Towards an IoT Framework for Wellness Assessment

Katherine McLeod and Petros Spachos
School of Engineering, University of Guelph, Guelph, ON, Canada

***Abstract*—Wellness assessment can provide important data to improve the health of an individual. However, constantly monitoring individual wellness has challenges due to the different and several activities people participate in throughout the day. The availability and popularity of low-cost and inexpensive Internet of Things (IoT) devices can alleviate this issue. In this work, an IoT framework is presented to examine the relationship between an individual's wellness and their surrounding environment. It uses an IoT device to collect data and forwards them using WiFi and Bluetooth Low Energy (BLE). The participants in this study are two groups of ten undergraduate students at the University of Guelph. Each group took the experiment at different times of the year. Each participant is given an Android smartphone equipped with an application, in order to complete a brief psychological survey three times per day. During the periods of completion, an IoT device in their possession is reading environmental data. The five environmental variables collected are temperature, humidity, air pressure, luminosity, and noise level. Upon submission of the survey, the results of the survey and the environmental data are sent to a server via WiFi. According to experimental results, the first group to complete the experiment indicated a correlation between stress and noise, while the second group indicated a correlation between distress and light.**

***Keywords*— Correlation analysis, Coefficient, Pearson, Kendall, Spearman, Monitoring, Sensors, Real-time system, Smartphones, Testbed, Healthcare, Mobile application, Bluetooth low energy, Environmental sensors, Intelligent systems.**

I. Introduction

Mental health and general wellness are becoming a growing concern as research in the field increases. While the cost of mental healthcare 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 Canada's population will have or have had a mental illness by the age of 40 [1], a contributing factor to the cost of mental healthcare 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 [1]. This degree of research and attention to the issue incents a healthcare system such as Canada's to increase spending in the area. The cost of healthcare relating to mental illness in Canada was estimated to be $42.3 [2]. 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 [3]. 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 paper presents the experimental results of a system designed to evaluate the relationship between individual wellness and one's environment. The system makes use of an Internet of Things (IoT) device communicating via Bluetooth Low Energy (BLE) communication protocol. IoT devices can form a growing network of intercommunicating devices. The network enables the machine-to-machine collection and exchange of data [4], [5]. BLE is a communication standard which is advantageous in low-cost and low-power-consumption design. For that reason, it is useful in applications of small-scale data transfer such as the proposed system.

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 all sent to the researchers' server via a secure WiFi network.

This work expands our previous work in [6], [7] and presents the experimental results of twenty participants. All participants are undergraduate students at the University Of Guelph. The twenty students were split into two groups of ten: Group A and Group B. Each group was asked to complete the survey two to three times per day over a separate period of ten days. Once the experiment was completed, a correlation analysis was completed using three correlation coefficient types: Kendall, Pearson, and Spearman.

The rest of this paper is organized as follows: Section II provides a review of the related work. Section III provides a full description of the proposed system, followed by Section IV, which describes the psychological surveys selected. Section V presents the methods used for the correlation analysis in this study. The experimental procedure is in Section VI and Section VII discusses the experimental results. Section VIII concludes the work.

II. Related Works

In the IoT era, mobile sensors have been used in a variety of experimental methods to accurately assess an individual's wellness [8]–[11]. In [12], wearable sensors and smartphone

usage are used to draw correlations to academic performance, self-reported sleep quality, stress, and mental health. Surveys were completed by participants, including the Pittsburgh Sleep Quality Index (PSQI), the Perceived Stress Scale (PSS), and the Mental Health Composite Scale (MCS). 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. The wearable sensors achieved nearly a 90% classification accuracy for PSQI, PSS, and MCS.

In [13], 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 healthcare, a division of healthcare with consistently low funds. 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 (QIDS), the Altman self-rating mania scale, a brief measure of assessing generalized anxiety disorder (GAD-7), and a quality of life questionnaire (EuroQol EQ-5D). While complete results were not yet available, the initial results clearly demonstrate consistency in the actigraphy and social networking levels of a healthy control compared to a participant with a diagnosed borderline personality disorder. In [14], a similar framework is described which determines a correlation between wellness and environmental factors. The environmental factors studied are temperature, humidity, and luminosity, with a correlation determined between luminosity and general wellbeing over an experimental period with 21 participants.

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 [15], 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. They hypothesize that this connection is advantageous in cases such as elderly patients due to pure simplicity. In [16], 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. In [17], the smartphone application that was developed for this project was described.

The introduced system contains elements of these works: collecting data from environmental sensors for comparison to results of mental health-related surveys. However, the evident advantage of our proposed system is the focus on individual environmental factors retrieved from IoT devices. This effort should allow the identification of correlation for each of our five selected environmental factors. Our system also has a more in-depth survey process and evaluates correlation using three coefficients, Kendall, Pearson, and Spearman.

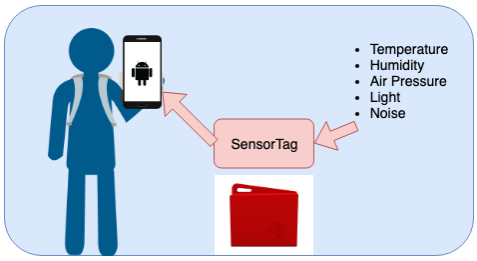


Fig. 1: Data collection from SensorTag to smartphone.

III. System Overview

The presented system has three components: an IoT SensorTag device, an Android smartphone, and a server. Each participant is equipped with a smartphone and a SensorTag device. The application asks the user to complete a brief survey while connected to the SensorTag via BLE. While answering questions, the SensorTag is collecting data regarding five environmental variables: temperature, humidity, air pressure, luminosity, and noise level. Upon submission of the survey, the data is all sent to the server via WiFi.

The system framework is shown in Fig. 1. The participant is equipped with an Android smartphone and a SensorTag device. The collected data is transferred to the server via WiFi.

A. Hardware

The following is a list of the hardware materials and their specifications:

1) LG Nexus 5 Smartphone: A requirement of our system is an Android smartphone to contain the designed mobile application. We used Nexus 5 with the Android 6.0.1 operating system. The device has BLE functionality and the option to connect to WiFi; both requirements for our system. A developed mobile application used by the participants was uploaded to the smartphone prior to the experiment [17].

2) Texas Instruments SensorTag IoT Device: The SensorTag is a small, portable device containing ten sensors [18]. The model 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 software. The SensorTag and the majority of the included sensors are manufactured by Texas Instruments.

Of the ten sensors on board, the five listed in this section are used in this experiment:

i. Humidity Sensor (HDC1000)
ii. Ambient Temperature Sensor (HDC1000)
iii. Barometric Pressure Sensor (BMP280)
iv. Ambient Light Sensor (OPT3001)
v. Digital Microphone (SPK0833)

B. Mobile Application

A mobile application was developed to connect with the mobile sensor and collect all the data [17]. Once the device has been both registered and connected, the participant is able to

complete the survey. They have been asked to do this 2-3 times per day for ten days. To complete the survey, they select "Start Survey", which brings them to a new screen which displays all the questions in need of answers. Before pressing "Submit", each question must be answered. If each question has been answered and the phone is connected to the WiFi, the survey results and sensor data will be successfully sent to the server over WiFi. At this point, the participant will receive a dialog box indicating the successful transmission, and the application will close. If there is an issue (the phone not being connected to WiFi etc.) then the user will be notified about it and given another chance to "Submit" the same data.

IV. Description of Selected Wellness Surveys

The mobile application given to the participants asks them to complete a survey 2-3 times per day. Each survey includes questions from three psychological surveys. The surveys were selected in order to inquire about a variety of aspects of an individual's current wellness. This includes stress, distress, and sleep quality. Importantly, the questions and possible responses have been modified from their original format 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 over extended period of time. The questions from the three surveys described in this section were used. In addition to the questions below, an additional question was added: "How many people are around you right now? (i.e. in the same room)". This question essentially provides a sixth environmental variable: the presence of other people in the participant's surroundings.

As previously noted, the questions from the official surveys described in this section 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 we are interested in immediate wellness, and the participants will answer the questions multiple times a day. To demonstrate, 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 wellbeing. These modifications are reflected in Tables I, II, and III.

A. PSQI

The PSQI [19] was selected and modified to achieve quantifiable data for the participant's sleep quality the night before taking the survey. 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 asking about the quality of sleep. All questions can be seen in Table I.

B. PSS

The PSS [20] was selected to measure the participant's level of stress at the time of the survey. Our modified PSS consists of 10 questions asking about the presence of various symptoms of stress. All modified PSS questions can be seen in Table II.

TABLE I: PSQI questions answered by a participant.

Question	Possible Responses
When did you go to bed last night?	8-8:30pm, 8:30-9pm etc.
How many hours did you spend in bed last night?	0-1 hour, 1-2 hours etc.
How many hours of sleep did you get last night?	0-1 hour, 1-2 hours etc.
Last night, did you go to sleep within 30 minutes?	Yes/No
Last night, did you wake up in the middle of the night?	Yes/No
Last night, did you get up to use the bathroom?	Yes/No
Last night, did you have trouble breathing properly?	Yes/No
Last night, did you cough or snore loudly?	Yes/No
Last night, did you feel too cold?	Yes/No
Last night, did you feel too hot?	Yes/No
Last night, did you have bad dreams?	Yes/No
Last night, did you have pain?	Yes/No
Did you take medicine to help you sleep last night?	Yes/No
Have you had trouble staying awake in the past 24 hours?	Yes/No
Have you had trouble keeping enthusiasm to get things done in the past 24 hours?	Yes/No
How would you rate last night's sleep overall?	1, 2, 3, 4, 5

TABLE II: PSS questions answered by a participant.

Question	Possible Responses
Do you feel upset by something that happened unexpectedly?	Yes/No
Do you feel unable to control the important things in your life?	Yes/No
Do you feel stressed?	Yes/No
Do you feel confident about your ability to handle your personal problems?	Yes/No
Do you feel that things are going your way?	Yes/No
Do you feel that you are able to cope with all the things you have to do?	Yes/No
Do you feel that you are able to control the irritations in your life?	Yes/No
Do you feel that you are on top of things?	Yes/No
Do you feel anger because of things that are outside of your control?	Yes/No
Do you feel difficulties are piling up so high that you could not overcome them?	Yes/No

C. K10

The K10 [21] was selected and modified to measure the participant's level of distress at the time of the survey completion. Our modified PSS consists of 10 questions pertaining to the relevance of various feelings of distress. Of note, the survey asks whether the participant feels hopeless, nervous, or depressed. All modified K10 questions can be seen in Table III.

V. Methods for Correlation Analysis

Correlation analysis for the collected data is done using 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

TABLE III: K10 questions answered by a participant.

Question	Possible Responses
Do you feel tired for no good reason?	Yes/No
Do you feel nervous?	Yes/No
Do you feel so nervous that nothing can calm you down?	Yes/No
Do you feel hopeless?	Yes/No
Do you feel restless or fidgety?	Yes/No
Do you feel so restless that you can not sit still?	Yes/No
Do you feel depressed?	Yes/No
Do you feel that everything is an effort?	Yes/No
Do you feel so sad that nothing can cheer you up?	Yes/No
Do you feel worthless?	Yes/No

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. 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 IV.

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 the case that no correlation 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 a survey result". For the purposes of this experiment, the p value must be lower than the standard 0.05 to be considered statistically significant and highlighted in the results to be discussed.

A. 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 τ value, in place of the r value, is given as:

$$\tau = \frac{(\#\ of\ concordantpairs) - (\#\ of\ discordantpairs)}{n(n-1)/2} \tag{1}$$

TABLE IV: Categorizing correlation coefficients (r value).

Weak or low	less than 0.35
Moderate or modest	0.36-0.67
Strong	0.68-1.0
Very Strong	greater than 0.9

B. 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 the true association. That is why it is not appropriate for use outside normal distribution. The r value is given as:

$$r = \frac{\sum (x_i - x)(y_i - y)}{\sqrt{[\sum (x_i - \bar{x})^2] \sum [(y_i - \bar{y})^2]}} \tag{2}$$

where x_i and y_i are the values of x and y for the i th iteration.

C. 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:

$$r = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \tag{3}$$

where d_i is the difference in ranks for x and y.

VI. Experimental Procedure

In this work, twenty participants were recruited and divided at random into two groups of ten: Group A and Group B. Group A was given materials for five days and then Group B follow the same process. After a month of the last experiment, each group was given again the materials for five days, 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 before participating to help ensure unbiased results. For each five-day session of the experiment, the following setup was followed:

1) A smartphone and a SensorTag were loaned to each participant. A training session took place individually with each participant to instruct them on how to properly position the SensorTag for proper data collection, register and connect the SensorTag to the application. The recommended placement of the SensorTag is close to the person and oriented on a surface such as a desk such that the light sensor is facing upwards. They were asked to complete the survey honestly 2-3 times per day for the five days.
2) Data is collected to the research server over a five-day session. Each time a survey is completed, three comma-separated value (CSV) files are sent to the server: one

TABLE V: Correlation coefficients between all survey results in Group A.

	# of People	PSQI	PSS	K10
Kendall correlation				
# of People		-0.0385	-0.1762	-0.2202
PSQI	-0.0385		0.0771	0.2206
PSS	-0.1762	0.0771		**0.4619**
K10	-0.2202	0.2206	**0.4619**	
Pearson correlation				
# of People		-0.0517	-0.2234	-0.2191
PSQI	-0.0517		0.0945	0.2817
PSS	-0.2234	0.0945		**0.5715**
K10	-0.2191	0.2817	**0.5715**	
Spearman correlation				
# of People		-0.0421	-0.2157	-0.2618
PSQI	-0.0421		0.0943	0.2598
PSS	-0.2157	0.0943		**0.5397**
K10	-0.2618	0.2598	**0.5397**	

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.

VII. Results and Discussion

Group A provided 101 valid survey submissions following the omission of 18 outliers due to zeroed sensor values. Group B provided 81 submissions over the same time following the omission of four outliers for similar reasons. There was a lot of deviation in terms of the number of daily submissions from each participant.

To analyze the associations between variables, Kendall, Pearson, and Spearman coefficients were calculated. The results of the two groups have been kept separate as they represent results over two distinct periods and can be compared to one another.

1) Correlation Analysis of Survey Responses: As shown in Table V, the survey results from Group A show a moderate Kendall (0.4619), Pearson (0.5715), and Spearman (0.5397) correlation between the PSS and K10 results. In Group B, this same correlation was even stronger, with a Kendall value of 0.5147, a Pearson value of 0.6218, and a Spearman value of 0.6395, shown in Table VI. This indicates a correlation between stress and distress. Additionally, in Group B, lesser moderate correlations are evident between the K10 and PSS results, and the number of people present in the environment. While interesting, this is less relevant as it was not confirmed by the other Group.

2) Correlation Analysis of Survey Responses to Environmental Variables: The strongest correlation available in Group A is that between the K10 results and light, resulting in a Kendall correlation of -0.2996, a Pearson correlation of -0.3187, and a Spearman correlation of -0.4018, shown in Table VII. In Group B, as shown in Table VIII, this correlation

TABLE VI: Correlation coefficients between all survey results in Group B.

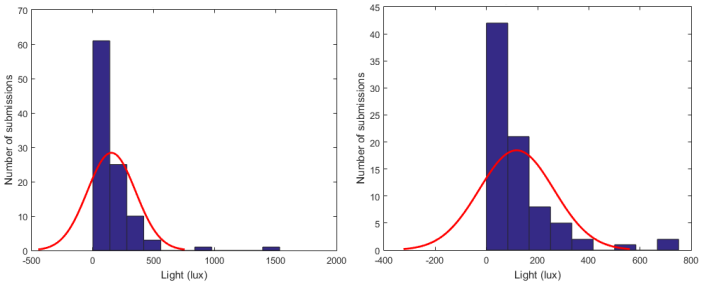
	# of People	PSQI	PSS	K10
Kendall correlation				
# of People		-0.1328	-0.3128	-0.3751
PSQI	-0.1328		0.1863	0.2542
PSS	-0.3128	0.1863		**0.5147**
K10	-0.3751	0.2542	**0.5147**	
Pearson correlation				
# of People		-0.1143	-0.3554	-0.4213
PSQI	-0.1143		0.1453	0.2353
PSS	-0.3554	0.1453		**0.6218**
K10	-0.4213	0.2353	**0.6218**	
Spearman correlation				
# of People		-0.1672	-0.3651	-0.4311
PSQI	-0.1672		0.2241	0.3471
PSS	-0.3651	0.2241		**0.6395**
K10	-0.4311	0.3471	**0.6395**	

TABLE VII: Correlation coefficients between environmental variables and surveys in Group A.

	# of People	PSQI	PSS	K10
Kendall correlation				
Temperature	0.2431	-0.0542	-0.0532	-0.1574
Pressure	0.0178	-0.0317	-0.0962	-0.1432
Humidity	-0.1487	0.1298	0.1762	0.1387
Light	0.2342	0.0253	-0.1756	**-0.2996**
Noise	0.1544	-0.0104	-0.1689	-0.0752
Pearson correlation				
Temperature	0.2654	-0.0972	-0.0834	-0.1792
Pressure	0.0489	-0.0034	-0.0892	-0.1506
Humidity	-0.1587	0.1976	0.1345	0.1567
Light	0.2687	0.0541	-0.2234	**-0.3187**
Noise	0.2101	-0.0187	-0.2256	-0.0745
Spearman correlation				
Temperature	0.2832	-0.0723	-0.0789	-0.1781
Pressure	0.0324	-0.0347	-0.1164	-0.1873
Humidity	-0.1965	0.1753	0.2574	0.1782
Light	0.2843	0.0641	-0.2476	**-0.4018**
Noise	0.1895	-0.0782	-0.2917	-0.1673

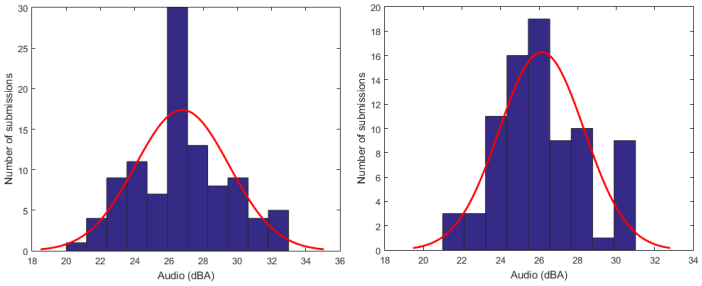
TABLE VIII: Correlation coefficients between environmental variables and surveys in Group B.

	# of People	PSQI	PSS	K10
Kendall correlation				
Temperature	-0.1153	0.0681	0.1314	0.1782
Pressure	-0.1463	0.1561	0.1982	0.1462
Humidity	0.2254	0.0567	-0.1832	-0.1349
Light	0.1871	0.0358	-0.1453	0.1681
Noise	0.2741	-0.0541	**-0.3847**	-0.2219
Pearson correlation				
Temperature	-0.1541	-0.0561	0.2249	0.2378
Pressure	-0.1561	0.1467	0.1356	0.1754
Humidity	0.2981	0.1498	-0.1561	-0.1853
Light	0.1765	0.0591	-0.2785	-0.2456
Noise	0.2974	0.0495	**-0.4865**	-0.1874
Spearman correlation				
Temperature	-0.1458	0.0743	0.2136	0.1865
Pressure	-0.1561	0.1871	0.1459	0.1763
Humidity	0.2643	0.0705	-0.1759	-0.1672
Light	0.2486	0.0782	-0.2357	-0.2251
Noise	0.2908	-0.0785	**-0.5316**	-0.2784



(a) Group A. (b) Group B.

Fig. 2: Light data distribution.



(a) Group A. (b) Group B.

Fig. 3: Noise data distribution.

was weak, at -0.1783 for Kendall, -0.2663 for Pearson and -0.2311 for Spearman. However, there is a strong correlation in Group B for noise. The correlation between ambient noise and PSS results was a -0.3847 Kendall coefficient, a -0.4865 Pearson coefficient and a -0.5316 Spearman coefficient.

It is hypothesized that the discrepancy between Group A and Group B results can be explained with distribution data. As shown in Fig. 2, Group A has a greater variation in light values than Group B, which might be an explanation for the acquired survey data. Similarly, Fig. 3 shows that Group B had a greater variation in noise values.

VIII. Conclusion

In this paper, a system is presented to evaluate relationships between individual wellness and their surrounding environment using IoT and BLE technology. In total, five variables were evaluated: temperature, humidity, air pressure, light, and noise. An experiment was conducted with 20 participants split into two groups of ten. The first group of ten saw a moderate correlation between light and distress. The second group, however, saw a decrease in the strength of this correlation but an increase in the correlation of noise versus stress. Overall, it appears that when a greater variation is present in the data for the environmental variable, there is a greater chance of a strong correlation.

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