A low-cost, low-power system that uses IoT, BLE, and WiFi technology to assess an individual’s immediate wellness and five variables to describe their surroundings, allowing for the correlation of one’s environment to their wellness.

- Experimental results are presented evaluating the correlation of individual wellness to one’s environment for over 50 university students during three different seasons.

- The system and experimental conditions were approved by the University of Guelph Research Ethics Board in 2018 and updated in 2019.

- The correlation analysis presented is broad: five environmental variables (temperature, humidity, air pressure, light, and noise) are tested for association with three psychological surveys (PSQI, PSS, and K10) using three correlation coefficient types (Kendall, Pearson, and Spearman).
• The work presented here has appeared at a conference [10], with an additional magazine and journal currently submitted.

• A system that has future potential to evaluate an individual’s wellness based on their surroundings.

1.6 Organization

The remainder of this thesis is organized as follows:

• Chapter 2 provides a review of related literature on the topics of mental health, psychological surveys, IoT in health care, how environmental sensors are used to assess wellness, and how correlation is analyzed in the engineering discipline.

• Chapter 3 describes the methodology used for this thesis. Provided is a detailed outline of IoT, various communication technologies, correlation analysis and the coefficients employed in this project, and a description of the psychological surveys employed in this project.

• Chapter 4 describes the setup for the experiment, including all of the hardware used and the mobile application developed.

• Chapter 5 describes the conditions for the initial tests, Experiment 1, and Experiment 2. Also detailed are the instructions that were given to each participant before beginning and a description of how the correlation coefficients were interpreted.
• *Chapter 6* presents the results of the experiment and analyzes the correlation data.

• *Chapter 7* summarizes the findings, concludes the work, and suggests future steps for this project.
Chapter 2

Background and Related Works

This chapter presents background information and an assessment of academic works related to the themes of this thesis. Specifically, we look at the global impact of mental health, how surveys are used to assess wellness, current applications of some of the technology used in this system, and an evaluation of how correlation is analyzed in engineering.

2.1 Global Impact of Mental Health

Mental health and general wellness are becoming a growing concern as research in the field increases. While the cost of mental health care continues to increase worldwide, the economic drain caused by mental health issues increases in kind. As a global issue, it is approached differently in every region and country. Additionally, there are social variables that impact the
likelihood of developing mental illness. In this section, we will present the scope of the global mental health landscape given current research, the cost imposed on health care systems and economies worldwide, and some cases in which a mobile system could be of use.

Governments are currently grappling with how to properly address mental health within their health care systems in terms of budget and methodology. An American article circa 2017 states that “current treatments and the dominant model of mental health care do not adequately address the complex challenges of mental illness” [7]. Globally, the World Health Organization (WHO) warns that the current challenges are dire. In 2016, the WHO declared depression to be the leading cause of disability worldwide [7]. Mental illness as a whole accounts for one third of adult disability and over two thirds of those individuals will never receive adequate care [7]. That is the case in South Africa, where 1 in 3 South Africans will develop a mental disorder in their lifetimes. Mental illness accounts for one third of adult disability and over two thirds of those individuals will never receive adequate care [11]. To address the concern, South Africa devoted 2.7% of its 2005 health budget to mental health care. While this is more than twice the percentage paid by Ghana and Uganda, it is much lower than high-income countries. For example, the United Kingdom devoted 10.8% of its health care budget in the same year to mental health concerns. South Africa does intend to close this gap. They have committed to increasing that budget by 30% by 2030 [11].

While South Africa’s spending statistics meet the global average, they
are lower than many other low- and middle-income countries. As noted, various factors impact the prevalence and likelihood of mental illness and are important considerations in the approach to a solution. Poverty is one factor that is linked to mental illness worldwide [7]. Variables related to poverty that increase the likelihood of mental illness include social class, housing, food insecurity, and education. In South African research, it was noted that individuals with HIV are at higher risk of mental illness [11]. For that reason, the national government’s suggested approach includes an increase in HIV care, screening, and prevention.

The Canadian Mental Health Association (CMHA) reports that 50% of the Canada’s population will have or have had a mental illness by the age of 40 [5], a contributing factor to the cost of mental health care in the country. In recent years there has been a strong concern for the student demographic. Suicide ranks as the leading cause of death among Canadians aged 15-24 as reported by the CMHA [5]. This degree of research and attention to the issue incents a health care system such as Canada’s to increase spending in the area. The cost of health care relating to mental illness in Canada was estimated to be $42.3 billion in 2011 [6]. As noted, the research methods and approaches to mental health vary by country. Similar statistics exist in the United States, a country of similar economic standing and demography. In the US, the leading cause of disability among people aged 15-44 is a depressed mood [7]. Additional research determined that this particular subset of disability accounts for over a $31 billion loss for the economy in
terms of annual loss of productivity. Mental health is becoming increasingly expensive in first world countries due to both cost of care and productivity loss.

Another group of individuals at greater risk of mental illness is refugees, who are at risk of anxiety, depression, and post-traumatic stress disorder (PTSD). An armed conflict in Syria began in 2011, resulting in mass displacement of their population [9]. By 2017, the UN Refugee Agency had registered approximately five million Syrian refugees. In Syria, their incidence of mental illness may have been increased due to exposure to war-related trauma, including the death of loved ones and the destruction of homes. In their host countries, there are additional stresses, including overpopulation in refugee camps, access to financial support, and access to paid work. Studies indicate the prevalence of PTSD in these populations to be 12.9% and that of depression to be 7.6%. For comparison it is estimated that 3.3% and 4.4% of the general population suffer from PTSD and depression, respectively. While some host countries provide mental health care to refugees, the WHO is also looking for solutions. One promising solution for this demographic is E-health solutions. Particularly, there is an interest in mobile access to mental health support. A study in a Za’atari refugee camp determined that 90% of Syrians in that camp had access to a smartphone, 60% of whom used only that phone for internet access. Therefore, this solution seems promising to provide access to as many people as possible.

It seems that as countries across the world increase spending on mental
health, there will be a desire for low-cost solutions. E-health mobile solutions certainly provide this. A mobile solution to mental health, such as the system presented in this article, can be low-cost, low-power, and accessible.

2.2 Psychological Surveys used to Assess Well-being

Psychological surveys can be a useful tool for assess mental health or well-being of an individual. There are several factors that are important to identify before using them in research: Are their results specific to a demographic? Has the survey been tested with a wide number of subjects? Are the results reliable? How has it been used in past research?

In this section, several surveys have been identified as having questions pertinent to the interests of this thesis. This section will identify the quality of those surveys and analyze some cases in which they are used in industry or research.

2.2.1 Pittsburgh Sleep Quality Index

The PSQI survey provides a quantitative but subjective measure of one’s sleep quality and patterns. The questions posed inquire into the subject’s sleep quality over the past 30 days, however the period of time has been shortened to periods such as two days or two weeks for the needs of certain
studies [12]. The first four questions are more open-ended, asking for the time
the subject went to bed, how long it took to go to sleep etc. The following 14
questions ask for the frequency of the following occurrences, among others:
do you get hot, have bad dreams, or pain? The last question asks the subject
to rate their overall sleep on a scale.

It appears that the PSQI scale can be used research of specific demo-
graphics, as well at those that cross demographics, and a varying number of
subjects. [13] details a study in which 80 muslim women with breast cancer
in Qom, Iran were asked to fill out a selection of surveys concluding signif-
icant correlation between PSQI data and select questions from a spiritual
well-being scale. In a broader demographic and a larger subject group, 1,037
sleep clinic patients in Tehran were asked to fill out a number of sleep qual-
ity surveys concluding significant correlation between PSQI and the Insomnia
Severity Index.

It has also been used in surveys of demographics of noncomplaining
elderly subjects [14], schizophrenia patients [15], insomniacs with a post-
menstrual syndrome [16], and HIV-infected african-american women of child-
bearing age [17]. These cases listed have a variety of numbers of subjects from
53 [16] to 144 [17] subjects. It is evident that this survey can be successfully
employed for any demographic, and a range in the number of subjects.
2.2.2 Perceived Stress Scale

The PSS was developed to respond to issues observed by health researchers in the 60s and 70s [18]. Researchers noted the objectivity of stressful events. Essentially, an event is only stressful if the subject perceives it as such. This degree of perception had not previously been accounted for in quantitative measures of stress. [18] presents the PSS, a 14 question survey to measure stress globally. The paper presents data to conclude adequate reliability and is suggested for the examination of the role of non-specific appraised stress [18].

Like with the PSQI, it appears that the PSS has been successfully implemented over a wide variety of demographics with a range in the number of subjects. It has been used in demographics of Spanish young and middle-aged adults [19], newly diagnosed cancer patients receiving specific vaccine treatments [20], South African adults [21], middle school teachers [22], and early adolescents [23]. These studies listed surveyed anywhere from 30 [20] to 473 [19] subjects with successful results. Significantly, the fact that [23] used the PSS to significantly and positively correlate stress to spirituality in a group of 53 adolescents is of interest to our study as we will be testing a similar demographic.
2.2.3 Kessler Psychological Distress Scale

The K10 survey was developed by Kessler and his colleagues to measure the level of stress and severity of psychological symptoms in population studies [24]. The survey is now widely used in population-based epidemiological studies to measure current distress. It has been observed to have good psychometric properties, given a Chronbach’s alpha of 0.89 [24] which indicates reliability of a test.

Like the other two surveys discussed, the work related to the K10 survey showcases a variety of demographics and population sizes. [24] studies a group of 892 medical students in Saudi Arabia. [25] looks at 166 asylum-seeking children in Australian detention facilities. Finally, [26] looks at a sample of 724 English-speaking adults in the United States designed to comprise of a variety of nationalities.

2.3 Internet of Things Applications in Health Care

Over time, technology has been used more and more often to solve issues in our society. One of the tools being used to solve problems in many fields is the Internet of Things (IoT) devices [3] [4]. A benefit achievable through many IoT-based solutions is the production of low-cost and low-power models. Many fields already have commercially viable IoT options,
including smart parking, precision agriculture, and water usage management [3]. Health care, as an application of IoT, is a promising but still developing application.

The IoT has been identified by many as a potential solution for the increasing demands on health care systems since IoT has previously allowed for automation in many industries. In [3], an end to end IoT health care system is proposed identifying the key components necessary for a functional model and introduces an array of technologies that fit the requirements. Many IoT-based models are being used in academic research, while others are sold commercially and used in industry.

As noted, there has already been commercial success for IoT systems in other fields. The research done in these fields proves the theory that remote health care monitoring using IoT devices is possible. There are many benefits to this possibility. A remote, low-cost system increases the accessibility to health care in more remote locations where it is difficult to access a medical facility. Monitoring patients remotely allows for more beds available in medical facilities, which reduces some strain of the health care system due to overcrowding. Additionally, the option to be monitored remotely increases the sense of independence for many patients, which in turn improves well-being. This is particularly true for the elderly demographic, who often lose independence when moving into specialized supervised homes. While there are many advantages to using IoT in health care applications, possible disadvantages exist. Large amounts of data need to be transferred between devices
and stored in cloud storage. This provides a great security risk, as the data is sensitive. Furthermore, remote systems must be robust since there will not be technicians on hand to fix issues on the regular. For example, the devices ideally shouldn’t need to be calibrated too often or have their batteries too low to function properly.

The disadvantage with the greatest risk is security concern, and it is therefore very important to identify any possible security concerns in these systems. [4] identifies several security requirements specific to IoT health care systems. Confidentiality ensures that no transferred medical data is accessible to intruders of the system. Integrity ensures that the transferred data is not altered in any way en route. Fault tolerance means that when a fault is present in the system, the system can continue running with unaffected security. The challenges in building an IoT security system with these requirements are also some of the benefits to the system at large: a low-power CPU device with low memory and low energy has inherent limitations in terms of design.

Figure 2.1 shows a broad selection of current IoT applications in health care. Given the current demand for solutions to mental health concerns worldwide and the success of IoT systems as health care solutions, it follows that IoT should be used as a solution to mental health. In fact, systems have been designed to monitor psychological symptoms using smartphones and mobile sensors [27, 28]. This thesis presents a framework inspired by [29, 30], which sought to correlate light and temperature variables to general
wellness.

2.4 Environmental Sensors to Assess Wellness

Since the invention of the IoT, mobile sensors are being used with increasing frequency to accurately evaluate a subject’s wellbeing. This has been documented in both industry practices and academic experiments. Some of the systems are similar to ours in that they focus of mental wellness, while other carry the additional component of tracking physical symptoms. This section is a collection of the works with a focus on the monitoring and assessment of mental wellness using a combination of mobile phones, mobile sensors, and personal surveys.

In [28], a smartphone-based system was created to remotely monitor the symptoms, behavior, and physiology of psychiatric patients. The purpose of this design was to create a low-budget approach to mental health care, a division of health care with consistently low funds. An increased monitoring of mental health would be advantageous to health services as mental illness has an indirect effect on life expectancy and often co-occurs with chronic illness [28]. At the beginning of this study, over 100 participants completed several psychiatric questionnaires to be repeated on a weekly basis. These surveys include a quick inventory of depressive symptomology, the Altman self-rating mania scale, a brief measure of assessing generalized anxiety dis-
order, and a quality of life questionnaire. For this system, an application was
developed to make use of the sensors on a Samsung Galaxy S III. The appli-
cation records actigraphy levels, ambient light levels, social network activity,
and participant physiology (blood pressure and temperature). While com-
plete results were not yet available, the initial results clearly demonstrate a
consistency in the actigraphy and social networking levels of a healthy control
compared to a participant with diagnosed borderline personality disorder. In
[30], a similar framework is described which determines a correlation between
wellness and environmental factors. In this case, the environmental factors
studied are temperature, humidity, and luminosity, with a correlation deter-
mined between luminosity and general wellbeing over an experimental period
with 23 participants.

In [27], wearable sensors and smartphone usage are used to evaluate cor-
relation to students’ academic performance, self-reported sleep quality, self-
reported stress, and self-reported mental health. The study gave wearable
sensors to 66 student participants over 30 days, achieving 1,980 days of data.
Several surveys were completed by participants before beginning, including
the Pittsburgh Sleep Quality Index (PSQI), the Perceived Stress Scale (PSS),
and the Mental Health Composite Scale. Each participant wore a collection
of wearable sensors on their wrist for the duration of the experiment: an
accelerometer, light sensor, actigraphy monitor (to monitor quantity and du-
ration of physical activity), skin temperature sensor, and skin conductance
sensor (to measure sympathetic nervous system activity). Many associations
were determined with classification accuracies ranging from 67-92%. PSQI groups were in turn related to sleep regularity, confirming a hypothesized relationship between high stress levels and low sleep quality. In particular, the wearable sensors achieved close to a 90% classification accuracy for PSQI, PSS, and MCS.

Bluetooth communication is commonly used in these eHealth systems to communicate between technologies such as smartphones and wireless sensor networks due to its low-cost, low-power consumption nature. In [31], it is determined that a combination of Bluetooth and near-field communication technology allows for the initiation of communication between two devices following a brief period of proximity. The paper hypothesizes that this connection is advantageous in cases such as elderly patients due to pure simplicity. In [32], a study where Bluetooth technology was used to create a non-invasive wireless monitoring device for pediatric hospital environments is described. Their prototype consists of an Arduino-based sensor network communicating wirelessly to an Android application. Sensors used included temperature sensors in addition to other biomedical sensors. BLE technology was selected due to low power consumption and superior architecture to traditional Bluetooth technology.
2.5 Correlation Analysis in Engineering

A correlation analysis is a mathematical method of determining any existing association between two variables. In this thesis, we are specifically looking at correlation coefficients and their corresponding p values. In brief, the correlation coefficient is a measure from -1 to 1 that indicates the strength and direction of association between two variables. A coefficient of 1 indicates a perfect linear relationship, while a measure of 0 indicates that no association exists. The details of the various methods to calculate these functions (Kendall, Pearson, and Spearman) are explained in depth in Section 3.6. This section looks at the various methods that this statistical phenomenon is employed in the field of engineering.

In [33], researchers in the Department of Civil Engineering at California Polytechnic University perform and present a correlation analysis of subjects taking a Fundamentals of Engineering exam, the first step to become a licensed engineer in the United States. The intention of the analysis was to use the subjects on the test as variables to highlight areas of concern. The study used Pearson’s coefficient and its related p value to establish correlation. This study concluded the presence of statistically significant correlation among many subject pairs across morning and afternoon sessions. The statistical significance is determined from the p values.

In [34], researchers in Indonesia use correlation analysis methods to study earthquakes in the region. They explain that geomagnetic signals are asso-
ciated with earthquake occurrences, but that strong signal correlation on earthquake-less days is required to confirm these precursors as valid. Sample data was used from several days across a few different years. The Spearman rho was used as a measure of the strength of relationships in this case. The paper classifies the strength of the relationship between the signals measured by several observatories as "strong to very strong" based on a rho threshold of 0.60.

While [33] made use of the Pearson coefficient, and [34] used the Spearman coefficient, [35] measures both. This paper is a data set provided by researchers in India seeking to correlate knowledge, study time, and exam performance. This study concludes that they can differentiate each individual user based on their results. This identification is done by applying linear regression following the calculation of both types of correlation coefficient.

[36] also uses both the Spearman and Pearson coefficients in their correlation analysis. Theirs is an analysis of the compressive strength of concrete with the aim of comparing Spearman to Pearson. It observes through its analysis that the Pearson coefficient measures the linear relationship between two continuous variables while the Spearman coefficient is based on the rank values rather than the raw data. They conclude that both are approximations, and advise follow-up research.

It is evident based on the equations presented in Section X and the data presented by [36] that different correlation coefficients are more effective in different situations. While each have advantages, all are approximations. It
is therefore ideal to measure more than one type of correlation and have the results of the two formulae confirm one another such as in [35] and [36].
Figure 2.1: IoT applications in health care [3] [4].
Chapter 3

Methodology

This chapter describes the methodology of this thesis, starting with an overview of the system framework. Then we look more specifically at the technology used, the methods used to evaluate correlation, and the surveys used to assess wellness.

3.1 Framework

In this system, we have had as many as 17 participants in possession of the materials and sending data to our server at a time. The system, as seen by each participant, is shown in Figure 3.1. Each participant is equipped with a SensorTag device and an Android smartphone. The SensorTag is an IoT device equipped with ten sensor, four of which are being used in this system. The smartphone is equipped with an application designed to
communicate with the SensorTag via BLE. While the participant is answering psychological survey questions on the application, the SensorTag device is collecting raw sensor data for our five environmental variables (temperature, humidity, air pressure, light, and noise) and sending it to the application via BLE. The survey questions take approximately 2-3 minutes to complete, during which time the app is collecting sensor data. Once the participant selects to "submit" the survey, both the sensor data and responses to the survey questions are sent to the research server over campus WiFi.

On the server, we receive three CSV files for each survey submission: a configuration file, the survey responses, and the raw sensor data. All files are mapped to the participant’s SensorTag’s Bluetooth address ID, but no identifying information. The full data set for each experiment comprises of all these CSV files from submissions from the duration of the experiment. From these raw files, average sensor data is calculated for each submission.
and a correlation analysis is completed for the experiment.

The specific hardware components of the system are detailed in Chapter 4.

3.2 Internet of Things

IoT is a network of millions of small devices capable of interacting with one another. The network communicates using IP connectivity without any human intervention. The IDC reports that there will be 30 billion devices on the Internet network by 2020 [37]. Thanks to its growing use in a wide variety of industries, it is expected that IoT enabled devices and services will generate over $1.9 trillion by the same year [37].

These devices on the network include smartphones, wearables, cameras, tablets, smart watches, and other ‘intelligent’ objects. These devices intercommunicate using technology such as radio-frequency identification, Bluetooth, or WiFi. An example of this communication is your phone using Bluetooth communication to connect to your car’s system.

There are several advantages to IoT that make it ideal for this thesis. The sheer vastness of the network ensures efficiency and familiarity. People use IoT devices every day without much thought, meaning that most people are familiar with Bluetooth and WiFi connections. Public places have WiFi connection readily available to the public.

Thanks to the availability and advantages of IoT devices, they have found
uses in many applications and research fields. The devices have been applied to coal mine production, to sense and control hazards without risking human life [38]. Specifically, mines rely on the reliability of IoT devices such as monitoring equipment. There are other systems as well that very clearly rely on the safety of the IoT network. For example, a component of smart home technology is an interactive key management protocol. [39] presents a security analysis that presents several possible schemes resilient to attacks. Such resiliency would also be important in smart home technology such as smart smoke detectors and smart doorbells. Similarly, the health care applications presented in Section 2.3 benefit from the same advantages of low-cost, low-power, and possible safety protocols.

Additionally, IoT presents the opportunity to reach a broad demographic of people. Thanks to the wide availability of connected devices such as smartphones, and connections such as LGE and WiFi, communities that previously struggled to connect to other regions are finding solutions. For example, [9] details how smartphone devices can provide a solution for Syrian refugees in UN camps dealing with symptoms of PTSD. [40] details the advantages and possibilities for IoT in rural communities. This reach is excellent for the future prospects of systems such as the one presented in this thesis.
3.3 Communication Technologies

Many communication protocols exist for the transfer of data between devices. Each standard has its benefits and is therefore best suited to systems with certain characteristics. The following is a comparison of a couple communication standards considered for this system:

- **BLE**: BLE is ideal for this project due to Android integration. Android 4.3 introduced a built-in platform to support BLE [41]. This allows for applications such as ours to discover devices, query for services, and communicate data. BLE transfers data between two devices in close proximity to one another. This should help to reduce outliers in our system, which requires the two devices to be with the person at the time of data collection. Most significantly, BLE was designed for the purpose of lower power consumption than Classic Bluetooth. This is ideal for an experiment such as this one, which will take place over an extended period of time. Low power consumption in the communication between our participants’ devices should allow for more consistent and accurate results.

- **WiFi**: WiFi is the popular term for the bands of the wireless spectrum available for public use without government license. It is available today due to a 1985 ruling by the United States Federal Communications Commission [42]. WiFi is most commonly used in Wireless Local Area Networks (WLAN). The most commonly used frequency bands are the...
first two to become available: 2.4GHz and 5GHz. WiFi’s high availability makes it ideal for use with the IoT and its devices. For this system, a university WiFi network is used to transmit data. Using this secure network to send data to a university server helps to ensure a secure transaction.

- **ZigBee**: The ZigBee communication standard is designed for low-data-rate, short-range wireless communication and is mainly used for battery-powered designs [43]. Like BLE and WiFi, a low cost and low data rate are both design requirements. As such, designs necessitate that most time is spent in some form of ”sleep mode”. Examples of strong ZigBee applications include an at-home patient blood pressure monitoring system that transmits data to a local server, and the monitoring of architectural structures [43].

All three of these communication protocols are strong options for this system given the following requirements: low cost, low power, small amounts of data. In order to select a protocol to send sensor data from the SensorTag to the mobile application, the power consumption was measured for each of the three options. Fig. 3.2 shows the power consumption results of a test in which data was transferred from the SensorTag to a smartphone using the same sensors used in this experiment. In this figure, BLE is labelled as ”Bluetooth” and ZigBee is labelled as ”Sub Giga”. BLE was selected for this experiment because, as shown in this graph, it has the lowest power
consumption. WiFi, while it has a high power consumption, is used to send
data from the smartphones to the research server due to range, simplicity,
and availability.

### 3.4 Description of Psychological Surveys

Psychological surveys can be a useful tool in measuring wellness if selected
and used properly. In this thesis, we are interested in the general wellness of
the individual at the time they are completing the survey. We will measure the usefulness of the surveys in question by the WHO’s definition of mental health: "a state of well-being in which the individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to his or her community" [44]. The collection of surveys selected to include in the dataset includes questions concerning stress levels, and ability to cope/work through said stress. Additionally, we are interested in one’s sleep quality and a variety of other factors. We believe that this selection of questions is not dependant on a specific age, gender, or other type of demographic. Additionally, we believe these questions to be particularly pertinent to the student demographic participating in this study.

The mobile application given to the participants invites them to take a survey 2-3 times per day. When the "Start Survey" button on the application is selected, questions from three existing psychological surveys are presented to the participant and must all be answered before submitting. The surveys were selected in order to inquire about a variety of aspects of an individual’s current wellness, including stress and sleep. Importantly, the questions and possible responses have been modified from their original form to reflect the fact that we are only interested in the participant’s wellness at the time they are completing our surveys, rather than an extended period of time. The three surveys described in this section were used for each of the three experimental periods described in this thesis. Following the initial testing
phase, an additional question was added: "How many people are around you right now? (ie. in the same room)". This question essentially provides a sixth environmental variable, without use of a sensor: the presence of other humans in the participant’s space.

As noted, the questions from the three official surveys have been modified for this experiment. The PSQI, PSS, and Kessler Psychological Distress Scale (K10) present questions pertaining to an individual’s wellness over the past 30 days. This time frame is not relevant to our experiment as the participants will take the surveys 2-3 times per day. For example, one PSQI question reads "During the past month, how would you rate your sleep quality overall?", while all PSS questions begin "In the last month,..." and the K10 questions begin with "During the last 30 days,...". For this reason, the questions have all been modified to reflect the individual’s immediate well-being. These modifications are reflected in Tables 3.1, 3.3, and 3.2.

3.4.1 Pittsburgh Sleep Quality Index

The PSQI [45] was selected and modified for to achieve a quantification of the participant’s sleep quality the previous night. Since the surveys are taken by the participant 2-3 times per day, this survey is only presented during the first submission of the day. This is because the participant’s answers will not change until the next morning. Our modified PSQI consists of 17 questions inquiring into quality and duration of sleep, which can be seen in Table 3.1.
<table>
<thead>
<tr>
<th>Question</th>
<th>Possible Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td>When did you go to bed last night?</td>
<td>8-8:30pm, 8:30-9pm etc.</td>
</tr>
<tr>
<td>How many hours did you spend in bed last night?</td>
<td>0-1 hour, 1-2 hours etc.</td>
</tr>
<tr>
<td>How many hours of sleep did you get last night?</td>
<td>0-1 hour, 1-2 hours etc.</td>
</tr>
<tr>
<td>Last night, did you go to sleep within 30 minutes?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Last night, did you wake up in the middle of the night?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Last night, did you get up to use the bathroom?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Last night, did you have trouble breathing properly?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Last night, did you cough or snore loudly?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Last night, did you feel too cold?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Last night, did you feel too hot?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Last night, did you have bad dreams?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Last night, did you have pain?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Did you take medicine to help you sleep last night?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Have you had trouble staying awake in the past 24 hours?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Have you had trouble keeping enthusiasm to get things done in the past 24 hours?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>How would you rate last night’s sleep overall?</td>
<td>1, 2, 3, 4, 5</td>
</tr>
</tbody>
</table>

Table 3.1: PSQI questions answered by participant.

### 3.4.2 Perceived Stress Scale

The PSS [46] was selected and modified to quantify the degree to which the participant is feeling stressed at the time of the survey. Our modified PSS consists of 10 questions inquiring into the presence or lack of various symptoms of stress, which can be seen in Table 3.2.
<table>
<thead>
<tr>
<th>Question</th>
<th>Possible Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Do you feel upset by something that happened unexpectedly?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Do you feel unable to control the important things in your life?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Do you feel stressed?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Do you feel confident about your ability to handle your personal problems?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Do you feel that things are going your way?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Do you feel that you are able to cope with all the things you have to do?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Do you feel that you are able to control the irritations in your life?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Do you feel that you are on top of things?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Do you feel angered because of things that are outside of your control?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Do you feel difficulties are piling up so high that you could not overcome them?</td>
<td>Yes/No</td>
</tr>
</tbody>
</table>

Table 3.2: PSS questions answered by participant.

3.4.3 Kessler Psychological Distress Scale

The K10 [47] was selected and modified to quantify the participant’s level of psychological distress at the time the survey is taken. Our modified PSS consists of 10 questions pertaining to the relevance of various feelings of distress. For example, the survey asks whether the participant feels hopeless, nervous, or depressed. These questions can be seen in Table 3.3.
<table>
<thead>
<tr>
<th>Question</th>
<th>Possible Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Do you feel tired for no good reason?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Do you feel nervous?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Do you feel so nervous that nothing can calm you down?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Do you feel hopeless?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Do you feel restless or fidgety?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Do you feel so restless that you can not sit still?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Do you feel depressed?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Do you feel that everything is an effort?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Do you feel so sad that nothing can cheer you up?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>Do you feel worthless?</td>
<td>Yes/No</td>
</tr>
</tbody>
</table>

Table 3.3: K10 questions answered by participant.

3.5 Range and Units of Environmental Variables

It will be important when analyzing correlation between survey results and environmental variables to ensure that there is an appropriate range to each of our variables. To be sure of this, this section will analyze what values should be expected for each variable, and what should be omitted as outliers. Additionally, this section provides an analysis of what can be expected given the units being measured. An analysis of the specific sensors used will be presented later.
3.5.1 Temperature

The ambient temperature in this system is being measured in degrees Celsius (°C). The centigrade scale is the standard unit of temperature as per the International System of Units (SI). This unit of measurement is ideal for our system, which measures environmental impact on human participants in Canada, as it is the standard measurement used in this country. It is generally considered ideal for human use as the point of 0°C represents the freezing point of water.

Statistics Canada reported in 2006 that most Canadian households reported to keep their homes between 20°C and 22°C during daytime and from 16°C to 18°C at night [48]. For the purposes of this project, anything between 15 and 30°C will be considered a reasonable indoor temperature and a range to achieve for good correlation.

It is also possible that participants take the survey outdoors, as the University of Guelph WiFi network can be accessed anywhere on campus. Given that some experiments were completed in Canadian winters, lower temperatures are possible and will not be omitted.

3.5.2 Humidity

In this system, humidity is measured in percentage. When measured in percentage, humidity refers to the degree to which the air has been saturated.

Health Canada recommends that indoor spaces be kept between 30 and
55% for comfort and health [49]. This is a range that will be sought for good correlation calculations. However, it is possible that spaces are significantly dryer or more humid.

### 3.5.3 Air Pressure

In this system, barometric pressure is measured in kilopascal (kPa). The definition of a kilopascal is the pressure exerted by a 10 g mass on an area of one cubic centimetre. This is the system of measuring pressure recognized by the IS.

Atmospheric pressure (at sea level) is 101.3kPa. Barometric pressure varies only slightly with the weather. For that reason, it will be difficult to achieve any correlation with this variable, but it will be analyzed nonetheless. From testing the SensorTag device over time, it is expected that the variation will only be +/-1 kPa.

### 3.5.4 Light

The light values in this system are measured in lux, the SI unit measuring illuminance [50]. Lux are related to lumens, the SI unit representing luminosity such that one lux is equal to one lumen per square metre. As such, the difference between a lux and a lumen is that a lux measures the area of concentration of the light. Lux are ideal for this system as it measures the intensity of light as perceived by the human eye. Since our system is
measuring the impact of environmental variables on human participants, we are only interested in measuring light as seen by the human eye. The light sensor has been programmed to measure in lux units. Table 3.4 shows a variety of lux levels expected in different environments. For this variable, it is expected that most participants will take the survey within the indoor lighting range. However, there will likely be exceptions where participants choose to take the survey outdoors.

### 3.5.5 Noise

This system measures noise in terms of dBA. This is an A-weighted decibel. While a decibel commonly measures the intensity of sound, it is done on a logarithmic scale and can therefore be weighted. The A-weighting makes the readings less sensitive to very high and very low frequencies, more appropriate to what is heard by the human ear.

The microphone on the SensorTag measure noise in dBA. Tests were done with the device to decide upon a reasonable range. A quiet room generally measured around 23 dBA. A room with several people and significantly more noise measured closer to 30 dBA.

<table>
<thead>
<tr>
<th>Environment</th>
<th>Light (lux)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sunlight</td>
<td>107,527</td>
</tr>
<tr>
<td>Overcast day</td>
<td>1,075</td>
</tr>
<tr>
<td>Normal work office</td>
<td>250</td>
</tr>
<tr>
<td>Homes</td>
<td>150</td>
</tr>
</tbody>
</table>

Table 3.4: Light levels expected in different environments [1].
<table>
<thead>
<tr>
<th>Weak or low</th>
<th>≤ 0.35</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moderate or modest</td>
<td>0.36 - 0.67</td>
</tr>
<tr>
<td>Strong</td>
<td>0.68 - 1.0</td>
</tr>
<tr>
<td>Very Strong</td>
<td>≥ 0.9</td>
</tr>
</tbody>
</table>

Table 3.5: Categorizing correlation coefficients (r value) [2].

### 3.6 Correlation Analysis

Correlation analysis for this experiment is done using a few different correlation coefficients. A correlation coefficient measures the degree of linear association between two variables and is one of the most frequently reported statistical variables in research. It is so frequently used before it is an excellent gauge of how strong or significant an association is between two variables.

The correlation coefficient, r, is a measure from -1 to 1 which has both magnitude and direction [2]. A coefficient of 0 indicates no association, and the association gets stronger as it approaches magnitude 1. A coefficient of 1 would indicate a perfect linear relationship. However, this is unlikely in an experimental setting. As data points diverge from the line indicating a linear relationship, the correlation coefficient decreases. Additionally, the sign does not indicate the strength of a relationship, but rather whether it is a "direct" or "inverse" association. The strength of a correlation coefficient can be roughly categorized as in Table 3.5 [2].

It is possible to achieve a non-zero r value for a relationship in which no correlation exists. Therefore it is important to analyze the significance of these values. This can be done by calculating a p value in addition to
the r value. The p value considers the chances of observing the given r value at random in a case that no correlation actually exists. The p value takes into account the sample size. A small p value indicates a statistically significant r value, which allows for the rejection of the null hypothesis. In the case of this experiment, the null hypothesis states ”there is no correlation between this environmental variable an survey result”. For the purposes of this experiment, the p value must be lower than the standard 0.05 [51] to be considered statistically significant and highlighted in the results to be discussed.

The remainder of this section describes the calculations and appropriate uses for the three correlation coefficients measured in this experiment.

### 3.6.1 Kendall

The Kendall Rank Coefficient evaluates the degree of similarity between two sets of ranks among a set of objects. The calculation is made based in part on the number of inversions in the rankings as one goes down the list. The tau value, in place of the r value, is given as [52]:

\[
\tau = 1 - \frac{2(D)}{n(n-1)/2} \tag{3.1}
\]

where D is the number of inversions in the rankings.
3.6.2 Pearson

Pearson’s Product Moment correlation coefficient is used when both variables are normally distributed. This coefficient is affected negatively by extreme values, which can exaggerate or minimize the degree of true association. That is why it is not appropriate for use outside normal distribution. The r value is given as [53]:

\[ r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\left[ \sum (x_i - \bar{x})^2 \right] \left[ \sum (y_i - \bar{y})^2 \right]}} \]  \hspace{1cm} (3.2)

where \( x_i \) and \( y_i \) are the values of \( x \) and \( y \) for the with iteration.

3.6.3 Spearman

The Spearman Rank Coefficient is appropriate in similar cases to Pearson, but accounts for the extreme values. It is appropriate in cases where one or both variables are skewed or ordinal. Mathematically, it assigns ranks and treats them as scores to calculate correlation among the set. The r value is given as [54]:

\[ r = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \]  \hspace{1cm} (3.3)

where \( d_i \) is the difference in ranks for \( x \) and \( y \). It will be important to use the Spearman coefficient when analyzing the light variable, as it is expected that most participants will take the survey within the indoor lighting
range with exceptions where participants choose to take the survey outdoors. Spearman will account for any extreme values.

3.6.4 Correlation in Matlab

Matlab is the program used to calculate correlation coefficients in this thesis. The function *corr()* is used to calculate all three types of correlation coefficient previously described [55]. The following code samples the use of the *corr()* function for this thesis:

```matlab
1 [rho,pval]=corr(all, 'Type', 'Spearman');
2 submatrix = rho(1:5, 6:46);
3 SpearmanCoeff = ...
   array2table(rho,'Rows',row,'Variables',col);
4
5 submatrixP = pval(1:5, 6:46);
6 SpearmanPValues = ...
   array2table(pval,'Rows',row,'Variables',col);
```

In this sample, the *corr()* function is using a CSV file named ”all” to calculate each the Spearman correlation coefficients between each column. This occurs in Line 1, where two matrices are calculated: ”rho” returns the correlation coefficients, while ”pval” contains the related p values. The subsequent code in this sample exists to map these values to tables using the *array2table()* function, with labeled rows and columns such that thy can be
analyzed. It is noteworthy that Matlab recognizes the default maximum p value to consider rho significant to be 0.05 [55].
Chapter 4

Experimental Setup

This chapter describes the specifics of the system. All of the hardware used as well as the design of the mobile application will be described in detail.

4.1 Hardware

The following section is a list and description of the physical materials and their specifications that were given to each participant in the study for use during the duration of the experiment.

4.1.1 LG Nexus 5 Smartphone

The Android smartphone used for each of the three stages of this experiment is the Nexus 5, which is created by LG Electronics. The Nexus 5 runs the Android 6.0.1 operating system. The device has BLE functionality
and connects to WiFi. The mobile application used by the participants was uploaded to the Nexus 5s prior to each phase of the experiment.

### 4.1.2 Texas Instruments SensorTag IoT Device

Figure 4.1 shows the details of the SimpleLink Bluetooth low energy/multi-standard SensorTag and identifies the sensors used for this experiment. It is a small, portable collection of IoT enabled sensors [56]. The model of SensorTag used for this experiment contains a CC2650 wireless MCU, which provides significantly low power consumption from the 3V coin cell battery and is compatible with Android programming. It contains 10 low-power MEMS sensors which communicate with the cloud via BLE within minutes. The SensorTag and the majority of the included sensors are manufactured by Texas Instruments [57]. Of the ten sensors on board, the five listed in this section are used in this experiment. For those that are not used in every phase, it is indicated below:

- **Humidity Sensor**: The HDC1000 humidity sensor[57] with integrated temperature sensor measures both humidity and temperature using a capacitive sensor. This particular sensor is advantageous due to accurate measurements and low power consumption. It is also importantly robust as its location is protected from its surroundings while still able to sense the environment. The temperature sensor component has a range of -40°C to 125°C. For our framework, the humidity sensor will
measure two environmental variables: humidity and ambient temperature.

- **Barometric Pressure Sensor**: The BMP280 barometric pressure sensor[57] is an absolute barometric pressure sensor. This sensor is specifically designed for use with mobile applications. It also has the advantage of low power consumption, making it ideal for this experiment which increases power consumption by making use of multiple sensors.

- **Ambient Light Sensor**: The OPT3001 Ambient Light Sensor[57] measures the luminosity to the device from any luminous source, as visible by the human eye. The sensor is specifically designed for systems which involve human interactions with light, making it ideal for measuring the ambient light of the participants’ surroundings in the proposed system. From this system, it is important that the participants ensure that the SensorTag’s light sensor is positioned such that it is exposed to ambient during the collection of data.

- **9-axis Motion Tracking Device Accelerometer, Gyroscope and Compass**: The MPU-9250 MotionTracking Device[57] combines a 3-axis gyroscope, 3-axis accelerometer, 3-axis magnetometer, and a Digital Motion Processor (DMP). The DMP, in conjunction with the three 3-axis sensors, is able to output 9-axis output to the dedicated I2C serial bus. For this system, the MotionTracking device will be used
to track the participant’s physical activity throughout the day in terms of magnitude and duration. This sensor was used in the initial testing phase, but not the experimental periods that followed. It was theorized at that time that having the device in motion would interfere with the ability to directly read data to other sensors, particularly the ambient light sensor.

- **Digital Microphone**: The SPK0833 digital microphone [58] is the ambient audio sensor component of the SensorTag. As opposed to the other sensors, the microphone is manufactured by Knowles rather than Texas Instruments. Furthermore, while all other sensors communicate with BLE via the I2C bus, the microphone has its own PDM communication. Within our system, the microphone will be used to sense the magnitude of ambient sound in the participants’ surroundings, regardless of the source of noise. This sensor was not used in the initial testing phase, but was used in both experimental periods.

Table 4.1 indicates more specifications of the five sensors used.

### 4.2 Mobile Application

A mobile application was developed for the use of the participants on their loaned Nexus 5s during the experimental period. The application was improved and modified following the initial testing phase, but functionality remained the same.
Figure 4.1: Image of the Texas Instruments SensorTag with relevant sensors labeled.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Sensor</th>
<th>Units</th>
<th>Range</th>
<th>Period Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature</td>
<td>HDC1000</td>
<td>Celsius (°C)</td>
<td>-40 to 125</td>
<td>100 ms to 2.55 s</td>
</tr>
<tr>
<td>Humidity</td>
<td>HDC1000</td>
<td>Percentage</td>
<td>0 to 100</td>
<td>100 ms to 2.55 s</td>
</tr>
<tr>
<td>Air Pressure</td>
<td>BMP280</td>
<td>Kilopascal</td>
<td>30 to 110[59]</td>
<td>100 ms to 2.55 s</td>
</tr>
<tr>
<td>Light</td>
<td>OPT3001</td>
<td>lux (lux)</td>
<td>0.01 to 83,000</td>
<td>100 ms[60] to 2.55 s</td>
</tr>
<tr>
<td>Noise</td>
<td>SPK0833</td>
<td>A-weighted decibel (dBA)</td>
<td>-</td>
<td>0.1 ms to 10 ms[61]</td>
</tr>
</tbody>
</table>

Table 4.1: Specifications for sensors used in experiments.

The process of using the application for one survey session is described in the flow chart in Figure 4.3. The app is designed to allow the participant to register their SensorTag using the unique address identification. Once
(a) Registering the SensorTag by Bluetooth address

(b) Confirmation of registration of SensorTag device

(c) Home screen displays sensor readings of a quiet, bright room

(d) Having selected "Start Survey", a dialog box appears

(e) Survey in process of being completed

(f) Having "Submit", a confirmation receipt appears

Figure 4.2: Screenshots of registering your SensorTag and submitting a survey.
Figure 4.3: Flow chart detailing a single session with the mobile application.
registered, the participant has the ability to connect and disconnect the device themselves as a troubleshooting and battery-saving measure. As part of the participant’s training, they are able to ensure a connection to the SensorTag and check that the readings from the sensors are reasonable (i.e. do not indicate a low battery) before commencing the survey. The survey is to be completed several times a day. The participants are instructed that they must be connected to University of Guelph WiFi to send their results, and that there should be several hours between each submission to avoid stagnation of results.

The home screen of the application, shown in Figure 4.2a allows the participant to register their SensorTag using BLE and ensure that it is connected to the application before beginning. In Figure 4.2a, the user has selected "Scan for Devices" and can see the option to register their SensorTag’s address in the top right corner of the app. When they select this option, they are presented the dialog in Figure 4.2b, which allows them to verify the full address identification of the device to which they would like to connect.

Once connected, the participant is returned to the home page, as seen in Figure 4.2c. This screen now shows the address of the SensorTag and the current readings from all enabled sensors. This allows the user to check that data is being read reasonably before beginning. Often, the first sign that the coin cell battery of the SensorTag is low, is when the temperature sensor begins reading a value of -40 degrees Celsius. This was explained to the participant as part of their training so that they can identify
any issues instead of submitting data that would need to be omitted as an outlier due to faulty batteries.

Once the participant is ready to begin a survey, they select the “Start Survey” button on the home screen. As long as they are already registered and connected to the SensorTag, this button will take them to the survey screen, seen in Figure 4.2e. This screen allows the user to answer each of the 33 survey questions provided. Once each question has been answered, the user can press the “SUBMIT” button. If any questions remain unanswered, the user will be notified to complete the entire survey. Otherwise, if all questions contain an answer, the survey results and sensor data is sent to the server via WiFi and the user is notified of a successful transaction before exiting the app as in Figure 4.2f. In the case of an incomplete transaction due to connectivity issues, the user is given the opportunity to connect to campus WiFi before trying to submit the same results once more.

As shown in Figure 4.3, the survey need only be completed three times per day, at which point no further action is required until the next day.
Chapter 5

Experimental Conditions

At this time, four experiments have taken place: initial testing, a first experimental, a second experiment, and a third experiment. For each phase, the following procedure is followed:

1. A smartphone and a SensorTag is loaned to each participant. A training session takes place individually with each participant to instruct them on how to properly position the SensorTag for data collection, connect the SensorTag to the application, and complete the survey. For the later two phases during which movement is not being recorded, the recommended placement of the SensorTag is close to their person and oriented such that the light sensor is facing upwards, ideally on a table in front of them. They are instructed to complete the survey questions on the application as truthfully as possible two to three times a day for the duration of the experimental period.
2. Data is collected to the research server over a five day period. Each time a survey is completed, three comma separated value (CSV) files are sent to the server: one configuration file, one with sensor data, and one with survey results. They are each identifiable by the SensorTag’s Bluetooth address and the time of submission, but not by any identifying factors of the participant.

3. Following the experimental period, the participants return the loaned materials. At this point, the data is analyzed and evaluated.

The reasoning for completing multiple experiments is twofold. The time passed between experiments allowed for the analysis of student wellness at various times of the year, during different seasons. Table 5.1 shows the timeframes for each of the four experiments. Second, as the experiments progressed, it became experimentally evident that a larger number of participants resulted in more robust correlation analysis. For this reason, we sought to recruit a larger number of participants for each experiment.

<table>
<thead>
<tr>
<th>Initial Testing</th>
<th>June 2018</th>
</tr>
</thead>
<tbody>
<tr>
<td>First Experiment</td>
<td>October 2018</td>
</tr>
<tr>
<td>Second Experiment</td>
<td>November - December 2018</td>
</tr>
<tr>
<td>Third Experiment</td>
<td>March 2019</td>
</tr>
</tbody>
</table>

Table 5.1: Timing of each experiment.

The following chapter describes in detail the unique conditions of each experiment and the instructions given to each participant.
5.1 Instructions to Participants

Prior to beginning each experiment, each participant was asked to attend a training session with the researcher. The objectives of this meeting were as follows:

- Educate the participant on their rights and the efforts to protect their privacy and data for the experiment, and have them sign a consent form denoting these points as approved by the University of Guelph’s Research Ethics Board.

- Explain the expectations of them during the experiment and demonstrate use of the application.

- Lend the participant a phone and SensorTag for the duration of the experiment.

When giving the participant instructions for their participation, the instructions were as follows:

1. Place the SensorTag on a flat surface such that the light sensor is oriented face up (demonstrate) when ready to complete the survey.

2. Turn on the SensorTag using the button on the side before opening the app. Check by making sure the green light is blinking.

3. Check the sensor readings on the home screen of the app for reasonability. The first sign that the SensorTag’s battery is dying is zero

57
readings from a sensor. Contact the researcher if a replacement battery is needed.

4. Complete the survey 2-3 times per day (demonstrate) when/if on campus. Make sure multiple submissions in a day are several hours apart. Must be connected to University of Guelph WiFi to submit the survey.

5.2 Varying Conditions for Each Experiment

5.2.1 Initial Testing

Before beginning formal experiments, an initial testing phase was completed over the course of a week. The purpose of this experiment was mainly to ensure that data could be successfully received by the server with a minimal number of outliers. This stage allowed the opportunity for the participants to provide feedback concerning the use of the application so that changes could be made prior to the first experiment.

For this stage, materials were given to six University of Guelph engineering students working with the researchers at the time. For the duration of the experiment, each participant was equipped with a Nexus 5 phone with the mobile application and a SensorTag with a charged 3V coin cell battery. Some of the participants were familiar with the project before testing. Those who weren’t met with the researcher for an explanation of how to use the application and ensure valid data was received from the SensorTag. The par-
Participants were asked to complete the surveys as truthfully as possible, and were not privy to information concerning the results of the experiment.

At the end of the experimental period, data from one of the participants was omitted as an outlier due results that indicated malfunctioning sensors from the SensorTag. Due to this omission of an entire user, the training procedure was modified to train future participants to identify a malfunctioning SensorTag before their data needs to be omitted.

For each submission sent to the server, three comma separated value (CSV) files were created: a configuration file, a file containing the results of the survey questions, and a file containing all sensor data from the survey period. For each survey submission, the data for each of the five variables was averaged. The exception is the movement variable, for which the standard deviation of accelerometer data was calculated. For the survey results, an integer score was achieved for two categories: questions related to sleep, and questions related to general wellness by incrementing by one for a positive answer such as the response "Do you feel nervous? NO". An example of these processed results can be seen in Table 5.2.

Of the submissions received to the server, 20 were valid (not omitted at outliers). Outliers were identified as zero values read from sensors. As noted, this is due to a dying battery and the training process was modified to help the participant identify this. Twenty submissions was not a sufficient number to properly analyze correlation. However, the testing period was successful in that participants were able to send reasonable data to the server without
Table 5.2: Session results from a session during the testing period.

5.2.2 First Experiment Conditions

For this first experimental phase, eight subjects were selected to provide results over a period of five days. The participants included three men and five women, all of whom are students at the University of Guelph School of Engineering. Similar to the testing phase, the results were parsed and checked for outliers. This left valid data from seven participants.

Measures were taken to ensure that results would be equally valid from each participant. Each participant was given the same experimental method instructions, only differing by clarifying survey questions when necessary. They were also given the same materials: the same model of phones and SensorTags, with the SensorTag batteries checked for a full charge to ensure the most accurate sensor data possible.

Prior to beginning the experiment, the participants met individually with
one of the researchers to receive instructions concerning the details of the experimental method.

There were two major updates made since the initial testing phase, which are reflected in the sample results displayed in Table 5.3. The first update was replacing the movement variable with noise. This is believed to be a more significant variable and does not present the problem of affecting data from other sensors by having a SensorTag in motion. The second update is to separate the survey results by survey type, rather than by topic of the question. The results for the sensor data and survey results were otherwise calculated the same way as they were in the initial testing phase. For each submission in each phase, the data for each variable was averaged. For the survey results, an integer score was achieved for each of the three psychological surveys by incrementing by one for a positive answer such as the response “Do you feel nervous? NO”.

<table>
<thead>
<tr>
<th>Address ID B0B448BE8C00</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average temperature (°C)</td>
</tr>
<tr>
<td>Average pressure (kPa)</td>
</tr>
<tr>
<td>Average humidity (%)</td>
</tr>
<tr>
<td>Average light (lux)</td>
</tr>
<tr>
<td>Average noise amplitude (dBA)</td>
</tr>
</tbody>
</table>

Survey responses

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>PSQI Score</td>
<td>16</td>
</tr>
<tr>
<td>PSS Score</td>
<td>6</td>
</tr>
<tr>
<td>K10 Score</td>
<td>9</td>
</tr>
<tr>
<td>Number of people in the environment</td>
<td>1-4</td>
</tr>
</tbody>
</table>

Table 5.3: Session results from Address ID B0B448BE8C00.
Of the submissions received to the server, 61 were valid. Distribution was charted for each environmental variable in the 61 submissions. Figures 5.1a through 5.1e demonstrate reasonable normal distribution for each variable. Of greatest importance in these charts is the range of the variables. Correlation will only be appropriately measured if there is sufficient variation in the variables. For example, the noise variable should show a range that includes both empty rooms and rooms with noise that likely indicates the presence of others.

5.2.3 Second Experiment Conditions

The purpose of the second experimental set was to run the same procedure from the first experimental set, approximately a month later during colder weather and a more stressful part of the semester, but with a larger data set. For this phase, 20 subjects were recruited. The subjects were all undergraduate students at the University of Guelph. Unlike the two prior phases, none of these students worked in the same laboratory as the researchers and therefore had no familiarity with the project. This helped ensure veracity of results. Furthermore, a majority of the participating undergraduate students live on the University of Guelph campus, meaning they were able to provide results to the server over a longer period throughout the day. This is ideal to provide results with a variation in temperature and light.

For this phase, the 20 subjects were divided randomly into two groups of 10. For the first week of the experiment, Group A was given access to
Figure 5.1: Distribution charts for each environment variable of the 61 submissions in the first experiment.
the phones and Sensortags and asked to provide results over an experimental period of 5 days. The following week, Group B took their turn. Each group then had access to the materials for a second week, resulting in up to 10 days of experimental data from each of our 20 participants. The reason for the gap between possession of the phones for the participants was to ensure that they didn’t start answering the questions mindlessly once they had gotten used to them. This phase was carried out under the same conditions as the first experiment in terms of materials, outlier checking, and instructions to participants.

Of the submissions received to the server, 181 were valid. The distribution of each environmental variable for these submissions is seen in Figures 5.2a through 5.2e.

5.2.4 Third Experiment Conditions

A third experiment was conducted in March of 2019. The purpose of this final experiment was to test subjects in different seasonal conditions. An additional goal was to recruit more participants than the previous experiments. For this experiment, 34 participants took part for five consecutive days each. The conditions for the participants were the same in terms of training and expectations.

Of the submissions received to the server, 287 were valid. The distribution of each environmental variable for these submissions is seen in Figures 5.3a through 5.3e.
Figure 5.2: Distribution charts for each environment variable of the 181 submissions in the second experiment.
Figure 5.3: Distribution charts for each environment variable of the 287 submissions in the third experiment.
5.3 Evaluating Correlation

Once all data has been received from the described experimental period, correlation analysis is performed. The three types of correlation coefficient described in Section 3.6 were all deemed appropriate for this project based on their required variable conditions and were therefore all calculated for each submission. The purpose of measuring all three is to compare the results of calculating an association using three different equations. If correlation is confirmed by all three with the null hypothesis disproven, the association can be discussed with more confidence.

An emphasis will be placed on the Spearman and Pearson coefficients when discussing the results. Specifically, Spearman’s coefficient, which takes into account extreme values. We are looking for moderate correlation values that are confirmed by both Spearman and Pearson’s equations. The confirmation is important because Pearson’s coefficient is negatively affected by extreme values, ie. values that disrupt normal distribution. Spearman’s coefficient accounts for these. It has been observed in practice while testing this project that Matlab can calculate a high Pearson coefficient and a low Spearman coefficient for the same relationship, indicating the presence of extreme values.

While all correlation coefficients will be calculated, those that will be discussed are those confirmed to be at least modest in amplitude by two of our three coefficients. We will also check for statistical significance these
cases, and observe how often the null hypothesis is disproven even in the case of weak correlation. For this thesis, a statistically significant R value will be determined by a P-value of less than 0.05.
Chapter 6

Results and Discussion

For each experiment and each the three coefficient types, the following data is presented in tabular format: the correlation coefficients comparing the survey results to one another, the correlation coefficients (R values) comparing the survey data to the environmental variables, and the P-values comparing the survey data to the environmental variables.

Highlighted in the tables are the correlation coefficients that are at least moderate, as defined by Table 3.5. In the P-value tables, values of less than 0.05 are highlighted, as they disprove the null hypothesis and present statistical significance as explained in Section 3.6.

Following the presentation of all results, a discussion of the most significant ones across all three experiments will be presented. The results and subsequent analysis serve no diagnostic purpose.
<table>
<thead>
<tr>
<th></th>
<th>PSQI</th>
<th>PSS</th>
<th>K10</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Pearson correlation</strong></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>PSQI</td>
<td>0.3450</td>
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<td>0.5999</td>
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<td>PSS</td>
<td>0.5999</td>
<td>0.7277</td>
<td>0.7277</td>
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<td></td>
</tr>
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<td>0.2663</td>
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</tr>
<tr>
<td>PSS</td>
<td>0.4124</td>
<td>0.8456</td>
<td>0.8456</td>
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<tr>
<td><strong>Kendall correlation</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
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<td>0.2071</td>
<td>0.3241</td>
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<tr>
<td>PSS</td>
<td>0.3241</td>
<td>0.7056</td>
<td>0.7056</td>
</tr>
</tbody>
</table>

Table 6.1: Correlation coefficients between all survey results in the first experiment.

6.1 First Experiment

Of the 65 submissions received in the first experiment, four were omitted as outliers due to results that indicated malfunctioning sensors, leaving 61 valid submissions from seven participants over five days. There was high variation in the number of submissions throughout the week from each participant. While one participant only submitted once over the week, another submitted a total of 14 times.

6.1.1 Correlation Analysis of Survey Responses

First, correlation coefficients were calculated for each correlation type between each of the three survey sections and the additional question con-
Table 6.2: Correlation coefficients between environmental variables and surveys in the first experiment.

cerning the number of people around. These coefficients are presented in Table 6.1. The greatest Spearman correlation between different surveys (0.8456) exists between the K10 survey and the PSS survey, indicating a strong inverse relationship between stress level and psychological distress which is confirmed by a strong Pearson relationship. And additional Spearman correlation of a moderate 0.4124 was determined between PSQI and K10, indicating a cor-
Table 6.3: P-values between environmental variables and surveys in the first experiment.

relation between the sleep quality of the previous night and distress. K10 versus PSQI is also confirmed by Pearson. This confirmation is important because it indicates that the Pearson coefficient was not affected by extreme values.
6.1.2 Correlation Analysis of Survey Responses to Environmental Variables

Next, the correlation between the survey results and the environmental data is observed in Table 6.2. Moderate Spearman correlations exist here for three variables: temperature, humidity, and light. The strongest of these is a -0.5753 Spearman R-value between light and PSS, indicating a moderate inverse relationship between light and stress level. A similar correlation in terms of direction and magnitude (-0.5381) is seen between light and K10. Similarly, a moderate albeit weaker positive correlation is seen between temperature and all three surveys. A final moderate, inverse correlation is observed between humidity and PSS and K10. Similar values are presented by the Kendall and Spearman coefficients as a check on these values. All moderate correlations discussed in this section were confirmed as significant (P-value less than 0.05) by Table 6.3. The normal distribution of our five variables observed in Figure 5.1a to 5.1e means that Pearson correlation is valid, as is Spearman due to the ordinal nature of the variables.

6.2 Second Experiment

The second experiment, which had 20 participants participate for 10 days each, saw 205 submissions successfully sent to the server. Following the omission of outliers for low SensorTag batteries, 181 submissions were deemed valid. The correlation analysis of these submissions is presented in this sec-
<table>
<thead>
<tr>
<th></th>
<th>PSQI</th>
<th>PSS</th>
<th>K10</th>
</tr>
</thead>
<tbody>
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<td></td>
<td></td>
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<td></td>
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<tr>
<td>K10</td>
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<td>0.5659</td>
</tr>
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<td><strong>Spearman correlation</strong></td>
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<td></td>
<td></td>
</tr>
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<td>0.1066</td>
<td>0.1066</td>
<td>0.1978</td>
</tr>
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<td>0.1066</td>
<td>0.5223</td>
<td>0.5223</td>
</tr>
<tr>
<td>K10</td>
<td>0.1978</td>
<td>0.5223</td>
<td>0.5223</td>
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<tr>
<td><strong>Kendall correlation</strong></td>
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<td></td>
<td></td>
</tr>
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<td>PSQI</td>
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<td>0.4210</td>
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<tr>
<td>K10</td>
<td>0.1528</td>
<td>0.4210</td>
<td>0.4210</td>
</tr>
</tbody>
</table>

Table 6.4: Correlation coefficients between all survey results in the second experiment.

### 6.2.1 Correlation Analysis of Survey Responses

Table 6.4 presents the R-values of the correlation analysis between the surveys results of each submission. Similar to the first experiment, the greatest correlation across each coefficient type is the relationship between the PSS and K10 surveys, indicating a positive moderate correlation between stress and distress. The strongest of these correlation coefficients is a Pearson value of 0.5659. However, the Spearman value (0.5223) is slightly lower, likely indicating a reliance on extreme values in the Pearson case.
<table>
<thead>
<tr>
<th></th>
<th>PSQI</th>
<th>PSS</th>
<th>K10</th>
</tr>
</thead>
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<tr>
<td><strong>Pearson correlation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temperature</td>
<td>-0.1728</td>
<td>-0.0068</td>
<td>0.0106</td>
</tr>
<tr>
<td>Pressure</td>
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<tr>
<td>Light</td>
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<td>-0.1868</td>
<td>-0.2944</td>
</tr>
<tr>
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<td>-0.0221</td>
<td>-0.2497</td>
<td>-0.1566</td>
</tr>
<tr>
<td># of People</td>
<td>-0.0994</td>
<td>-0.2654</td>
<td>-0.3245</td>
</tr>
<tr>
<td><strong>Spearman correlation</strong></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Temperature</td>
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<td>-0.0067</td>
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<td>Pressure</td>
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</tr>
</tbody>
</table>

Table 6.5: Correlation coefficients between environmental variables and surveys in the second experiment.

6.2.2 Correlation Analysis of Survey Responses to Environmental Variables

No moderate correlation was observed in the second experiment, for any coefficient type, as seen in Table 6.5. The strongest of the weak correlations exist for the light, noise, and number of people variables. A negative Spearman correlation (-0.3223) seems to approach the moderate inverse re-
Table 6.6: P-values between environmental variables and surveys in the second experiment.

For the noise variable, a -0.2733 Spearman correlation exists for the PSS survey. This, while weak, is one of the highest correlations in this experiment, and is similar to the relationship observed between those variables in the first experiment. Finally, the number of people present in a space seems to
have a weak negative correlation to both stress and distress.

All Spearman coefficients discussed for this experiment were confirmed by trends in their related Pearson and Kendall values. Although none of these correlations reached the moderate threshold, it is important to determine which of the weak correlations are statistically significant. Table 6.6 shows the P-values for all the relationships discussed. The Spearman P-values indicate that all relationships between light, noise, and number of people are statistically significant with PSS and K10. This confirms the significance of the relationships discussed in this section.

### 6.3 Third Experiment

The third experiment had 34 participants participate for five days each. At the end of this period, 297 successful submissions had been made to the server. 10 submissions were omitted as outliers due to values that indicated low batteries on the SensorTags. This left 287 valid submissions to perform the following correlation analysis.

#### 6.3.1 Correlation Analysis of Survey Responses

Table 6.7 presents the correlation analysis R-values between the results of all three surveys. The analysis shows moderate positive Pearson and Spearman correlation between all three surveys. Like with the previous two experiments, the strongest relationship (0.5961 Spearman) exists between the
Table 6.7: Correlation coefficients between all survey results in the third experiment.

PSS and K10 surveys. This is encouraging as a repeated result as is shows a relationship between stress and distress as measured by our selected surveys.

6.3.2 Correlation Analysis of Survey Responses to Environmental Variables

Table 6.8 shows the R-values of the relationships between environmental variables and survey results for the third experiment. Table 6.9 shows the related P-values. Like in the second experiment, none of the R-values meet the threshold to deem moderate correlation. In fact, the magnitudes in this experiment are even lower. Again, we will analyze the strongest of the weak correlations and check which are statistically significant.
<table>
<thead>
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<th></th>
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<th>PSS</th>
<th>K10</th>
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</thead>
<tbody>
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<td>-0.0140</td>
<td>-0.0215</td>
</tr>
<tr>
<td>Light</td>
<td>-0.0576</td>
<td>0.0675</td>
<td>0.0570</td>
</tr>
<tr>
<td>Noise</td>
<td>0.1938</td>
<td>0.1408</td>
<td>0.1532</td>
</tr>
<tr>
<td># of People</td>
<td>-0.0816</td>
<td>-0.0201</td>
<td>-0.0886</td>
</tr>
<tr>
<td><strong>Spearman correlation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temperature</td>
<td>-0.1133</td>
<td>-0.0172</td>
<td>0.0568</td>
</tr>
<tr>
<td>Pressure</td>
<td>0.0541</td>
<td>0.0819</td>
<td>0.0350</td>
</tr>
<tr>
<td>Humidity</td>
<td>-0.0655</td>
<td>-0.0280</td>
<td>-0.1188</td>
</tr>
<tr>
<td>Light</td>
<td>-0.0294</td>
<td>0.0414</td>
<td>0.0352</td>
</tr>
<tr>
<td>Noise</td>
<td>0.1829</td>
<td>0.1940</td>
<td>0.1682</td>
</tr>
<tr>
<td># of People</td>
<td>-0.1029</td>
<td>-0.0129</td>
<td>-0.1141</td>
</tr>
<tr>
<td><strong>Kendall correlation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temperature</td>
<td>-0.0851</td>
<td>-0.0108</td>
<td>-0.0443</td>
</tr>
<tr>
<td>Pressure</td>
<td>0.0451</td>
<td>0.0667</td>
<td>0.0307</td>
</tr>
<tr>
<td>Humidity</td>
<td>-0.0393</td>
<td>-0.0215</td>
<td>-0.0829</td>
</tr>
<tr>
<td>Light</td>
<td>-0.0232</td>
<td>0.0355</td>
<td>0.0258</td>
</tr>
<tr>
<td>Noise</td>
<td>0.1435</td>
<td>0.1520</td>
<td>0.1360</td>
</tr>
<tr>
<td># of People</td>
<td>-0.0870</td>
<td>-0.0097</td>
<td>-0.0994</td>
</tr>
</tbody>
</table>

Table 6.8: Correlation coefficients between environmental variables and surveys in the third experiment.

The environmental variable with the strongest R-values in this experiment is noise. Noise shows Spearman correlations of 0.1829, 0.1940, and 0.1682 with the PSQI, PSS, and K10 surveys respectively. This trend is confirmed by the Pearson and Kendall values. All three of these relationships are statistically significant as confirmed by the Spearman, Pearson, and Kendall P-values in Table 6.9.
<table>
<thead>
<tr>
<th></th>
<th>PSQI</th>
<th>PSS</th>
<th>K10</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Pearson correlation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temperature</td>
<td>0.0600</td>
<td>0.8073</td>
<td>0.3448</td>
</tr>
<tr>
<td>Pressure</td>
<td>0.3617</td>
<td>0.1687</td>
<td>0.5484</td>
</tr>
<tr>
<td>Humidity</td>
<td>0.3667</td>
<td>0.6137</td>
<td>0.0656</td>
</tr>
<tr>
<td>Light</td>
<td>0.5890</td>
<td>0.3995</td>
<td>0.5624</td>
</tr>
<tr>
<td>Noise</td>
<td><strong>0.0017</strong></td>
<td><strong>0.0007</strong></td>
<td><strong>0.0040</strong></td>
</tr>
<tr>
<td># of People</td>
<td>0.0815</td>
<td>0.8441</td>
<td>0.0547</td>
</tr>
<tr>
<td><strong>Spearman correlation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temperature</td>
<td>0.0552</td>
<td>0.7714</td>
<td>0.3375</td>
</tr>
<tr>
<td>Pressure</td>
<td>0.3607</td>
<td>0.1663</td>
<td>0.5552</td>
</tr>
<tr>
<td>Humidity</td>
<td>0.2685</td>
<td>0.6363</td>
<td><strong>0.0443</strong></td>
</tr>
<tr>
<td>Light</td>
<td>0.6198</td>
<td>0.4852</td>
<td>0.5531</td>
</tr>
<tr>
<td>Noise</td>
<td><strong>0.0019</strong></td>
<td><strong>0.0010</strong></td>
<td><strong>0.0043</strong></td>
</tr>
<tr>
<td># of People</td>
<td>0.0818</td>
<td>0.8281</td>
<td>0.0535</td>
</tr>
<tr>
<td><strong>Kendall correlation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temperature</td>
<td>0.0600</td>
<td>0.8073</td>
<td>0.3448</td>
</tr>
<tr>
<td>Pressure</td>
<td>0.3617</td>
<td>0.1687</td>
<td>0.5484</td>
</tr>
<tr>
<td>Humidity</td>
<td>0.3667</td>
<td>0.6137</td>
<td>0.0656</td>
</tr>
<tr>
<td>Light</td>
<td>0.5890</td>
<td>0.3995</td>
<td>0.5624</td>
</tr>
<tr>
<td>Noise</td>
<td><strong>0.0017</strong></td>
<td><strong>0.0007</strong></td>
<td><strong>0.0040</strong></td>
</tr>
<tr>
<td># of People</td>
<td>0.0815</td>
<td>0.8441</td>
<td>0.0547</td>
</tr>
</tbody>
</table>

Table 6.9: P-values between environmental variables and surveys in the third experiment.

### 6.4 Discussion

While each of the three groups to participate thus far has produced different results, there are certainly trends worth analyzing. Table 6.10 summarizes every moderate to high Spearman correlation observed for which the null hypothesis was disproved.

It’s also worth summarizing all of the correlations for which the null
hypothesis was disproven, even if the correlation was considered weak by the R-value. Trends in statistical significance between experiments indicates that it cannot be said that no association exists between the two variables in question. Table 6.11 summarizes all of the correlations for which the null hypothesis could be disproven by the Spearman P-value. Only associations with the PSS and K10 surveys are listed here in order to isolate relationships with stress and distress.

From Table 6.11 there is evidently a trend towards being able to disprove the null hypothesis for certain environmental variables more than others. First it is of note how often significance of a relationship with stress is accompanied by significance to a relationship with distress. This is not surprising due to the moderate correlation observed between PSS and K10 results in each experiment.

The variables most often deemed part of statistically significant relationships are light and noise, for which four relationships each exist in Table 6.11.

Table 6.10: Summary of statistically significant moderate to high Spearman coefficients (R greater than 0.36).

<table>
<thead>
<tr>
<th>Experiment 1</th>
<th>PSQI, PSS, K10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature</td>
<td></td>
</tr>
<tr>
<td>Humidity</td>
<td>PSS, K10</td>
</tr>
<tr>
<td>Light</td>
<td>PSS, K10</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Experiment 2</th>
<th></th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>Experiment 3</th>
<th></th>
</tr>
</thead>
</table>
Table 6.11: Summary of statistically significant associations (the null hypothesis was disproved by the Spearman p value).

<table>
<thead>
<tr>
<th>Experiment 1</th>
<th>PSS, K10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature</td>
<td></td>
</tr>
<tr>
<td>Humidity</td>
<td></td>
</tr>
<tr>
<td>Light</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Experiment 2</th>
<th>PSS, K10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pressure</td>
<td>PSS</td>
</tr>
<tr>
<td>Light</td>
<td>PSS, K10</td>
</tr>
<tr>
<td>Noise</td>
<td>PSS, K10</td>
</tr>
<tr>
<td>People</td>
<td>PSS, K10</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Experiment 3</th>
<th>K10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Humidity</td>
<td></td>
</tr>
<tr>
<td>Noise</td>
<td>PSS, K10</td>
</tr>
</tbody>
</table>

Light was correlated with stress and distress in the first and second experiments, with an inverse magnitude. This indicated that as light increased, stress increased. A possible reason for the absence of this relationship in the third experiment is that light is more significant in winter months when it is dark more often.

Noise was statistically significantly correlated with stress and distress in the second and third experiments. This is an interesting relationship to analyze for a number of reasons. First, it should be noted that there is more confidence in the second and third experiments’ results thanks to the significantly increased number of submissions. Therefore, the lack of correlation or significant of the noise variable in the first experiment is not an eliminating factor. Of interest is that the correlation between noise and stress/distress, while always weak, changes polarity in the second experiment. The inverse
relationship to stress in the second experiment indicates that as noise increases, stress increases. This is likely explained by the same reason we performed experiments in different seasonal conditions: the second experiment took place during exams, which likely means that when the students were around others, they were preparing for an imminent exam. There also appears to be a similar trend in terms of polarity change for the number of people variable. This indicates that the more people in the room, the noisier it is, and this can have a varying effect on a student’s mood depending on the time in the semester. It is thanks to the statistical significance of the noise relationships in the second and third experiment that make this a relationship worth exploring further.

In summary, statistical significance indicates that the relationships between light and noise, and stress/distress exist and are worth investigating further.
Chapter 7

Conclusion

7.1 Contributions

This thesis presents a system that uses a smartphone and IoT technology to assess wellness in relation to one’s environment. A mobile application was designed to connect to a Texas Instruments SensorTag device and read data from five environmental variables via BLE: temperature, humidity, air pressure, light, and noise. The application reads this data while the participant uses the app to complete modified questions from three psychological surveys: the PSQI, PSS, and K10. The questionnaire takes approximately 2-3 minutes to complete. Once submitted, the data from the survey and the sensors is sent to a server using University of Guelph’s secure WiFi network.

Three experiments have been conducted for the system to date. In the first experiment, eight subjects participated over five days in the Fall of 2018.
Participants were all university students and were instructed to complete the survey approximately 3 times per day. By the end of the week, the server had received 61 valid submissions. A correlation analysis was done of these 61 submissions using Kendall, Pearson, and Spearman correlation coefficients. This analysis resulted in moderate Spearman coefficients between temperature, humidity, and light averages against the results of the PSS and K10 surveys. This result was aided by the disproval of the null hypothesis in all cases and indicates an association between those variables and stress/distress.

A second experiment was conducted in December for two purposes: to achieve a greater number of submissions, and an analysis in different seasonal conditions. There were 20 participants in the second experiment, split into two equal groups who alternated possession of the materials every 5 days with each participant given possession for 10 days total. This experiment didn’t have any correlation between environmental variables and surveys break the threshold for moderate correlation. However, relationships between light, noise, number of people present, and stress/distress were deemed statistically significant by the Spearman coefficient.

A third experiment with 34 participants over five days was completed in March of 2019. This experiment again saw no moderate correlation between our environmental variables and wellness survey results. However, the noise variable was positively and statistically significantly correlated to stress/distress, albeit weakly.

Over the three groups, the null hypothesis was most often disproved for
correlations between light and noise, and stress/distress as measured by our wellness surveys. Light is hypothesized to be more significant in the winter months, as it lost its significance in the March experiment. Noise appears to change polarities even when maintaining its significance, depending on the time of year. Both of these variables are worth investigating further, with more participants at different times of the year.

7.2 Future Work

While efforts were made to provide extensive experimental results on the system in question, improvements to the experimental process can be made. A greater number of participants would provide more confident correlation data. Incentives to complete the survey regularly and seek a variety of environmental conditions throughout the experimental period would be another improvement.

The next major step for this project would be to attempt to predict/assess one’s wellness based solely on the environment around them.
Bibliography


