Academic Paper

The Effect of Meteorological Factors on Bluetooth-based Contact Tracing

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1 Introduction

The first case of the COVID-19 (Coronavirus) disease originated from Wuhan, China in December 2019. The World Health Organization (WHO), an organization composed of various clinicians and national health agencies around the world, was quick to declare the disease an international concern of public health emergency on January 30, 2020 [1]. Ever since, the disease has been rapidly infecting populations across the world as it has spread to more than 185 countries, infected 163,869,893 individuals, and caused 3,398,302 deaths as of May 19, 2021 [2].

To address the global pandemic, WHO researchers, medical scientists, and clinicians, are desperately searching for new technology to decrease the spread of the disease as soon as possible. Recent studies have identified that smartphone contact tracing applications can implement promising Bluetooth technology that will support various healthcare entities to contain the disease and end this pandemic. The Bluetooth technology used to support these contact tracing applications will be detailed in **Section 1.1**.

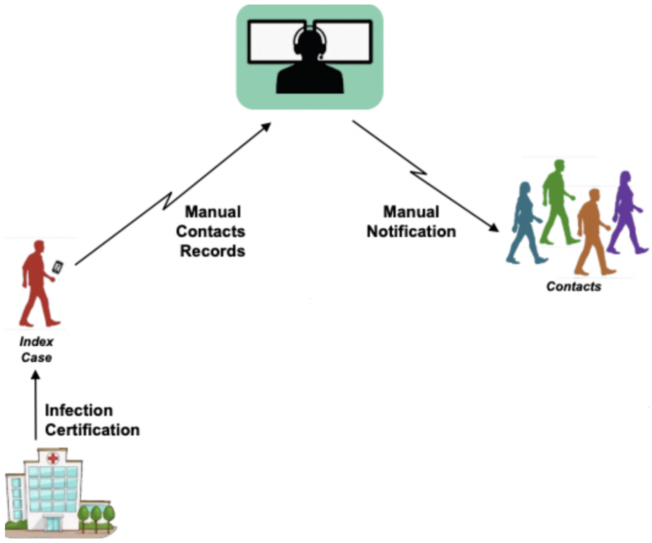
This paper narrows on the COVID-19 pandemic and the factors that affect the contact tracing applications that were recently deployed to solve the deadly consequences of the disease. This study will present a comprehensive correlation analysis of particular environmental factors, specifically the meteorological conditions of temperature, pressure, relative humidity, and wind speed on tracing application technology. This study will further recommend the tested conditions that need to be considered in tracing algorithms built by application developers.

1.1 Lit Review

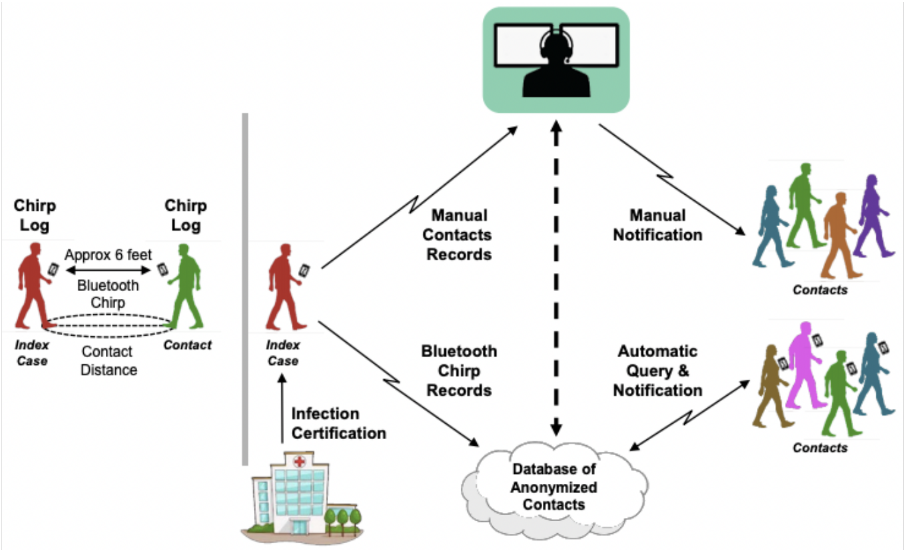
In order to understand why this study analyzes the effects of meteorological conditions on the performance of BLE contact tracing, it is important to examine the existing body of research on the subject.

COVID-19 is the disease borne from the SARS-CoV-2 virus that is communicated through respiratory droplets, most commonly transmitted by close contact between an initially infected individual, or index case, and another individual [3]. The virus is also known to spread prior to any noticeable symptoms from the index case [4]. As such, it is of essence to diminish the spread of the disease by minimizing the contact between an infected individual and non-infected individuals.

Currently, to minimize the spread of the disease through non-infected individuals, healthcare professionals and institutions work through a three step process: contact tracing, testing, and quarantining [5]. A representation of the contact tracing process commonly used by healthcare entities is provided in **Figure 1a**. The current method used is a manual approach that involves health professionals interviewing with infected individuals to determine possible chains of infection. After the interview, the healthcare professionals pass off the contact information to a call center. The call center then calls all the potentially infected individuals and notifies them to check for symptoms, get tested and finally quarantine.



(a) Manual contact tracing



(b) Automatic contact tracing

Figure 1: Process of manual versus automatic contact tracing process

While, in theory, this is a powerful tool to minimize the spread of the disease, the manual approach is inefficient and inaccurate for the scale of the COVID-19 pandemic [6]. However, identifying these close contacts, which are defined as individuals who have spent over 15 minutes within 6 feet (1.8 meters) of the index case [7], can be facilitated through automatic contact tracing applications that can be implemented on smartphones [8]. A representation of the automatic contact tracing approach is provided in **Figure 1b**. These applications are deployed on smartphones that can continuously emit Bluetooth low energy (BLE) "chirps," which other nearby phones can periodically detect. BLE is a low power wireless communication technology that can be used over a short distance to enable smartphone devices to communicate with each other [9]. These scanning phones record the identification codes emitted by the chirping phone along with the estimated power with which the chirp was received [9]. This estimated power helps to determine the proximity of an infected individual. These chirps are then logged into the respective chirp logs of the phones. When one of these individuals has been tested positive for COVID-19, healthcare entities are able to automatically push notifications to all the devices that have been connected with the index case through Bluetooth chirps to check for symptoms, get tested and finally quarantine.

The Government of Singapore was the first to launch a public application for their residents to facilitate contact tracing efforts in March 2020 [10]. The application then uses signal strength to determine the estimated distance between the two individuals [11]. This implementation sent exposure notifications relying on BLE signals based on the binary approach of indicating if two individuals were "too close" or "far enough" [12]. However, the application resulted in many inconsistencies in real-world performance. These inconsistencies resulted in two errors: sending false exposure notifications to individuals that were not actually in close contact with infected individuals or individuals that were in close contact with infected individuals were not receiving notifications [10].

The errors were actually expected because the distance estimated from Bluetooth chirps sent between smartphone devices varies greatly from the actual distance. Bluetooth signals are dramatically affected by where the phone is carried, the positions of the devices, and physical barriers, to mention a few [13]. However, the severity and correlation of these conditions on distance predictions is currently unknown and needs to be addressed.

To understand the large variation in current BLE contact tracing applications, it is necessary to understand the BLE technology phenomena. In context, BLE signaling for COVID-19 contact tracing is done through "advertisements", which are short messages that are repeatedly broadcasted Bluetooth chirps from a device at around 250 millisecond (ms) intervals. These advertisements contain data that include a random bit sequence generated by the broadcasting device, as well as the status of the broadcasting phone. These advertisements can occur on a set of three of the BLE frequency channels – 2402 MHz, 2426 MHz, or 2480 Mhz – which are often identified as low, mid, and high frequency ranges, respectively. However, a specific frequency channel is not set for tracing applications on smartphone devices as they naturally alter between frequency channels based on which channel is most efficient [14].

In COVID-19 automated contact tracing applications, the transmitted signal power is also encoded into the advertisement. As mentioned earlier, this allows the receiver device to estimate the power level of the signal transmitted. When implementing this phenomenon onto Android and iOS, the received signal power is referred to as a RSSI (Received Signal Strength Indicator) measurement. RSSI is commonly measured in milliwatts (dBm) and is estimated in 1 dBm increments. However, as mentioned earlier, the received signal patterns of BLE devices contain large variations in various environmental conditions. While most devices can only support RSSI advertisements of values of -100 dBm or greater, it is well known that the 2.4 GHz ISM radio band (Industrial, Scientific, and Medical radio band) produces variations in predicted distance and actual distance between devices to be quite large [15].

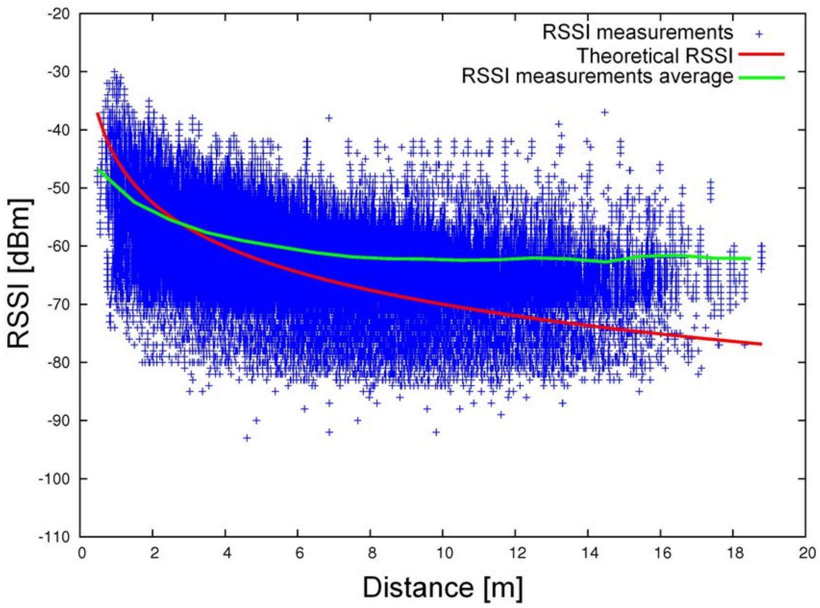


Figure 2: RSSI and theoretical RSSI measurements versus distance

Previous work has determined that distance is strongly correlated with RSSI measurements in controlled conditions, where all outside hindrances (physical barriers, other Bluetooth emitting devices, etc.) were removed [16]. However, even in controlled conditions, RSSI measurements varied greatly. Figure 2 models RSSI measurements over various changes in distance in this particular work. As depicted, the green line of best fit depicts the theoretical RSSI value, whereas the red line of best fit depicts the actual measurements. It is clear that the actual RSSI values do not match with the theoretical RSSI values and that there lies a statistical difference throughout the distances [16].

However, there are very few studies looking into why this significant disparity occurs. As mentioned earlier, studies have found that RSSI measurements were affected by how the phone is carried (i.e. the positions of the devices, physical barriers, etc.) The commonality between these conditions is that Bluetooth signals are in some form hindered in their travel from device to device. This study wants to take this a step further by studying the effects of altering the conditions of the air that the Bluetooth signals are travelling in. The four most common techniques to alter the conditions of air are changing the meteorological conditions of temperature, pressure, relative humidity, and wind speed [17]. Currently, there are no studies that have viewed the effect of RSSI in the mentioned meteorological conditions in the context of BLE contact tracing.

Being a relatively new field of study, there remains much to be learned to take full advantage of BLE contact tracing. Considering the unpredictability of RSSI, investigating the performance of BLE in various meteorological conditions promises to unlock even greater possibilities. It is hoped that results of this study will ultimately improve the efficacy of contact tracing applications. This research will be unique as it will find if a correlation exists between RSSI and temperature, pressure, humidity, and wind speed.

More specifically, this study endeavors to build a Bluetooth signal collection platform from a Raspberry Pi, small single-board computer, to explore the effects and correlation of four meteorological conditions, temperature, pressure, humidity, and wind speed, on radio signal strength (power of a Bluetooth signal). These findings can be useful for designing robust algorithms and protocols against the effects mentioned above.

2 Hypotheses

The following section defines the interrelated hypotheses used to test for a correlation between the tested meteorological factors and radio signal strength. If a strong linear correlation exists, it may be used to determine if an algorithm can be implemented to create a more reliable and accurate approach for an automated tracing application. The hypotheses for each meteorological condition are listed below.

- If devices are exposed to various changes in temperature (i.e. seasonal changes, body heat, etc.) then it will cause large variation in RSSI measurements. There will be a very strong correlation between temperature and RSSI which can be implemented for algorithms in contact tracing applications to increase efficacy.
- If devices are exposed to various changes in pressure (i.e. extreme weather conditions, elevation changes, etc.) then it will cause significant variation in RSSI measurements. There will be a very strong correlation between pressure and RSSI which can be implemented for algorithms in contact tracing applications to increase efficacy.
- If devices are exposed to various changes in relative humidity (i.e. weather conditions, season changes, etc.) then it will cause significant variation in RSSI measurements. There will be a very strong correlation between relative humidity and RSSI which can be implemented for algorithms in contact tracing applications to increase efficacy.
- If devices are exposed to various changes in wind speed (i.e weather conditions, season changes, etc.), then it will cause significant variation in RSSI measurements. There will be a very strong correlation between wind speed and RSSI which can be implemented for algorithms in contact tracing applications to increase efficacy.

These hypotheses were developed based on the findings of past studies that examined the effectiveness of using BLE technology for contact tracing applications. As mentioned in previous sections, these studies showed that, while BLE technology can be effectively used to predict the distance between two devices, there is large variation in measurement. Since Bluetooth chirps are signals that travel through the air, this paper predicts that altering the conditions through which the chirp travels will significantly impact the efficacy of contact tracing applications. As such, a very strong correlation between temperature, pressure, relative humidity, wind speed and RSSI is extremely likely. The interpretation of a very strong correlation is further discussed in **Section 3.3**, **Table 3**

3 Methods

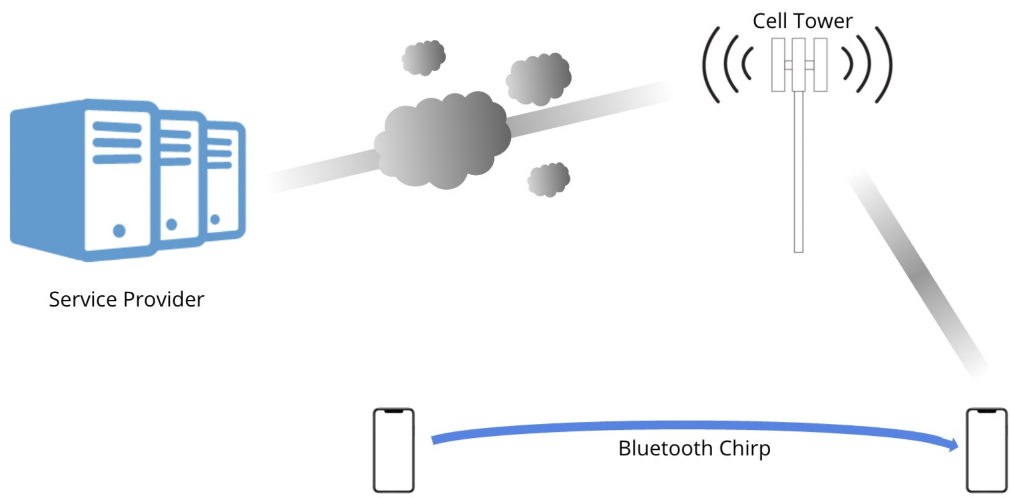
The experimental design, materials, and methods implemented in this study are detailed in the following sections.

3.1 Experimental Design

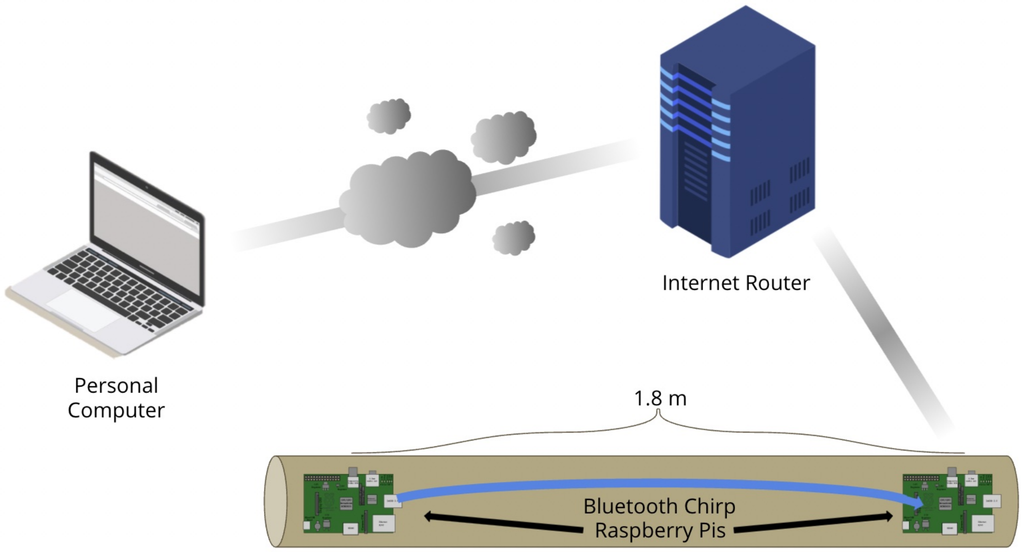
Before examining the setup of this particular study, it is important to understand the design setup of a real-world implementation of current tracing applications. **Figure 3a** models the real-world tracing application deployed on two smartphone devices. As modeled, when two devices are in close proximity to one another, Bluetooth chirps begin to be transmitted. After receiving these chirps, the receiving device keeps records of all the chirps in its personal chirp log. The chirp logs on the receiving devices are then periodically transmitted to cell towers in the nearby area, which can be easily accessible by various telecommunication service providers. In the case of COVID-19 tracing, healthcare entities can request service providers to view a particular device's chirp logs which can be filtered by location, day, and time. This allows healthcare entities to properly send out exposure notifications to the correct group of contacts.

The experimental design for this study is modeled in **Figure 3b**. As modeled, the experimental setup mimics the real-world network. However, instead of smartphones, two Raspberry Pis were utilized. Raspberry Pis were chosen in this particular study because they are easily accessible and programmable to collect RSSI measurements over a large period of time. While Raspberry Pis and common smartphone devices house similar Bluetooth modules, the key difference is that Raspberry Pis are incapable of connecting with cellular towers. As such, the Raspberry Pis were connected to a household Internet router through a wireless fidelity (WiFi) connection instead of a cellular tower. The chirp logs from the receiving device were then accessible through a device running macOS Big Sur 11.2.3 using a Secure Shell (SSH) client. The SSH client allows access to the command line of a Raspberry Pi which initiates remote access to the device if the device is on the same WiFi network. Specifically, the chirp log file was accessed using the SSH client.

The Raspberry Pis were positioned at a distance of 1.8 m apart in a completely insulated pipe. This was done so that the meteorological conditions inside the pipe could be altered artificially. This would minimize the effects from the surrounding area around the pipe from interfering with the conditions inside the pipe.



(a) Real-world tracing network setup



(b) RSSI measurement network setup

Figure 3: Comparison of real-world tracing network setup versus experimental measurement network setup

3.1.1 Wireless sensor network (WSN) Configuration and Deployment

This study created a WSN operating in 2.4 GHz ISM frequency band deployed in a suburban house in the Midwestern United States. The WSN consisted of two Raspberry Pi 4 Model B wireless computer modules, a NearSys sensor, a Internet Router/Provider, and a computer running MacOS.

The NearSys Sensor Array was used to measure the exact temperature, pressure, and relative humidity inside the pipe, while the wind speed measurements were given by the fan itself. Furthermore, the NearSys sensor was powered by the

Raspberry Pi that was receiving the Bluetooth chirps. The sensor was encased in a waterproof casing such that the water and moisture would not accumulate along the antennas of the sensor. The casing was put on around all sides of the sensor except for the antennas so that it could still make accurate measurement readings.

3.2 Data Collection

The method to collect data for this experiment is discussed in the following section. The application specially designed to be used to collect data measurements for this study is available on GitHub [18]. The application is written using the Python 3.7.3 programming language.

The Python programming language was used for this particular experiment because current implementations of contact tracing applications make use of a method of automated data analysis with machine learning. Machine learning is a branch of artificial intelligence that is based on the idea that computer algorithms can learn and identify patterns in data to automatically improve the algorithm. This is beneficial for contact tracing applications as it can scale-up faster, speed-up processing power, and outperform itself as it continues to learn from data.

Each meteorological condition was tested under 3 trials of similar structure. Through the testing of a particular meteorological condition, the other three conditions were kept at a constant value. Each condition was altered using the tools listed in **Table 1** to the ranges listed in **Table 2**. For temperature, it was increased to 50 C using a blow dryer and then decreased to -8 C using dry ice, For pressure, it was decreased to 63,000 Pa using a Vacuum pump and then released slowly until it naturally increased to 100,800 Pa. For relative humidity, it was increased to 85 % using a water sprayer and decreased to 30 % using moisture absorbing packets. For wind speed, continuous readings were not possible, however, it was increased from 20 to 60 km/h at 5 km/h intervals using a fan.

Table 1: Tools used to vary meteorological conditions

	Temperature	**Pressure**	**R. Humidity**	**Wind Speed**
Increase	Blow dryer	–	Water sprayer	Fan
Decrease	Dry ice	Vacuum pump	Absorbing packets	–

Table 2: Ranges of meteorological conditions

Temperature (°C)	Pressure (Pa)	R. Humidity (%)	Wind Speed (km/h)
-8 - 50	63,000 - 100,800	30 - 85	20 - 60*

* measurements taken at 5 km/h intervals

The collection of these measurements is a data set that can be used to determine the correlation of RSSI measurements on Raspberry Pi devices as a function of temperature, pressure, relative humidity, and wind speed.

3.3 Data Analysis

This section will discuss how the collected RSSI measurements will be analyzed. To begin, the data will be extracted from the chirp log file off the Raspberry Pis using the Pandas library. Pandas is a software library written for the Python programming language that is commonly used for data manipulation and analysis [19]. This particular software allows us to take the thousands of RSSI measurements and structure them into tables that are easy to read.

From here, the data tables were used to create scatter plots that aggregated the data from the trials in each experiment i.e. all 3 trials will be overlaid on top of one another for each meteorological condition. The scatter plots in this experiment will be created using Matplotlib. Matplotlib is a plotting software library for the Python programming language that provides an API (application programming interface) for the creation of various plots [20].

After creating the scatter plots, mathematical tools for the Python programming language, NumPy and SciPy, were used to create simple linear regression models [21, 22]. This was used to compute the line of best fit which allowed us to calculate the regression coefficient and correlation coefficient values, respectively.

Furthermore, this experiment is greatly interested in the correlation coefficient values, as they will be used to conduct a correlation analysis and ultimately determine whether a particular meteorological condition is correlated with RSSI measurements. **Table 3** is the interpretation of correlation coefficient values commonly used in medical-related research that will be used in particular study [23]. A negligible correlation will be assigned to a correlation coefficient of 0.00 to 0.30, a weak correlation will be assigned to a correlation coefficient of 0.30 to 0.50, a moderate correlation will be assigned to a correlation coefficient of 0.50 to 0.70, a strong correlation will be assigned to a correlation coefficient of 0.70 to 0.90, and a moderate correlation will be assigned to a correlation coefficient of 0.90 to 1.00.

Table 3: Interpretation of Correlation Coefficient

Correlation Coefficient	**Interpretation**
.90 to 1.00 (-.90 to -1.00)	Very strong positive (negative) correlation
.70 to 90 (-.70 to -.90)	Strong positive (negative) correlation
.50 to .70 (-.50 to -.70)	Moderate positive (negative) correlation
.30 to .50 (-.30 to -.50)	Weak positive (negative) correlation
.00 to .30 (.00 to -.30)	Negligible correlation

4 Results

We conducted experiments and gathered data by using the Methods highlighted in the previous section. Data from three different trials from each meteorological condition will be analyzed in this section. The goal is to find how temperature, pressure, relative humidity, and wind speed are correlated with RSSI.

4.1 Effects of Temperature on RSSI

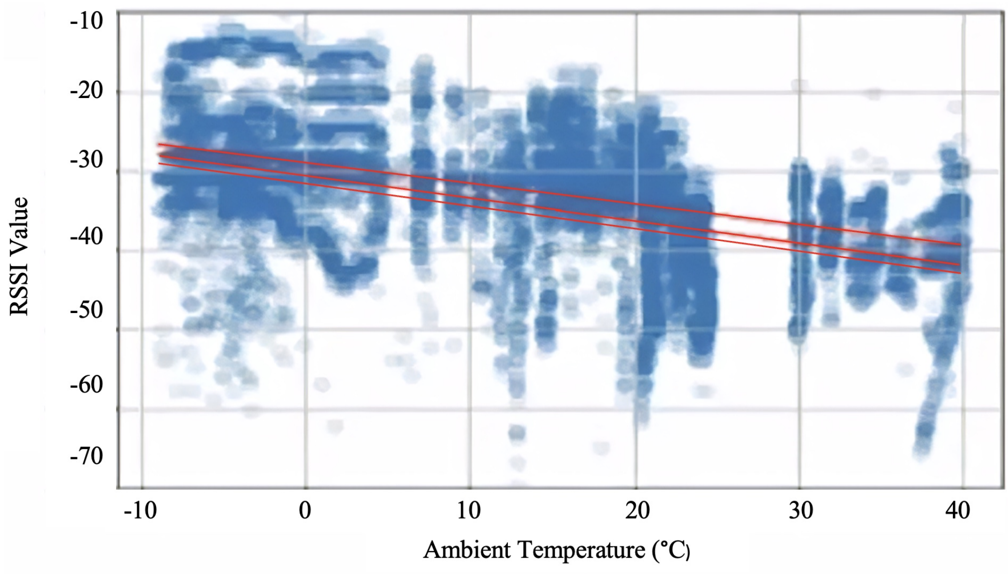


Figure 4: Linear regression model of RSSI change against temperature

Figure 4 plots the changes of temperature on RSSI and models an applied a simple linear regression for the three conducted trials, where the temperature is the explanatory variable for RSSI measurement variation. As can be seen, there is a clear relationship between temperature and RSSI, that is, when temperature rises, the RSSI decreases, and vice versa.

A linear, negative trend is observed through all three trials as depicted by the negative slopes of the lines of best fit throughout the three trials. However, the magnitude of RSSI at particular temperatures had great variation that led to slight variations in the regression coefficient among the three trials as can be seen from the differing lines of best fit. The average calculated regression coefficient for the three trials was *-0.27*. On average this accounts for a decrease of 1 RSSI by the rise of 3.5 C. The correlation coefficient for Trial 1 was *-0.52*, Trial 2 was *-0.51*, and Trial 3 was *-0.54*. Using the outlined correlation coefficient interpretation from Table 3, these values imply that RSSI variation is moderately correlated with changes in temperature.

A summary of the association between temperature and RSSI can be found in **Table 4** below.

Table 4: Summary of Temperature vs RSSI

Regression coef.	-0.27		
Correlation coef.	-0.52	-0.51	-0.54
R^2	0.27	0.26	0.29

4.2 Effects of Pressure on RSSI

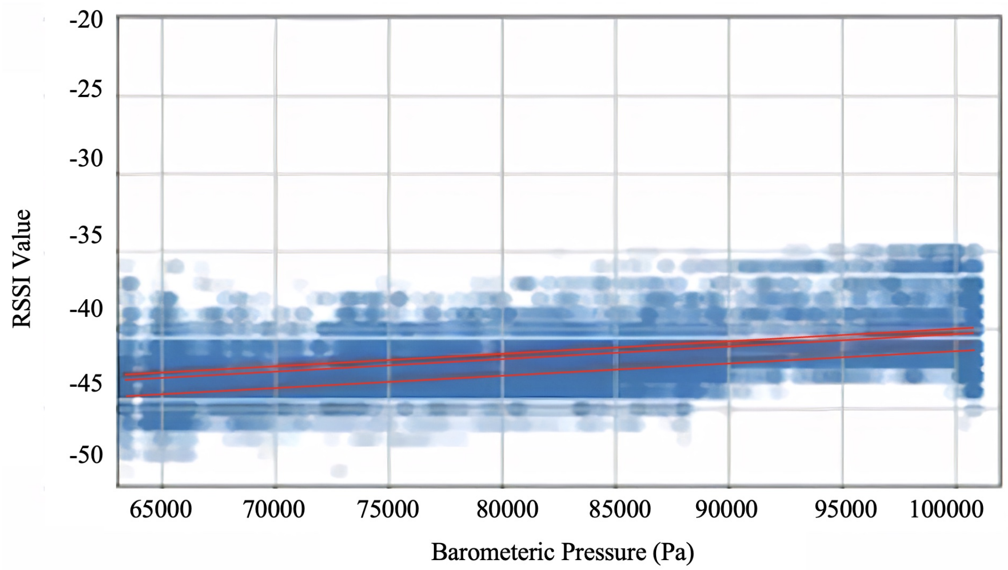


Figure 5: Linear regression model of RSSI change against pressure

Figure 5 plots the changes of pressure on RSSI and models an applied a simple linear regression for the three conducted trials, where the pressure is the explanatory variable for RSSI measurement variation. As can be seen, there is a clear relationship between pressure and RSSI, that is, when temperature rises, the RSSI increases, and vice versa.

A linear, positive trend is observed through all three trials as depicted by the slight positive slopes of the lines of best fit throughout the three trials. However, the magnitude of RSSI at particular pressures had slight variation that led to variations in the regression coefficient among the three trials as can be seen from the differing lines of best fit. The average calculated regression coefficient for the three trials was *0.0001*. On average this accounts for a decrease of 5 RSSI by the rise of 40,000 Pa. The correlation coefficient for Trial 1 was *0.83*, Trial 2 was *0.81*, and Trial 3 was *0.84*. Using the outlined correlation coefficient interpretation from Table 3, these values imply that RSSI variation is strongly correlated with changes in pressure.

A summary of the association between temperature and RSSI can be found in **Table 5** below.

Table 5: Summary of Pressure vs RSSI

Regression coef.	-0.0001		
Correlation coef.	0.83	0.81	0.84
R^2	0.69	0.66	0.71

4.3 Effects of Relative Humidity on RSSI

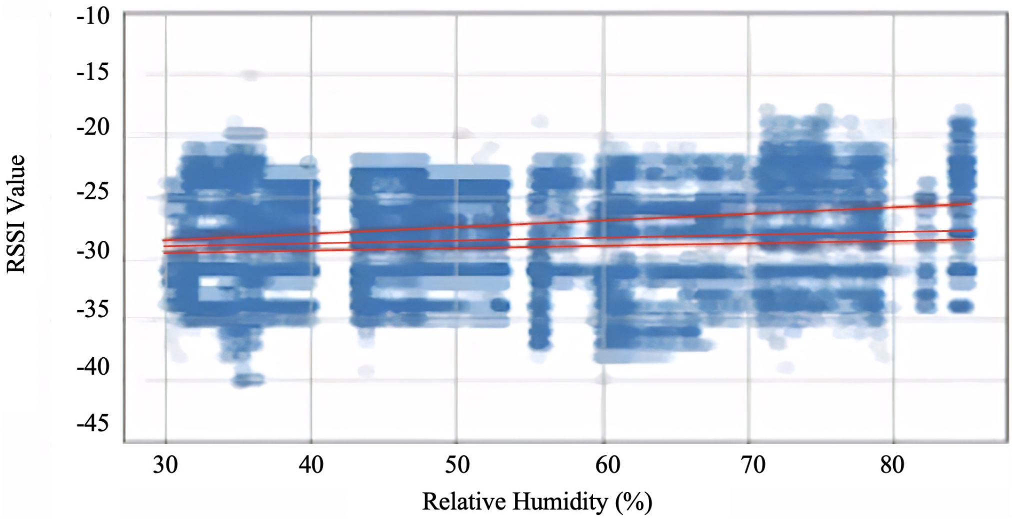


Figure 6: Linear regression model of RSSI change against relative humidity

Figure 6 plots the changes of relative humidity on RSSI and models an applied a simple linear regression for the three conducted trials, where the relative humidity is the explanatory variable for RSSI measurement variation. As can be seen, there seems to be no relationship between relative humidity and RSSI, that is, when relative humidity rises, the RSSI remains constant.

A constant trend is observed through all three trials as depicted by the close to zero slopes of the lines of best fit throughout the three trials. However, the magnitude of RSSI at particular relative humidities had great variation that led to slight variations in the regression coefficient among the three trials as can be seen from the differing lines of best fit. The average calculated regression coefficient for the three trials was less than 0.0001. While one of the trials showed a slightly positive trend, it is safe to assume that this was simply due to the natural variance of RSSI, as mentioned in **Section 1.1**.The correlation coefficient for Trial 1, Trial 2, and Trial 3 were all less than 0.01. Using the outlined correlation coefficient interpretation from Table 3, these values imply that RSSI variation is of negligible correlation with changes in relative humidities.

A summary of the association between relative humidity and RSSI can be found in **Table 6** below.

Table 6: Summary of Relative Humidity vs RSSI

Regression coef.	<0.0001		
Correlation coef.	<0.01	<0.01	<0.01
R^2	<0.01	<0.01	<0.01

4.4 Effects of Wind Speed on RSSI

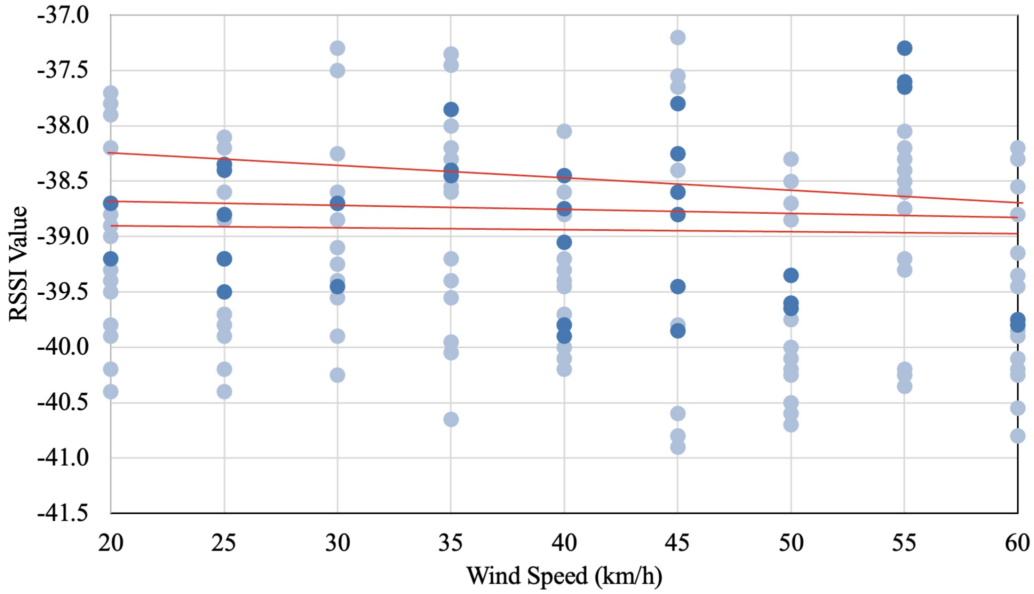


Figure 7: Linear regression model of RSSI change against wind speed

Figure 7 plots the changes of relative humidity on RSSI and models an applied a simple linear regression for the three conducted trials, where the relative humidity is the explanatory variable for RSSI measurement variation. While wind speed readings could not be taken, there are enough data points to view potential correlation. As can be seen, there seems to be no relationship between wind speed and RSSI, that is, when wind speed rises, the RSSI remains constant.

A constant trend is observed through all three trials as depicted by the close to zero slopes of the lines of best fit throughout the three trials. However, the magnitude of RSSI at particular wind speeds had great variation that led to slight variations in the regression coefficient among the three trials as can be seen from the differing lines of best fit. The average calculated regression coefficient for the three trials was less than 0.0001. While one of the trails showed a slightly negative trend, it is safe to assume that this was simply due to the natural variance of RSSI, as mentioned in **Section 1.1**. The correlation coefficient for Trial 1, Trial 2, and Trial 3 were all less than 0.01. Using the outlined correlation coefficient interpretation from Table 3, these values imply that RSSI variation is of negligible correlation with changes in wind speed.

A summary of the association between relative humidity and RSSI can be found in **Table 7** below.

Table 7: Summary of Wind Speed vs RSSI

Regression coef.	<0.0001		
Correlation coef.	<0.01	<0.01	<0.01
R^2	<0.01	<0.01	<0.01

5 Discussion

The results of this paper fills the gap in current literature by quantifying the effects of meteorological conditions on the performance of BLE contact tracing. This paper initially hypothesized that meteorological conditions would all have a very strong correlation with RSSI, however, this is false.

While meteorological conditions don't have a very strong correlation, a correlation still exists among particular conditions. It is clear that temperature and pressure have significant correlations to affect RSSI measurements, while relative humidity and wind speed have little to no effect at all. This means that changes in surrounding temperature and pressure of smartphone devices would cause the distance prediction based on RSSI to be inaccurate. This means it is of essence for application developers of contact tracing applications to prioritize building an algorithm taking the surrounding temperature and pressure of a device into account.

As mentioned in **Section 4.1 and 4.2**, RSSI decreases by 1 when temperature increases by 3.5 C. In application in the U.S., this could mean a potential difference of +/- 10 RSSI from seasonal weather changes. While not as significant as temperature, RSSI decreases by 5 over a change in pressure of 40,000 Pa. In application in the U.S., this could mean a potential difference of +/- 2.5 RSSI depending on elevation.

5.1 Limitations

While correlation is a good predictor of a potential causal relationship, it does not imply causation and could be caused by some other factor. The following sections will discuss the limitations of this paper and potential origins of error that may have been seen in this paper's results.

5.1.1 Temperature vs. Pressure

The correlation between the studied meteorological conditions and RSSI could partly be explained by the dependence of temperature and pressure. By Gay-Lussac's law, the pressure of a given amount of gas is directly proportional to the temperature at a given volume. Since the experimental design of this particular study involved using a closed pipe of fixed volume, it is probable that decreases made to pressure, also slightly decreased the temperature inside the pipe, and vice-versa.

As mentioned in **Sections 4.1 and 4.2**, temperature had a negative correlation while pressure had a positive correlation. Since temperature and pressure are directly proportional, it is likely that the temperature correlation is truly more negative and that the pressure correlation is truly more positive than what was found.

5.1.2 Sensor

The sensor used in this particular study was a NearSys Temperature and Pressure Sensor Array which is commonly used to record atmospheric conditions as a function of altitude. While this was easily programmable along with the Python programming language to be integrated into the RSSI collection application, sensors on smartphones are vastly different. Since the implementation of contact tracing applications will eventually be on smartphone devices and not Raspberry Pis, this paper cannot conclude if the similar sensor readings will be found on those devices.

Additionally, another point of error could have occurred from using only a singular sensor to measure the conditions of the entire pipe. Since the sensor was powered by the receiving Raspberry Pi, it is probable that the conditions at the end of the pipe were not consistent with the conditions of the entire pipe. In future studies, sensors are recommended to be placed across the entirety of the pipe and the average of these measurements be taken.

6 Conclusion

Contact tracing is a proven method to minimize the spread of diseases which makes automated BLE contact tracing a strong addition to the manual approach. Currently, BLE technology has been ineffective in accurately identifying contacts that are actually “too close” and those that are actually “far enough” from communicating the disease between individuals. Understanding the factors that cause impediments to the performance of this technology is important for healthcare entities in establishing the efficacy of automated exposure notifications in their response to COVID-19 and future diseases.

This paper analyzes the effects of four meteorological conditions – temperature, pressure, relative humidity, and wind speed – on the radio signal strength of Bluetooth signals on Raspberry Pi 2.4 GHz wireless modules in an indoor WSN. Experimental results find that the changes in temperature and pressure affect radio signal strength, while relative humidity and wind speed have negligible effects on radio signal strength. In general, temperature seems to have a strong negative influence, pressure seems to have a slight positive influence, while relative humidity and wind speed have no effects at all. These new findings could potentially be useful in designing more robust algorithms and approaches to BLE contact tracing.

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