An Experimental Framework For Wellness Assessment Using the Internet of Things

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Abstract—Everyday wellness assessment is a promising step towards improving the health status of an individual. This article presents an experimental framework to address the growing concern of individual wellness using the advantages of the Internet of Things (IoT). The introduced framework uses an IoT device to read data from five environmental variables and a smartphone application to examine any correlation between environmental parameters and wellness. Ambient temperature, barometric pressure, humidity, luminosity, and audio amplitude data from a mobile IoT device are collected while the user answers three psychological surveys, regarding sleep quality, stress, and distress. The data are forwarded to a server to examine any potential correlation. The feasibility of the framework was examined through experimentation. An experiment with 20 participants was conducted. According to experimental results, parameters such as the luminosity and ambient audio have an effect on individual well being.

Index Terms—Wellness Assessment, IoT system, Healthcare, Mobile Application, Health monitoring, Bluetooth Low Energy.

1 Introduction

Wellness is a growing concern across the world, particularly for young populations. As more research is conducted, there is a growing demand for mental health solutions in order to help alleviate the burden on health care systems. The cost of mental health is draining both due to the cost of care, as well as the lack of productivity on the economy. As countries begin to spend more on mental health care and wellness, the desire for low-cost solutions amplifies. The Internet of Things (IoT) provides low-cost, low-power, highly portable solutions to many industries. The growing network of IoT devices has been used extensively to solve problems in smart parking and agriculture. Its ability to allow for automation makes it an ideal solution to cut costs in health care as well.

This article presents a framework to examine any correlation between environmental data with an individual's wellness using an IoT device. The individual uses a developed Android application to answer psychological survey questions two to three times a day. While taking the surveys, the IoT device uses sensors to read five environmental variables: ambient temperature, barometric pressure, humidity, luminosity, and audio amplitude. The sensor data is sent from the IoT device to the Android application using Bluetooth Low Energy (BLE). Upon submission of the survey, the results and accompanying sensor data are sent through Wi-Fi (2.4Ghz), to a server for analysis. The purpose of the data analysis phase is to examine any correlation between environmental conditions and individual wellness.

The main contribution of this article is the experimental IoT- based framework for wellness assessment. An experiment with 20 participants divided into two groups was conducted to examine the feasibility of the proposed framework. The experiment lasted for one month, under different environmental conditions. While one group saw a correlation between distress and light, the other saw a correlation between stress and ambient audio.

The rest of this article is organized as follows: Section 2 describes the current state of mental health costs and services worldwide while Section 3 provides an overview of how IoT is currently being used and presents the proposed framework and Section 4 discusses the experimental method. Section 5 presents and discusses the results. Section 6 concludes the work.

2 Global Impact of Mental Health

Individual wellness is a growing concern worldwide. In recent years, there has been a particular concern for the student demographics, with suicide ranking as the leading cause of death among Canadians aged 15-24 as reported by the Canadian Mental Health Association (CMHA) [1]. The CHMA also reports that 50% of the nation's population will have or have had a mental illness by the age of 40 [1], a contributing factor to the cost of mental health care. This type of research and concern incentives 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 as $42.3 billion in 2011 [2]. In the United States, a country of similar economic standing and demographics, similar statistics exist. In the US, a depressed mood is the leading cause of disability among people aged 15-44 [3]. Further research determined that this subset of disability accounts for over a $31 billion loss for the economy in terms of annual loss of productivity. Mental health is becoming expensive in first world countries both due to the cost of care, and productivity loss.

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Many countries are currently grappling with how to properly address the issue of mental health within their health care systems. A 2017 article based in California states that current treatments and the dominant model of mental health care do not adequately address the complex challenges of mental illness [3]. 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 [3]. Mental illness as a whole accounts for one-third of adult disability and over two-thirds of those individuals will never receive adequate care [3]. 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 [4]. 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 in 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 [4].

While South Africa's 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 [3]. 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 [4]. For that reason, part of the country's suggested approach to mental health care is the increase in care, screening, and prevention of HIV.

As countries across the world increase spending on mental health, there will be a desire for low-cost and easy to use solutions. The inexpensive IoT devices with a plethora of sensors, along with low energy communication technologies, such as BLE, can be a promising solution.

3 Internet of Things in Health Care

3.1 IoT approaches and frameworks

Over time, technology is used to solve societal issues with more frequency and efficiency. Some of the tools being used to solve problems in many fields, include health care, are IoT devices [5], [6]. The IoT is a network of devices that communicate with each other machine to machine, enabling the collection and exchange of data [5]. The growing network will consist of an estimated 26 billion connected devices by the year 2020 [7]. A goal in many IoT-based solutions is the production of low-cost and low-power models. While health care is a promising but still developing application, many other fields already have commercially viable IoT options. Examples include smart parking, precision agriculture, and water usage management [5].

The IoT has been identified by many as a potential solution for the increasing demands on health care systems since IoT has allowed for automation in many industries. In [5], an end to end IoT health care system is proposed. It identifies the key components necessary for a functional model and introduces an array of technologies that fit the requirements. Many existing technologies are being used for research, while some are being used commercially.

As noted, there has already been a 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 allow for more beds available in medical facilities, which reduces some strain of the health care system due to overcrowding. Additionally, for many patients, the option to be monitored remotely increases the sense of independence which in turn improves wellbeing. This is particularly true for the elderly demographic.

While there are many advantages, some 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 should not need to be calibrated too often or have their batteries too low to function properly. In [6], several security requirements specific to IoT health care systems are identified. 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 should always be considered.

An IoT health care framework, similar to the one presented in [5], has three key components:

i. **Mobile sensor**. It is important for the sensors within the introduced framework to be small, portable, and externally wearable. These factors are important such that the framework will not be limited to a single location and are easy to replace without upending the full system.
ii. **Communication technology**. Short-range wireless communication technologies are preferable for transferring data from the sensors to a processing device. The data communication should not interferers with other wireless transmission in the area and should have low energy requirements to extend the lifetime of the mobile sensor.
iii. **Storage and processing**. Cloud storage and data processing are essential to store a large amount of data from a large number of patients.

There are existing systems at both the research and commercial level that fit this framework. Some systems are focused on the treatment or monitoring of a specific disease, while others are more geared toward remote monitoring. Systems have been designed to monitor psychological symptoms using smartphones and mobile sensors [8], [9]. This article presents a framework inspired by [10], which sought to correlate environmental variables to general wellness, using low-cost IoT devices.

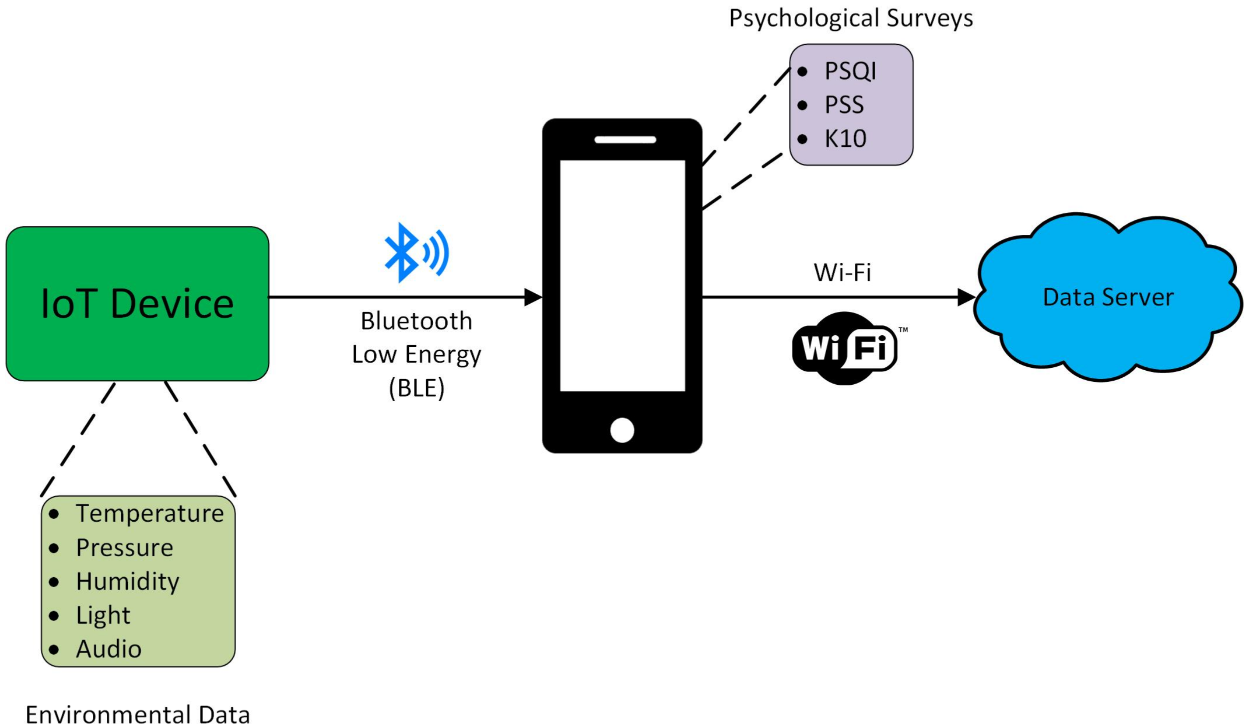


Fig. 1: Flowchart of the full framework, including the IoT device, the mobile application, and the server.

3.2 Proposed Framework

The introduced framework has three main components:

i. the SensorTag BLE device which collects the data and uses BLE to forwards them to
ii. the smartphone with the developed mobile application that also collects the responses of the surveys and which then uses Wi-Fi (2.4Ghz) to forward the sensor data and the responses to
iii. the server for storage and further processing.

A general flowchart of the full framework can be seen in Fig. 1. In this diagram, the SensorTag's four sensors that are used in this framework are highlighted. The temperature/ humidity, pressure, light sensors, and the microphone collect raw data for five environmental variables: ambient temperature, humidity, air pressure, luminosity, and ambient audio amplitude. The SensorTag forwards the raw data to the Android application through BLE. Then, the application forwards the survey responses and the sensor data to the server through Wi-Fi. The selection of Wi-Fi was due to the ethical standards of the study, and in order to transmit the data only through the University secure network. For future experiments, a Virtual Private Network (VPN) solution can be used and the users can also forward the data over Long Term Evolution (LTE) network. The communication between the sensor the server can be optimized in terms of energy consumption.

3.3 Communication Technologies

SensorTag can use three communication technologies: Wi-Fi (2.4GhZ), Sub-1Ghz and BLE, with power consumption 44.99 mA, 3.23 mA, and 1.92 mA respectively, at the stand by mode. Due to the low power requirements and BLE availability in smartphones, it made BLE a good choice. BLE is a short-range communication technology ideal for the proposed framework:

- It has the lowest requirements of 4.7mA when all the sensors transmit data to a smartphone.
- It can establish an encrypted connection, providing security.
- It is designed to work with IoT devices with limited energy resources.
- It does not interfere with other wireless technologies in the area such as Wi-Fi.
- Its low latency and high data rate are ideal for emergency medicine.
- The power consumption when the five sensors are transmitting drops to 2.67 mA and the estimated lifetime is approximately four days. To increase the lifetime of the SensorTag, it goes into sleep mode after the user submits the data.

The sensor data are forwarded to the smartphone through BLE. Then, when the user also answers the psychological surveys, the data are forwarded to the server through Wi-Fi. In this part, Wi-Fi was selected due to its availability and high transmission range. Users from different locations can use the same Wi-Fi to forward the data to the server. Encryption also applied at this point.

3.4 Hardware Requirements

The framework has two hardware components: the smartphone to hold the mobile application, and the mobile IoT device.

3.4.1 LG Nexus 5 Smartphone

The LG Nexus 5, running the Android 6.0.1 was used for the experiments. It has the required BLE functionality and Wi-Fi connectivity. The developed mobile application was uploaded to each smartphone prior to the experiment.

3.4.2 Texas Instruments SensorTag IoT Device

All of the sensors used for this experiment are on the SimpleLink Bluetooth low energy/ multi-standard SensorTag, which is a small, portable collection of IoT enabled sensors [11]. Of the ten sensors on board, the four listed in this section are used during the experiment.

i. **Humidity Sensor**: The HDC1000 humidity sensor 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. For our framework, the humidity sensor will measure two environmental variables: humidity and ambient temperature.
ii. **Barometric Pressure Sensor**: The BMP280 barometric pressure sensor is an absolute barometric pressure sensor. 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.
iii. **Ambient Light Sensor**: The OPT3001 Ambient Light Sensor measures the luminosity to the device from any luminous source, as visible by the human eye. For this framework, 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.
iv. **Digital Microphone**: The SPK0833 digital microphone is the ambient audio sensor component of the SensorTag. Within our framework, the microphone will be used to sense the magnitude of ambient sound in the participants' surroundings, regardless of the source of the noise. The microphone collects only the sound level and does not classify the sound.

The use of SensorTag has advantages, such as the low cost and the mobility, however, it also has some disadvantages, such as the limited sensors and the sensor accuracy. For the study presented in this article, SensorTag was used. However, the proposed framework and the mobile application can work with any other BLE enabled IoT device. Some human-body parameters, such as pulse and blood pressure can also be added in future versions of the IoT monitoring device, to provide more data for analysis.

3.5 Mobile Application

A mobile application was developed for the use of the participants on their smartphone during the experimental period. The process of using the application for one survey session is described in the flow chart in Fig. 2a. The purpose of the application is to allow the participant to connect to the SensorTag via BLE and proceed to complete and submit the psychological survey as directed. As seen in the flow chart, the user begins by checking that the SensorTag device is registered. They are then able to connect the device and are given the option to complete the survey. Upon submission of the survey, the application closes on its own, disconnecting from but not unregistering the SensorTag.

In Fig. 2b, it shows the home screen visible to the participant upon opening the application. They are given the option to "Register/Deregister Beacon" in order to identify their SensorTag's address. Once registered to the correct BLE device, the next step is to "Connect/Disconnect" the SensorTag. This button starts the BLE connection and is confirmed when the sensor values begin to show at the bottom of the screen as in Fig. 2b. Once this happens, the user can select "Start Survey".

Once the user has elected to start the survey, they are presented with the screen in Fig. 2b. This page shows the user the 33 questions required by the survey. They are given a warning before beginning that they will not be able to go back or submit until all 33 questions have been answered. Once all questions have an answer, the "SUBMIT" button can be successfully pressed. As long as the smartphone is connected to Wi-Fi, the user will receive a notification indicating success, and the application will close. In the case of a network error, the user is given the chance to resolve the issue before resubmitting the same results.

3.6 Description of Psychological Surveys

Three existing psychological surveys were selected to be adjusted and presented to the participants. The 33 questions from the surveys are presented to the participant when they select "Start Survey" on the application. The selection of questions is designed to cover a range of aspects concerning a person's wellbeing, including stress and sleep quality. In addition to the survey questions, the following 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 the use of a sensor: the presence of other humans in the participant's space.

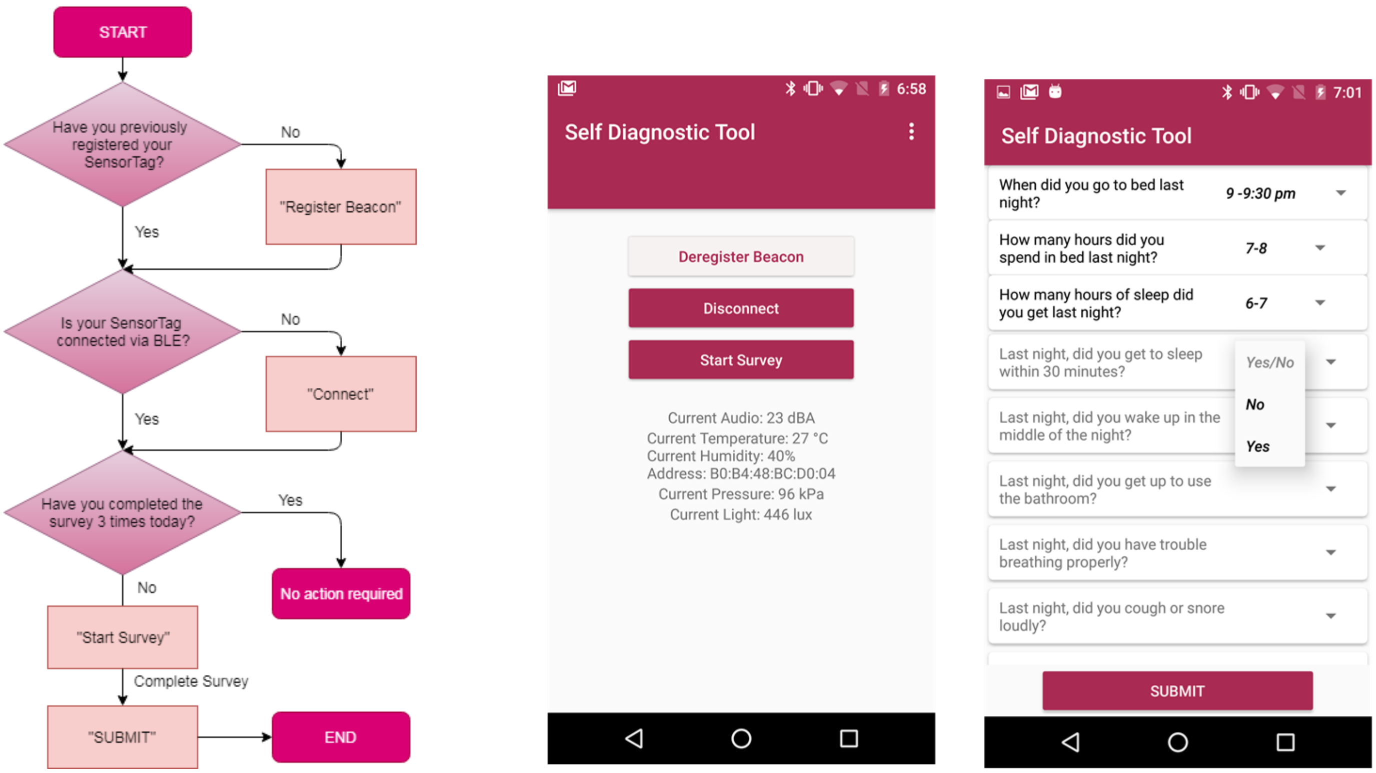
The questions and possible responses have been modified from their original form to reflect the fact that we are only interested in the participant's wellness at the time they are completing our surveys, rather than an extended period of time.

The three surveys selected for this framework are:

- **Pittsburgh Sleep Quality Index (PSQI)**: The PSQI [12] was selected and modified to achieve 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 because the participant's answers will not change until the next morning.
- **Kessler Psychological Distress Scale (K10)**: The K10 [13] was selected and modified to quantify the participant's level of psychological distress at the time the survey is taken.
- **Perceived Stress Scale (PSS)**: The PSS [14] was selected and modified to quantify the degree to which the participant is feeling stressed at the time of the survey.

4 Experimental Method

In order to examine the feasibility of the introduced framework, 20 participants with no prior familiarity with the



(a) Flowchart of the proposed model.

(b) Screenshot of the application's home screen and survey screen.

Fig. 2: Flow chart for the mobile application (2a) and screenshots of the application's two main screens (2b).

project were recruited. The participants were randomly split into two groups of 10, Group A and Group B. Group A was given materials for five days, from Oct. 15, 2018 to Oct. 20, 2018, then Group B, from Nov. 1, 2018 to Nov. 5, 2018. Then, each group was given a second week with the materials, from Nov. 25, 2018 to Nov. 30, 2018 for Group A and from Dec. 10, 2018 to Dec. 15, 2018 for Group B, resulting in up to ten days of results from each of the twenty participants. In this way, the participants experience different environmental conditions and different stress levels throughout the term. None of the participants had any familiarity with the project prior to participating to help ensure unbiased results. The complete study can be seen in [15].

4.1 Experimental Procedure

The following experimental procedure was carried out for each week:

1) A smartphone and a SensorTag is given 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.
2) Data is collected to the research server over a five day period. Each time a survey is completed, the files are sent to the server. The correlation analysis is done in Matlab. The smartphone application controls the SensorTag device. Ten minutes before each session, it wakes up the SensorTag and starts collecting data. When the user submits the data, the smartphone application puts the SensorTag back to sleep mode to save energy.
3) At the end of the experimental period, the participants return the devices. Then, the data is analyzed and evaluated. For each session, the data of each environmental variable is averaged and the survey scores are tallied such that each positive answer increments the score by one.

It should be noted that the number of participants is small and further experimentation with larger data sets is necessary. In this article, however, the experimentation is used to examine the feasibility of the introduced framework and to identify any preliminary correlation between different factors, before doing experiments with a larger population.

5 Evaluation of Correlation

Group A accounted for 101 valid submissions following the omission of 18 outliers due to sensor data that indicated a low battery level. Group B provided 81 results over the same amount of time with only 4 outliers omitted. It should be noted that there was a lot of deviation in terms of the number of submissions per participant. While some followed the instructions to submit 2-3 times per day, others did fewer.

Data were analyzed using Pearson, Spearman, and Kendall correlation coefficients. Pearson is the most widely used coefficient and is used to measure the degree to which there is a linear relationship so long as both variables are normally distributed. Spearman can be used for cases in which there is no normal distribution among one or both of the variables, as well as if the relationship is not linear.

Group A				
	# of People	PSQI	PSS	K10
Pearson Correlation				
Temperature	0.3798	-0.0985	-0.0857	-0.1678
Pressure	0.0306	-0.0013	-0.0700	-0.1448
Humidity	-0.1409	0.1835	0.1744	0.1349
Light	0.3074	0.0498	-0.2180	**-0.3212**
Audio	0.1957	-0.0196	-0.2103	-0.0964
Spearman Correlation				
Temperature	0.3093	-0.0749	-0.0664	-0.1668
Pressure	0.0212	-0.0366	-0.1097	-0.1572
Humidity	-0.1877	0.1672	0.2646	0.1634
Light	0.3578	0.0390	-0.2542	**-0.4056**
Audio	0.2036	-0.0124	-0.2276	-0.1112
Kendall Correlation				
Temperature	0.2572	-0.0573	-0.0521	-0.1296
Pressure	0.0192	-0.0325	-0.0945	-0.135
Humidity	-0.1524	0.1204	0.1899	0.1203
Light	0.2793	0.0274	-0.1867	**-0.3067**
Audio	0.1623	-0.0088	-0.1748	-0.0866

Group B				
	# People	PSQI	PSS	K10
Pearson Correlation				
Temperature	-0.1713	-0.0213	0.2564	0.2256
Pressure	-0.1600	0.1326	0.1446	0.1832
Humidity	0.3000	0.1304	-0.1486	-0.1478
Light	0.1998	0.0872	-0.2917	-0.2814
Audio	0.3242	0.0305	**-0.4785**	-0.2500
Spearman Correlation				
Temperature	-0.1624	0.0655	0.2259	0.1770
Pressure	-0.1413	0.1618	0.1509	0.1807
Humidity	0.2840	0.0896	-0.1695	-0.1486
Light	0.2542	0.0583	-0.2066	-0.2410
Audio	0.3420	-0.0604	**-0.5251**	-0.2953
Kendall Correlation				
Temperature	-0.1269	0.0521	0.1711	0.1469
Pressure	-0.1252	0.1345	0.1186	0.1582
Humidity	0.2187	0.0638	-0.1122	-0.1123
Light	0.1988	0.0440	-0.1505	0.1844
Audio	0.2889	-0.0451	**-0.3991**	-0.2501

TABLE 1: Correlation between variables and surveys for Groups A and B.

Spearman simply measures the degree of association and is appropriate to use when the scale of the variables in ordinal. Finally, Kendall measures the strength of dependency between the two variables. The correlation values for all three correlation types and both experiment groups are provided in Table 1.

In all the three correlations, Group A's greatest coefficient is the correlation between light and the K10 survey. While the highest value of -0.4056 is not very large, it is encouraging as the highest because this previous testing of this framework yielded similar results. Group B's results differ. The audio versus PSS survey correlation is the greatest, at -0.5251.

We further look at the distribution of sensor data to provide answers. While all four of these cases (light and audio values for Groups A and B) have a normal distribution, their range differs. For light, Group A ranged from 1 to 1534 lux while Group B ranged from 2 to 751. For audio, Group A ranged from 20 to 33 DbA while Group B ranged from 21 to 31 DbA. Group A saw a greater range and correlation for light while Group B saw the same effect for the audio variable. In can be speculated that both of these variables have strong potential for correlation, given enough data.

6 Conclusion

This article presents an experimental framework that addresses the need for low-cost, accessible solutions to everyday wellness assessment by using an IoT device and a smartphone. The goal of the framework was to also to examine any correlation between the wellness of our participants based on survey results, and five simultaneous environmental variables: temperature, humidity, barometric pressure, luminosity, and audio amplitude.

An initial experiment with 20 participants was conducted to examine the feasibility of the framework, and the results were processed in the server. According to experimental results, there was a correlation between the light and K10 distress scale for one group of the participants while there was also a correlation between the audio and the PSS stress scale. The results are inline with similar experiments in the area that uses different frameworks and devices. The introduced framework manage to provide everyday wellness data. However, further testing with more participants is necessary to verify the correlation that was found.

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