Validating the Accuracy of Low-Cost IAQ Sensors through Co-location

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Abstract

The popularity of low-cost indoor air quality (IAQ) sensors has surged in recent years. These devices provide new opportunities to assess and monitor indoor air quality in the built environment. However, previous research has shown that the accuracy and precision of these sensors can vary substantially. In this paper, the accuracy of carbon dioxide (CO_2) and fine particulate matter ($PM_{2.5}$) measurements from two consumer-grade low-cost IAQ sensors (the Airthings View Plus – CO_2 only and Air Gradient Pro - CO_2 & $PM_{2.5}$) are assessed. To gauge the performance of these sensors, co-location testing was conducted alongside two reference devices, Graywolf DSII-8 for CO_2 and Lighthouse Handheld 3016 for $PM_{2.5}$, respectively. The measurements from both low-cost sensors were highly correlated with the reference instruments. The Air Gradient CO_2 sensor measurements were more precise; however, it had a higher bias than the Airthings sensor.

Introduction

Canadians spend approximately 90% of their time indoors (Government of Canada, 2022). The indoor environment can have a major impact on human health and well-being. Thus, understanding indoor environmental conditions in buildings is key to improving indoor environmental quality.

Low-cost sensors are an effective way to monitor indoor pollutant concentrations, with applications in both the consumer market as well as field research. Low-cost sensors are widely accessible to consumers and affordable. These sensors can empower occupants to keep track of their indoor air quality and take proactive measures to minimize indoor pollution before it becomes a serious problem. Further, due to their low cost, these sensors can enable large-scale field studies in buildings to understand this challenge from a research perspective, which would otherwise be cost-prohibitive. In this paper, the performance of two low-cost sensors (Airthings View Plus and Air Gradient Pro) that are available on the consumer market, is assessed through co-location testing with higher-accuracy reference sensors.

Background

The US EPA considers a low-cost sensor to cost between $100 to $2500 (Williams et al., 2014). The higher end of this range, however, is likely inaccessible to many consumers. Thus, previous research has proposed an alternative upper limit of $500 (Zhang H. & Srinivasan, 2020. There is a wealth of previous literature on the performance of low-cost sensors. Figure 1 shows the measurement parameters commonly assessed, based on the review of 40 studies published between January 2018 to December 2023. These studies were found through Google Scholar, Scopus, and the Toronto Metropolitan University library database using various combinations of the keywords: “IAQ”, “low-cost sensors”, “indoor air quality”, “performance”, “laboratory”, “field”, and “evaluating”. The top two most commonly reviewed parameters in the literature were $PM_{2.5}$ and CO_2 concentrations. There were a total of 34 and 16 studies that included testing $PM_{2.5}$ and CO_2, respectively, in the 40 studies.

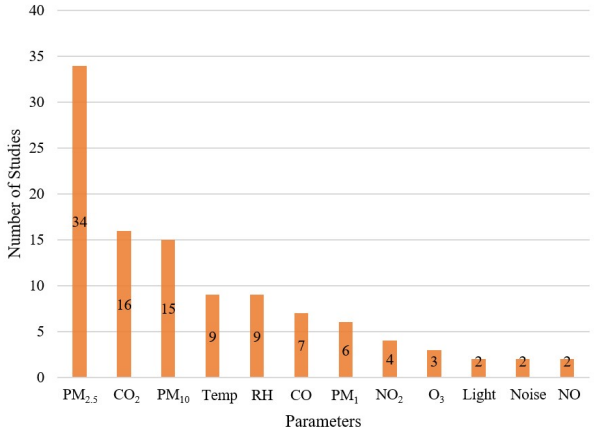

Figure 1: A literature review of most researched parameters

Monitoring $PM_{2.5}$ and CO_2 is important as high concentration levels of $PM_{2.5}$ can result in negative health effects (Government of Canada, 2021a, 2021b). CO_2 is a helpful proxy for indoor ventilation level and at high concentrations it could have an impact on one’s productivity (Cedeño Laurent et al., 2021).

While there have been many studies evaluating the sensor measurement performance for CO_2 and $PM_{2.5}$, there is currently a lack of standard practice in place for sensor performance evaluation (Karagulian et al., 2019). In this paper, we consider a total of six analysis methods to assess the performance of low-cost sensors, with the goal of developing a well-rounded procedure. This is completed through an analysis of the accuracy and precision of two popularly used low-cost indoor air quality sensors based on data collected through co-location testing with reference instruments.

Data Collection

Co-location testing was conducted to collect data on the performance of the Airthings View Plus and Air Gradient Pro sensors, using two reference instruments. The Graywolf

DSII-8 was used as a reference instrument for CO_2 data and the Lighthouse Handheld 3016 was used as a reference instrument for $PM_{2.5}$.

The Airthings View Plus is a low-cost sensor that is wireless, and battery operated. It uses a laser scattering optical particle sensor (Plantower PMS5003) and converts the signal directly to $PM_{2.5}$ concentrations in $\mu g/m^3$ based on internal algorithms (Airthings, 2024). It can measure fine particulate matter from 0 ~ 500 $\mu g/m^3$ and has an accuracy of ± 5 $\mu g/m^3$ + 15% of reading when $PM_{2.5}$ is under 150 $\mu g/m^3$ and ± 5 $\mu g/m^3$ + 20% of reading when $PM_{2.5}$ is above 150 ± 5 $\mu g/m^3$ + 15% (Airthings, 2024) at 10-minute intervals. The Airthings sensor measures CO_2 using a non-dispersive infrared (NDIR) sensor and measures CO_2 levels from 400 ~ 5000 ppm with an accuracy of ±50 ppm ±5 % (Airthings, 2024) at 5-minute intervals. This sensor was selected as it is popular and accessible in the North American market.

Similar to the Airthings sensor, the Air Gradient sensor uses the same optical particle sensor (Plantower PMS5003) for $PM_{2.5}$ measurements. The PMS5003 sensor can measure from 0 ~ 500 $\mu g/m^3$ with a counting efficiency of 50% at 0.3 $\mu g/m^3$ and 98% when greater than 0.5 $\mu g/m^3$ (Zhou Y, 2016). It's important to highlight that while both low-cost sensors utilize the same PMS5003 sensor, there is a discrepancy in how the manufacturers present their specifications. This difference might stem from corrections reported by the manufacturers; however, this information is not publicly available. The CO_2 sensor (SenseAir 8) used in the Air Gradient sensor uses NDIR technology and can measure CO_2 concentrations from 400 ~ 20,000 ppm with an accuracy of ±0.02% volume CO_2 ±3% of reading (SenseAir, 2022). The Air Gradient sensor collects both $PM_{2.5}$ and CO_2 data in 30-second intervals. This sensor was selected mainly because of its open-access software and hardware.

The Graywolf DSII-8 was used as the reference instrument for assessing the accuracy of CO_2 measurements from both low-cost sensors. The DSII-8 sensor uses NDIR technology and measures CO_2 concentrations from 0-10,000 ppm with an accuracy of ±2% of reading ±1 ppm (Graywolf Sensing Solutions, 2022). The Graywolf sensor can collect raw data at 1-minute intervals. It has been used as a reference sensor in previous studies (e.g., Baptista et al., 2022; Demanega et al., 2021; Moreno-Rangel et al., 2018).

The Lighthouse Handheld 3016 was used as the reference device for $PM_{2.5}$ measurements. The Lighthouse sensor uses a light scattering sensor and measures particle number concentration up to 8,000,00/ft^3. It has a counting efficiency of 100% for particles that are greater than 0.45 µm and contains bin sizes from 0.3-0.5, 0.5-1.0, 1.0-2.5, 2.5-5.0, and 5.0-10.0 µm (Lighthouse Worldwide Solutions, n.d.). This sensor has also been used in previous research (Zhang W. et al., 2022) and collects raw data at 1-second intervals. In addition, both reference sensors, Graywolf DSII-8 and Lighthouse Handheld 3016, were selected due to their affordability to other higher-grade instruments and their higher accuracy than low-cost sensors found on the market.

To evaluate the performances of the Airthings and Air Gradient sensors, the four indoor air quality sensors were co-located on a desk in an office of a house in downtown Toronto. The Air Gradient sensors collected both CO_2 and $PM_{2.5}$ data while the Airthings sensor was only able to collect CO_2 data as there was a discrepancy when logging $PM_{2.5}$ data.

While daily occupant activities continued naturally, CO_2 data was collected from May 23, 2023 – May 25, 2023, with a total of 396 data points. $PM_{2.5}$ data was collected from July 17, 2023 – July 19, 2023, with a total of 516 data points. These dates were selected as they provided the most amount of data points where the sensors consecutively logged without any time gaps. The 4 sensors logged 5-minute data and were then used for all statistical analysis.

Analysis Methods

Airthings and Air Gradient sensor performance was analyzed by comparing the concentration measurements with the reference instruments. From the literature review, we identified that some of the most used analysis methods were time-series comparison, linear regression and coefficient of determination, and Pearson correlation coefficient, with RMSE and the Bland-Altman analysis becoming more commonly used in recent studies. As such, these methods were applied in the analysis to assess sensor performance. In addition to these commonly used analysis methods, a paired t-test was also conducted to identify the mean differences between the low-cost sensors to the reference sensors. All analysis was conducted using Excel.

Prior to comparison, the Lighthouse Handheld 3016 measurements were converted from number to mass concentration with an assumed particle density of 1.7 g/cm^3 as the two low-cost sensors log in mass concentrations (i.e., $PM_{2.5}$). The number concentrations in each bin were first converted to volume concentrations based on Eqns (1.1) & (1.2), then to mass concentrations based on Eqns (1.3) & (1.4). Three bins (0.3-0.5 µm, 0.5-1 µm, and 1-2.5 µm) were totaled for $PM_{2.5}$ concentration.

$$r = \sqrt{upper\ limit \times lower\ limit} \quad (1.1)$$

$$V = \frac{4}{3}\pi r^3 \times N \quad (1.2)$$

$$M = V \times 1.7\ g/cm^3 \quad (1.3)$$

$$C = M/V \quad (1.4)$$

where r is the geometric mean of the particle diameter based on the upper and lower limits, V is the total particle volume, N is the number concentration in each bin, and C is the calculated mass concentration for each bin.

In addition to the 5-minute data analysis, aggregated 30-minute data was used to understand the impact of sampling

frequency on sensor performance. The 30-minute data were calculated by averaging CO_2 and $PM_{2.5}$ concentrations. The same analysis methods were then applied to the 30-minute data.

Linear Regression

Linear regression models were developed to identify the relationship between measurements from the low-cost sensors (dependent variable) and the reference sensors (independent variable). The coefficient of determination (r^2), calculated using Equation 2 describes the correlation between the dependent and independent variables found in the linear regression model.

$$r^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \quad (2)$$

where y_i is the dependent variable, $\hat{y}_i$ is the predicted dependent variable, $\bar{y}$ is the dependent mean.

Bland-Altman

Bland-Altman analysis was conducted to illustrate the bias between the low-cost and reference instrument data. First, the difference between the low-cost and reference sensors concentration levels, the median of the low-cost and reference sensors, and the standard deviation (σ) were calculated. The bias, upper level of agreement, and lower level of agreement are then calculated using eq. (3.1, 3.2, and 3.3). Lastly, these values are then plotted for visual examination.

$$Bias = \frac{\sum(y_i - x_i)}{n} \quad (3.1)$$

$$Upper\ LoA = Bias + 1.96 \times \sigma \quad (3.2)$$

$$Lower\ LoA = Bias - 1.96 \times \sigma \quad (3.3)$$

where y_i is the dependent variable, x_i is the independent variable, n is the number of data points, and σ is the standard deviation.

Pearson Correlation Coefficient

Pearson correlation analysis was included to analyze the correlation between the low-cost and reference instruments and is calculated using eq. (4). The coefficient (r) identifies the strength of the correlation between the sensors.

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \quad (4)$$

where x_i is the independent variable, $\bar{x}$ is the mean of the independent variable, y_i is the dependent variable, and $\bar{y}$ is the mean of the dependent variable.

RMSE

RMSE was calculated to quantify the mean difference between the low-cost data and the reference instrument, using eq. (5).

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \quad (5)$$

where $\hat{y}_i$ is the predicted dependent variable, y_i is the dependent variable, and n is the number of data points.

Paired T-Test

A paired t-test was conducted to test the mean of the low-cost and reference instruments to identify if they are significantly different. Furthermore, a normality test (Jarque-Bera Normality Test) was conducted to determine whether the difference between the low-cow sensors and the reference instruments was normally distributed to check for the assumptions of the paired t-test.

Two extreme CO_2 outliers were excluded from the analysis as they were likely caused by interference with the reference sensor (touching or moving the sensor). The outliers were identified as they were detectable when visually analyzing the time-series comparison graphs and were the only points that were above 850 ppm.

Results

The analysis results for the CO_2 and $PM_{2.5}$ measurements comparison are presented in this section.

CO2 Data Analysis

5-minute and 30-minute average CO_2 data analyses are highlighted in the following sections.

5-Minute Interval Data Analysis

Figure 2 shows the time-series comparison of CO_2 concentrations for the Graywolf sensor, Airthings sensor, and Air Gradient sensors. Through visual analysis, Airthings sensor data seems to be closer in value to the Graywolf sensor, with some overestimation. It can also be seen that all elevated concentration periods were captured by both sensors. Further, the low-cost sensors follow consistent trends when compared to the Graywolf sensor. However, the Air Gradient sensor seems to be consistently underreporting the CO_2 concentration levels when compared to the Graywolf sensor.

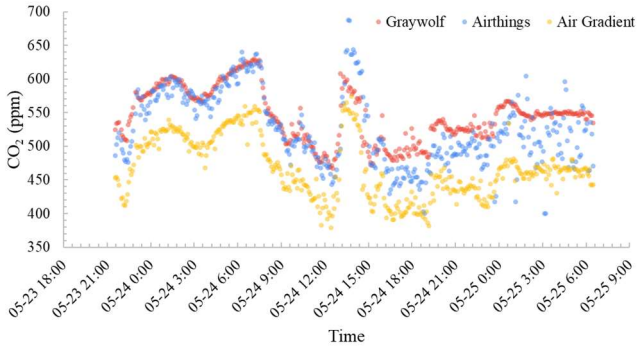

Figure 2: 5-minute interval CO_2 concentration time-series comparison

A linear regression plot comparing the Graywolf sensor data to the Airthings and Air Gradient sensor data is illustrated in Figure 3. A r^2 value of 0.68 was reported when comparing Airthings and Graywolf data. This indicates that 68% of the data was explained by the regression model.

Furthermore, a r^2 of 0.87 was reported when comparing Air Gradient and Graywolf data. This stronger correlation is also indicated by the data points falling closer along the line

of best fit in Figure 3. The results show that the Air Gradient sensor has a stronger correlation with the Graywolf sensor when compared to the Airthings based on both the r^2 and visual comparison.

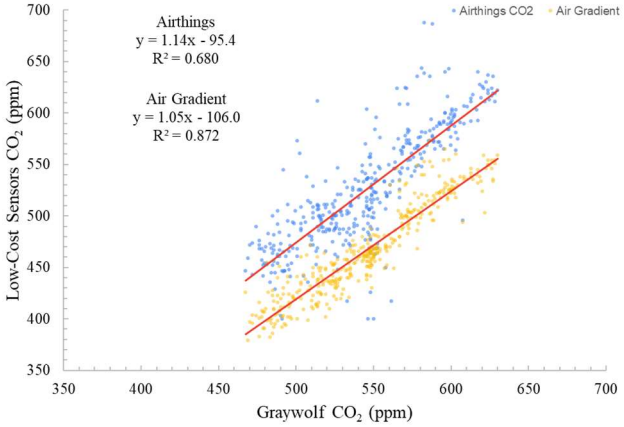

Figure 3: 5-minute interval CO_2 linear regression plot comparing Graywolf and Airthings, and Graywolf and Air Gradient

Figure 4 shows the Bland-Altman analysis comparing Graywolf and Airthings sensors and Graywolf and Air Gradient sensors in a) and b). Figure 4(a) shows there is more of a disagreement when the mean CO_2 concentration is less than 550 ppm. When the CO_2 concentration increases, there is less of a difference between values as the data points are closer to the bias line. The Airthings sensor bias was determined to be 19.42.

Figure 4(b) shows the Air Gradient sensor has a higher bias of 78.34 when compared to the Airthings sensor, indicating that the Airthings sensor is the more accurate sensor. However, the data points are closer to the bias line indicating its measurements are more precise. Similar to the Airthings, it shows more of a disagreement when the mean CO_2 concentration is less than 500 ppm and more of an agreement with increases in CO_2 concentrations.

Table 1 summarizes the 5-minute interval Airthings and Air Gradient sensors results of the Pearson correlation coefficient, the RMSE, and the paired t-test. When comparing the 5-minute interval Pearson correlation coefficient values of the low-cost sensors, Air Gradient has a greater value of 0.93 (p=0.000) when compared to the Airthings. This again, indicates that the Air Gradient sensor has a stronger correlation with the Graywolf sensor, confirming the findings from the linear regression.

RMSE values of 37 ppm and 80 ppm were determined when comparing the Graywolf with Airthings and Air Gradient sensor, respectively. This also indicates that the Airthings sensor measures closer in value. Lastly, results from both paired t-tests conducted using a confidence interval of 95% between Graywolf and Airthings and Graywolf and Air Gradient concluded significant differences between their mean concentrations and the Greywolf concentrations.

Table 1: Additional 5-minute interval analysis method results

Low-Cost Sensor	**Pearson Correlation Coefficient**	**P-value**	**RMSE**	**Paired t-test**
Airthings	0.82	0.000	37	0.000
Air Gradient	0.93	0.000	80	0.000

30-Minute Averaged Data Analysis

The following section shows the analysis results of the averaged 30-minute measurements.

Figure 5 shows the 30-minute averaged time-series comparison between Graywolf, Airthings, and Air Gradient. Like the 5-minute interval time-series comparison found in Figure 2, it is evident that Airthings sensor data is closer in value to the Graywolf sensor, with some overestimation and the Air Gradient sensor is underreporting CO_2 concentrations.

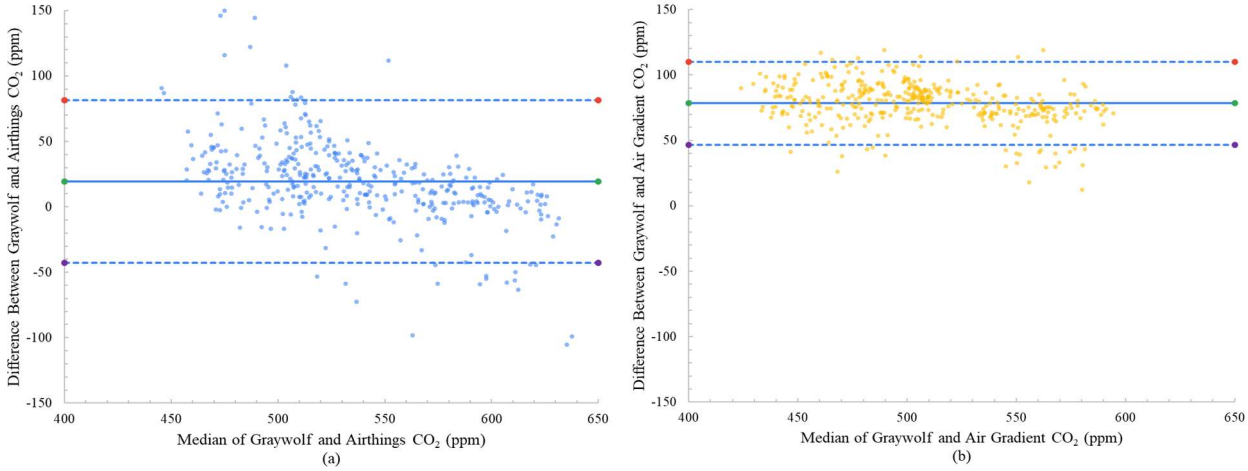

Figure 4: Bland-Altman analysis for CO_2 concentration measurements by (a) Airthings and (b) Air Gradient at a 5-minute interval

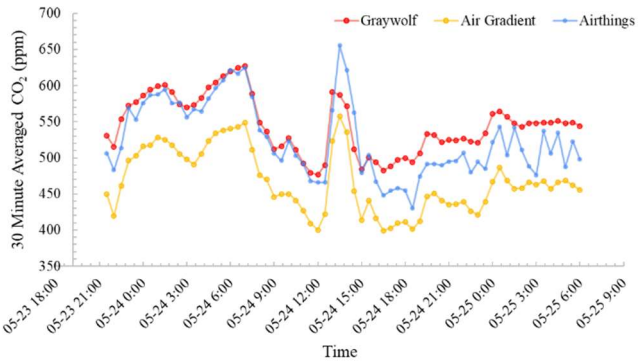

Figure 5: 30-minute interval CO_2 concentration time-series comparison

A linear regression plot comparing the Graywolf sensor data to the Airthings sensor data and the Air Gradient sensor data is illustrated in Figure 6. The linear regression model shows that the r^2 value increased from 0.68 to 0.79 for Airthings and 0.87 to 0.92 for Air Gradient. This indicates that averaging the measurements into a longer sampling interval improves the correlation between the low-cost and reference sensors. This is expected because averaging removes the fluctuations in concentrations.

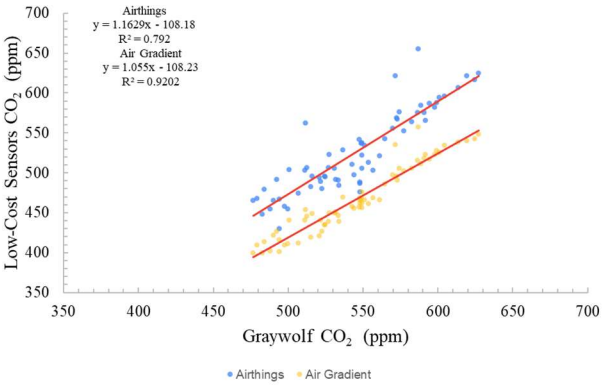

Figure 7: 30-minute interval CO_2 linear regression plot comparing Graywolf and Airthings, and Graywolf and Air Gradient

A Bland-Altman plot comparing Graywolf and Airthings and the Graywolf and Air Gradient sensors' 30-minute interval data is illustrated in Figure 7. Plot (a) illustrates the Airthings sensor and plot (b) illustrates the Air Gradient sensor. Both plots show less data points that fall out of the bounds of the upper and lower limits of agreements. The bias lines remain unchanged from the bias calculated for the 5-minute data. After analyzing the results for the 30-minute interval data found in Table 2, the Airthings and Air Gradient sensors had a stronger Pearson correlation coefficient with an absolute increase of 7% and 3%, respectively. Furthermore, both sensors had a slightly smaller RMSE value than compared to the 5-minute RMSE values. Similar to the 5-minute t-test results, the 30-minute t-test results concluded significant differences.

Table 2: Additional 30-minute interval analysis method results

Low-Cost Sensor	**Pearson Correlation Coefficient**	**P-value**	**RMSE**	**Paired t-test**
Airthings	0.89	0.000	31	0.000
Air Gradient	0.96	0.000	78	0.000

$PM_{2.5}$ Data Analysis

5-minute and 30-minute average $PM_{2.5}$ data analyses are highlighted in the following sections.

5-Minute Interval Data Analysis

Figure 8 shows the time-series comparison of $PM_{2.5}$ concentration between Lighthouse and Air Gradient sensors. Overall, during the sampling period, the Air Gradient sensor seems to be consistently overreporting the $PM_{2.5}$ concentration levels when compared to the Lighthouse sensor. In addition, it captured some elevated concentrations that were not captured by the Lighthouse. This is unexpected as reference instruments generally are more capable of capturing elevated concentrations from

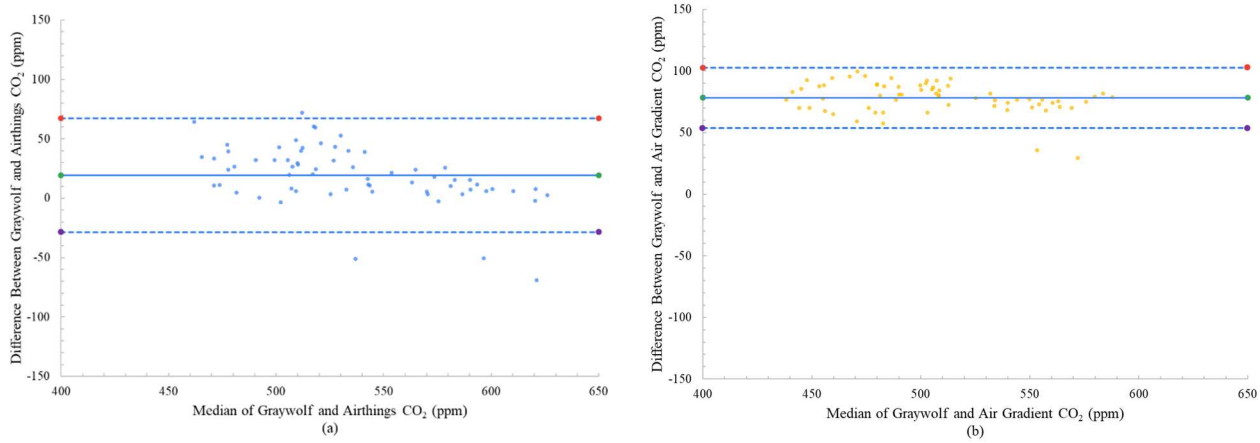

Figure 6: Bland-Altman analysis for CO_2 concentration measurements by (a) Airthings and (b) Air Gradient at a 30-minute interval

different emission sources (Singer & Delp, 2018). Furthermore, the Lighthouse sensor has higher counting efficiencies for most particle sizes when compared to the Air Gradient. This discrepancy is likely caused by the counting algorithm used by the Air Gradient sensor.

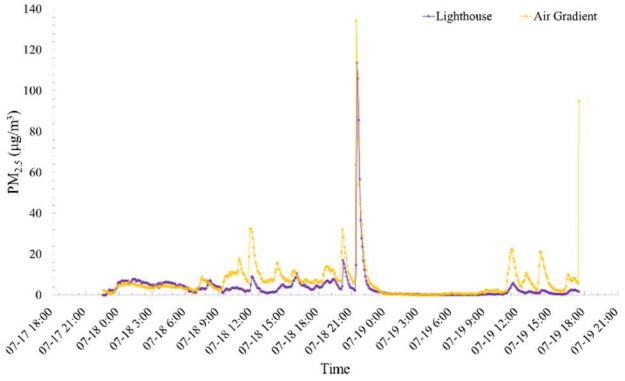

Figure 8: 5-minute interval $PM_{2.5}$ concentration time-series comparison

A linear regression plot comparing the Lighthouse sensor data to the Air Gradient sensor data is illustrated in Figure 9. With a r^2 of 0.83 was reported, the results indicate that 83% of the Air Gradient can be explained by the regression model. In addition, this linear regression plot shows that majority of the data points are clustered at 0,0 and funnel out when the $PM_{2.5}$ concentration increases in both the Air Gradient and Lighthouse sensors.

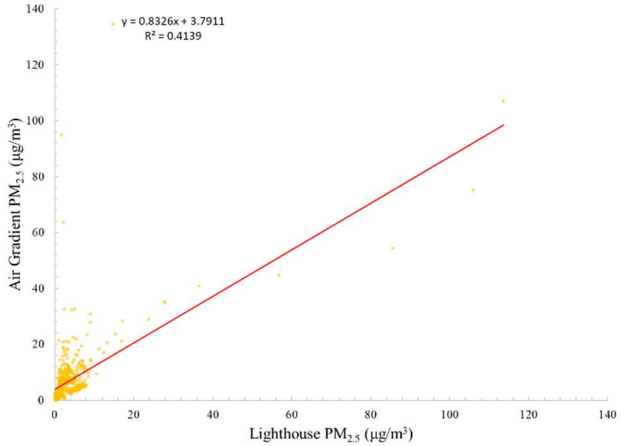

Figure 9: 5-minute interval $PM_{2.5}$ linear regression plot comparing Lighthouse and Air Gradient

A Bland-Altman plot comparing Lighthouse and Airthings sensors is illustrated in Figure 10 This Bland-Altman analysis determined the bias to be -3.15. Figure 10 illustrates that the majority of the data points are located closer to the lower limits of agreement.

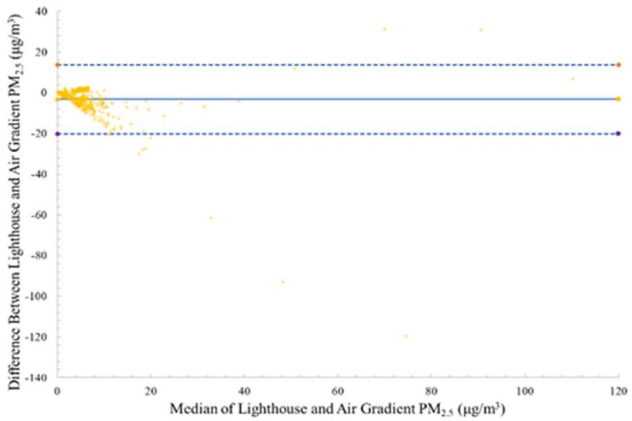

Figure 10: Bland-Altman analysis for $PM_{2.5}$ concentration measurements by Air Gradient at a 5-minute interval

Table 3 summarizes the 5-minute interval results of the Pearson correlation coefficient, the RMSE, and the paired t-test. Analyzing the 5-minute data, the Pearson correlation coefficient was determined to be 0.64 with a p-value of 0.000 when comparing the Lighthouse and Air Gradient sensors. An RMSE value of 9 was determined when comparing the Lighthouse sensor and Air Gradient sensor data. Lastly, paired t-tests conducted between Lighthouse and Air Gradient concluded significant differences.

Table 3: Additional 5-minute interval analysis method results

Low-Cost Sensors	**Pearson Correlation Coefficient**	**P-value**	**RMSE**	**Paired t-test**
Air Gradient	0.64	0.000	9	0.000

The 5-minute interval dataset was then averaged into 30-minute intervals and the analysis methods were conducted and are presented in the following section.

30-Minute Averaged Data Analysis

As seen in Figure 11, the Air Gradient sensor still is overreporting the $PM_{2.5}$ concentration levels when averaged to 30-minute intervals, as compared to the Lighthouse sensor. Figure 11 does not portray the elevated spikes of $PM_{2.5}$ like how it is illustrated in Figure 8. This indicates that converting the data into 30-minute intervals can skew the accuracy of the data.

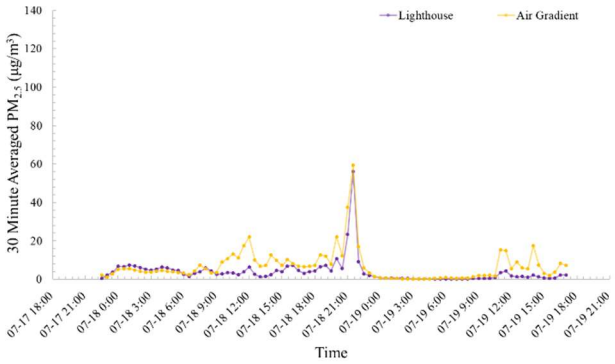

Figure 11: 30-minute averaged $PM_{2.5}$ time-series comparison

A linear regression plot comparing 30-minute $PM_{2.5}$ averaged data for the Lighthouse sensor data to the Air Gradient sensor data is illustrated in Figure 12. A r^2 of 0.748 was reported. Figure 12 shows less data points that funnel out and stray away from the line of best fit compared to Figure 9, resulting in a greater r^2. Therefore, the 30-minute interval provides slightly skewed results.

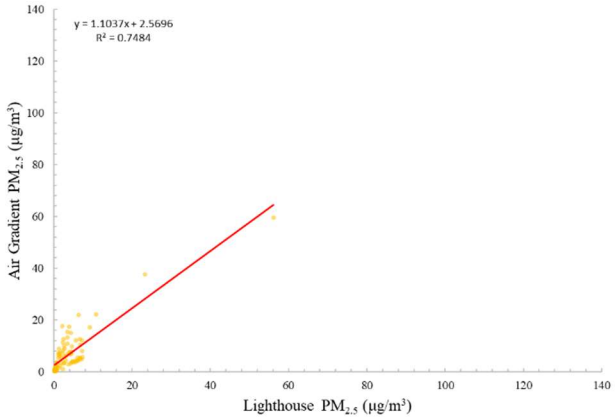

Figure 12: 30-minute averaged $PM_{2.5}$ linear regression comparing Lighthouse and Air Gradient

A Bland-Altman plot comparing Lighthouse and Air Gradient sensors is illustrated in Figure 13. This plot illustrates fewer data points scattered across the lower limits of agreement as the mean increases.

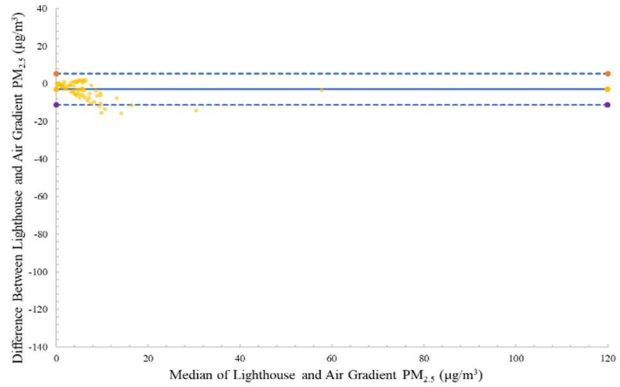

Figure 13: Bland-Altman analysis for $PM_{2.5}$ concentration measurements by Air Gradient at a 30-minute interval

Table 4 summarizes the 30-minute interval results of the Pearson correlation coefficient, the RMSE, and the paired t-test. The Pearson correlation coefficient was determined to be greater than the 5-minute interval Pearson correlation coefficient by 23% and the RMSE value was slightly smaller than the 5-minute interval RMSE value. Like the 5-minute interval paired t-test results, the paired t-test concluded significant differences as well.

Table 4: Additional 30-minute interval analysis method results

Low-Cost Sensors	Pearson Correlation Coefficient	P-value	RMSE	Paired t-test
Air Gradient	0.87	0.000	5	0.000

Discussion

In this work, the analysis of the CO_2 data revealed differences in how the Airthings and Air Gradient sensors performed compared to the Graywolf sensor. The $PM_{2.5}$ data revealed differences in how the Air Gradient sensor performed compared to the Lighthouse sensor. The six analysis methods provide different performance characteristics for each low-cost sensor to provide a comprehensive review of the sensors. If only the Pearson correlation coefficient had been calculated, the Air Gradient sensor would have exhibited better performance than the Airthings for CO_2 measurements. However, if only the RMSE had been calculated, the Airthings sensor would have exhibited a greater performance as the sensor had the lowest RMSE values when evaluating the CO_2 concentrations.

By conducting several analysis methods this results in a well-rounded performance evaluation for the low-cost sensors being tested. In this study, the Airthings sensor was proved to be more accurate for CO_2 measurement based on the results of the Bland-Altman test, the time series visual comparison, and the RMSE calculation. On the contrary, the Air Gradient sensor is seen to follow the Graywolf sensor's trendline more closely than compared to the Airthings sensor for CO_2 measurement based on the Pearson correlation coefficient, time series visual comparison, linear regression, and the coefficient of determination.

From the analysis results, it is challenging to determine which sensor has a better monitoring performance for CO_2 as it depends on which characteristic, precision, or accuracy, is more important for the application. For instance, the Airthings sensor provides more accurate CO_2 measurements over time, but the Air Gradient sensor is more suitable for analyses, such as air change rate estimation, that rely on the changes in CO_2 concentrations over time. Overall, both low-cost sensors perform adequately, and their performance is

generally suitable for occupants monitoring indoor CO_2 concentrations. Additionally, the Air Gradient sensor exhibits reliable performance when compared solely to the Lighthouse sensor $PM_{2.5}$ measurements.

There were a few limitations and future research recommendations identified in this study. Firstly, there could have been more data points included in the analysis. A total of 396 and 516 data points were included in the analysis of CO_2 and $PM_{2.5}$. respectively. A longer monitoring time can further enhance the analysis of a low-cost sensor and provide a more complete picture of how it responds to different concentrations.

Secondly, using multiple of the same sensors would be beneficial and provide a better understanding of the reliability of each sensor's data. The consistency of each model of sensor can be identified, and this will contribute to a greater understanding of each sensor's performance.

Lastly, conducting frequent checks on the low-cost sensors to ensure they are still successfully logging. In this study, the Airthings sensor stopped logging data, therefore resulting in no $PM_{2.5}$ data available for comparison to the Lighthouse sensor. As sensors can have technical problems, frequent check-ins on the sensors can help mitigate this case.

Conclusion

Monitoring indoor air quality is crucial and can help improve human health and comfort. Low-cost air quality sensors are an affordable way to implement indoor air quality monitoring and take preventative measures. Six different analysis methods were implemented in this study to provide a well-rounded understanding of the performance assessment of the low-cost sensors. Through evaluating the CO_2 and $PM_{2.5}$ data from each sensor, it was concluded that the Airthings sensor exhibited greater accuracy, however, the Air Gradient exhibited greater precision for CO_2 measurements. This is recommended in future work as certain analysis methods quantify different parameters such as accuracy and precision.

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