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NEBRASKA DEPARTMENT OF EDUCATION

TO: Clerk of the Legislature
FROM: Dr. Brian L. Maher, Commissioner of Education
SUBJECT: Project Report "The Efficacy of Air Filters in Classrooms on Student Academic and Learning Outcomes"
DATE: 04/6/2026

To whom it may concern:

The project assessed the impact of portable air purifiers (PAPs) on classroom air quality (study 1), student illness-related absenteeism (study 2), and students' attendance and academic and learning outcomes (study 3) in 317 classrooms within 51 elementary schools in Nebraska. The project implemented a cluster-randomized controlled trial with two cohorts of participating classrooms, randomly assigned to have a PAP installed in their classrooms for an academic year. The PAPs installed varied in type, each featuring an added filtration layer. The control condition was a functioning filter-less PAP that circulated air only. Three intervention filter conditions used a HEPA (High Efficiency Particulate Air) filter (treatment 1), a HEPA plus active carbon (gas-phase) filter (treatment 2), and a HEPA plus active carbon plus GUV (Germicidal Ultraviolet) (treatment 3).

Study 1 examined the impact of PAPs on classroom indoor air quality (IAQ). Ventilation rates, which measure the amount of clean outdoor air entering classrooms, were also calculated. As an indirect indicator of IAQ, ventilation rates were included as a confounding variable in the statistical model to adjust for differences in IAQ across schools and classrooms. Results showed that intervention conditions (with PAPs) effectively reduced particle pollution in classrooms, but there was no evidence of reductions in gas-phase contaminants such as VOCs and ozone in the studied classrooms.

Study 2 obtained illness-related absenteeism (IRA) data from NDE to study the potential causal relationship between PAP use and IRA. Results suggest that intervention conditions (with PAPs) decreased IRA during the fall and spring seasons, but there was little reduction in winter, indicating that further research is needed to explore this seasonal variation.

Study 3 found minimal evidence that portable air purifiers in classrooms improved elementary students' attendance or academic achievement. Although attendance, NSCAS English language arts, and NSCAS mathematics outcomes improved slightly from the prior non-intervention year, these improvements occurred equally across intervention and control classrooms, suggesting they were due to broader factors unrelated to the intervention. Attendance was positively related to academic performance, but because the PAP intervention did not increase attendance, it also did not indirectly affect student achievement. When investigating potential differential intervention effects across demographic groups such as gender, race or ethnicity, English learner status, free or reduced lunch eligibility, and rurality, the study found that students who were minoritized, English learners, and eligible for free/reduced lunch had lower academic outcomes in general, consistent across control and intervention conditions. There were minimal isolated and inconsistent effects regarding intervention-related differential effects, and the overall pattern indicated limited differences in intervention effects due to demographic characteristics of students or schools. Overall, the findings indicate that installing portable air purifiers in classrooms did not produce measurable overall academic or attendance benefits within the timeframe of this study.

Special note: About 20-40% of student-level data were ultimately excluded from analyses due to unavailable prior-year or demographic information or duplicate student records. A large percentage of students were reported under multiple teachers, and in many cases, the teachers were in different intervention conditions, which confounded and contaminated the potential treatment effects if included. Very little information was lost at the classroom level, however. As the intervention was assigned at the classroom level, the number of participating classrooms was the critical sample size; thus, the loss of student-level information impacted the precision of within-classroom averages but not the overall precision of the intervention evaluation.

Sincerely,

Brian L. Maher

Brian L. Maher, Ed.D.
Commissioner of Education

The Efficacy of Air Filters in Classrooms on Student Academic and Learning Outcomes

I. Introduction

Pursuant to *Neb. Rev. Stat.* § 79-10, 110.03, the Nebraska Department of Education (NDE) is required to submit a report upon completion of the pilot program.

II. Background

The experimental study was conducted in 317 school classrooms in Eastern Nebraska over two consecutive school years, 2022-23 and 2023-24. Different types of filters were assigned to multiple classrooms within each school. The classrooms included in the research were assigned to one of four conditions (one Control condition and three Treatment conditions), with 85% allocated to the experimental conditions (35% to Treatment 1 (T1), 30% to Treatment 2 (T2), and 20% to Treatment 3 (T3)) and 15% to the control condition. More details on the school recruitment, experimental design, treatment specifications, and equipment pictures are provided in the attached report.

III. Data

The following data was collected over the duration of the project:

1. Particulate pollution (Fine and Coarse Particles)
2. Total Volatile Organic Compounds (TVOC)
3. Ozone Concentrations
4. Carbon dioxide (logged for 2 years to estimate ventilation rates in classrooms)
5. Temperature and Relative Humidity
6. Illness-Related Absenteeism Data (from NDE)
7. Classroom teacher names (to identify classrooms)
8. Student Academic Performance data (English and Math test scores from NDE)

The measurement and data collection methodology is explained below:

- Particle count measurements were performed for one day at each school building for both fall and spring semesters. The data from the 24-hour continuous measurement were separated into occupied and unoccupied periods. On visits to each classroom, a location was selected to place the particle counter, which was positioned such that it could reflect an average condition of the room, taking care to ensure it was neither too close nor too far from the purifier, nor close to the supply/return grills, nor in the direction of any air drafts.
- Total volatile organic compounds and ozone concentrations were measured in all classrooms for approximately 15 minutes during unoccupied periods. The ozone monitor produces noise, and the TVOC probe must be set up each time it is disconnected from the computer or power source. To minimize disruptions and potential disturbances caused by researcher activities, it was decided to conduct these measurements when classrooms were unoccupied—either during outdoor activity sessions, breaks, or after school hours, while capturing near-occupied time conditions.

- The HOBO loggers (CO_2 loggers) were installed in classrooms alongside gateway devices to continuously record Carbon dioxide (CO_2), Temperature (T), and Relative Humidity (RH) throughout the academic year.

IV. Summary

The summary of the results is as follows:

1. The filters in treatment conditions T1 and T2 consistently achieved the most significant reductions in both fine and coarse particles, while T3 showed weaker or inconsistent performance, especially during occupied times (more detailed results are presented in the attached report). The difference in classroom performance among PAPs is attributed to their clean air delivery rate (CADR) specifications, with higher-CADR models performing better. Overall, we found PAPs to be effective in reducing particle pollution in classroom settings. The portable air purifiers did not significantly reduce TVOC or ozone levels in the classrooms we tested, likely because those classrooms had low pollution levels. However, this analysis did not account for variations in classroom ventilation rates, which may contribute to differences in classroom air quality and filter performance. Also, there was no control/interference on the use of fragrances and other supplies for class activities, which generate TVOC. It is possible that TVOC levels were reduced by the air purifiers, but may be offset by the occupants' TVOC-generating activities.
2. We found that installing PAPs in classrooms also reduced illness-related absenteeism (IRA). We also anticipated that increasing classroom ventilation rates would lower IRA, as bringing in clean air would improve indoor air quality (IAQ). However, we did not observe the association expected in ventilation. One possible reason for this inconsistency is that we obtained IRA data from NDE using teachers' names as identifiers. The NDE data lacked classroom numbers; instead, classrooms were identified by teachers' names. In the dataset, a significant number of students (about 40%) were linked to multiple classrooms within their schools, and entries for these students were excluded from the analysis. This removal of many entries may have distorted the dataset and affected the results.
3. Study 3 found minimal evidence that portable air purifiers in classrooms improved elementary students' attendance or academic achievement. Although attendance, NSCAS English language arts, and NSCAS mathematics outcomes improved slightly from the prior non-intervention year, these improvements occurred equally across intervention and control classrooms, suggesting they were due to broader factors unrelated to the intervention.

V. Conclusions or Recommendations

The portable air purifiers effectively reduced particle pollution in classrooms and decreased illness-related absences (IRA). A reduction in the IRA was observed with the use of PAPs during the fall and spring seasons compared to classrooms with PAPs without filters. However, there was no evidence that PAPs lowered gas-phase pollutants, such as TVOC and ozone, in the classrooms included in our sample. From a policy and practice perspective, this study suggests that portable air purifiers represent a valuable but limited tool. PAPs are effective at improving classroom air quality and may help mitigate exposure to airborne particles, particularly in under-ventilated environments. However, they should not be expected to produce immediate or profound improvements in academic performance when implemented in isolation.

VI. Appendices or Attachments

1. Report Attached

The Efficacy of Portable Air Filters in Classrooms on Indoor Air Quality, Absenteeism, and Student Academic Outcomes

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Author Note

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ABSTRACT

The project assessed the impact of portable air purifiers (PAPs) on classroom air quality (study 1), student illness-related absenteeism (study 2), and students' attendance and academic and learning outcomes (study 3) in 317 classrooms within 51 elementary schools in Nebraska. The project implemented a cluster randomized control trial with two cohorts of participating classrooms randomly assigned to have a PAP installed in the classroom for an academic year. The PAPs installed varied in type, each featuring an added filtration layer. The control condition was a functioning filter-less PAP, which served to circulate air only. Three intervention filter conditions used a HEPA (High Efficiency Particulate Air) filter (treatment 1), a HEPA plus activated carbon (gas-phase) filter (treatment 2), and a HEPA plus gas-phase filter plus GUV (Germicidal Ultraviolet) (treatment 3).

Study 1 examined the impact of PAPs on classroom indoor air quality (IAQ). Ventilation rates, which measure the amount of clean outdoor air entering classrooms, were also calculated. As an indirect indicator of IAQ, ventilation rates were included as a confounding variable in the statistical model to adjust for differences in IAQ across schools and classrooms. Results showed that intervention conditions (with PAPs) effectively reduced particle pollution in classrooms, but there was no evidence of reductions in gas-phase contaminants such as VOCs and ozone in the classrooms studied.

Study 2 obtained illness-related absenteeism (IRA) data from NDE to study the potential causal relationship between PAP use and IRA. Results suggest that intervention conditions (with PAPs) decreased IRA during the fall and spring seasons, but there was little reduction in winter, indicating that further research is needed to explore this seasonal variation.

Study 3 found minimal evidence that portable air purifiers in the studied classrooms improved elementary student attendance or academic achievement. Although attendance, NSCAS English language arts, and NSCAS mathematics outcomes improved slightly from the prior non-intervention year, these improvements occurred equally across intervention and control classrooms, suggesting they were due to broader factors unrelated to the intervention. Attendance was positively related to academic performance, but because the PAP intervention did not increase attendance, it also did not indirectly affect student achievement. When investigating potential differential intervention effects across demographic groups such as gender, race or ethnicity, English learner status, free or reduced lunch eligibility, and rurality, the study found that students who were minoritized, English learners, and eligible for free/reduced lunch had lower academic outcomes in general, consistent across control and intervention conditions. There were minimal, isolated, and inconsistent effects regarding intervention-related differential effects, and the overall pattern indicated limited differences in intervention effects due to demographic characteristics of students or schools. Overall, the findings indicate that installing portable air purifiers in classrooms did not produce measurable overall academic or attendance benefits within the timeframe of this study.

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Keywords: indoor air quality, portable air purifiers, ventilation, student academic outcomes, sickness-related absenteeism, randomized trial

The Efficacy of Portable Air Filters in Classrooms on Indoor Air Quality, Absenteeism, and Student Academic Outcomes

More than 50 million US students attend elementary, middle, and high schools, and, on average, they spend more than 6 hours a day for about 180 days per year in school (US Department of Education). Students' academic performance and illness-related absenteeism are influenced by the indoor air quality (IAQ) of their classrooms (Gaihre et al., 2014; Kielb et al., 2015; Mendell & Heath, 2005; Shendell et al., 2004; Wargocki & Wyon, 2017)

A recent quasi-experimental study by Gilraine (2020) found that classrooms installed with air filters are associated with improved mathematics and English scores. Gilraine used data collected during the largest gas leak in United States history. Although no evidence of natural gas pollutants was found in the school environments, the offending gas company installed air filters in every classroom, office, and common area for all schools within five miles of the leak. This study provides evidence that classroom air filtration could be a promising and cost-effective intervention to improve students' academic performance.

Previous work conducted by the UNL's research team also discovered connections between poor classroom air quality and lower students' academic performance in 220 classrooms in the Midwest region. In addition, the team identified that nearly 70% of these sampled classrooms were not meeting the suggested ventilation rate by ASHRAE Standard 62.1 (Deng & Lau, 2019). As reported in Kabirikopaei et al. (2021), a higher ventilation rate during the fall (cooling) season is associated with higher reading scores. Similarly, Mendell et al. (2016) found a potential positive association between classroom ventilation rate and learning, based on data from 150 classrooms in California. In UNL's study, fine particle counts and ozone (O_3) and carbon monoxide (CO) concentrations were all associated with students' learning outcomes and were suggested for investigation in a future experimental study.

The motivation for this experimental study was to conduct a randomized intervention to compare the effects of improved indoor air quality with portable air purifiers (PAPs) on students' learning and sickness-related absenteeism.

Research Questions

The research questions for this project are:

1) Is there a difference between the indoor air contaminant levels in the classrooms with and without the installed PAPs?
2) As the ventilation rate was identified as an important factor in the previous literature, after controlling the ventilation rate in the classrooms, are students in the classrooms with PAPs associated with reduced sickness-related absenteeism when compared to those in the control classrooms?
3) After controlling student demographics, grade, school district, rurality, etc., do students in classrooms with PAPs achieve higher academic and learning outcomes than students in the control condition?

These research questions are investigated through three independent studies reported in the remainder of this document.

Study 1: Effect of Portable Air Purifiers on Indoor Air Quality in Classrooms

Method

Portable air purifiers were installed in 317 classrooms across 51 elementary schools in Nebraska. The research team randomly assigned these classrooms to treatment and control conditions over two consecutive school years, 2022-23 and 2023-24. The distribution of school districts and the corresponding number of classrooms are listed in Table 1.1.

Table 1.1. Recruitment years, schools, and the number of classrooms.

Year	District	Schools	Classrooms
2022-2023	1	10	80
	2	10	66
	3	4	23
	Others	6	31
2023-2024	1	7	80
	2	4	15
	3	10	22
Total		51	317

The research team collected particle count data from 284 classrooms during the Fall and Spring semesters. These classrooms were from grades 3, 4, and 5 across five school districts in Nebraska. The recruitment aimed to include both public and private schools, as well as rural and urban areas. Most participating schools (80%) were public and located in city areas, with only a few private schools from cities. No private rural schools took part in the study. School demographics are reported in Figure 1.1

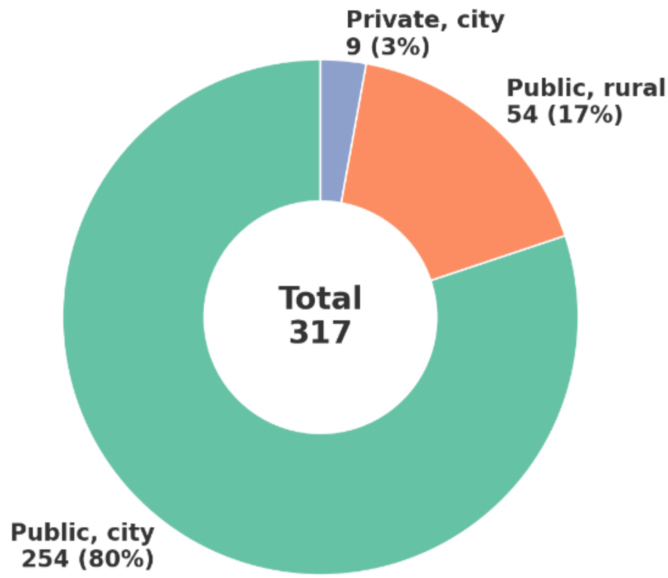

Figure 1.1. School demographics

The experimental setup involved installing air purifiers with various air purification technologies in selected classrooms of the school buildings. Different types of filters were assigned to multiple classrooms within each school. The participating classrooms were divided into four groups: one Control condition and three Treatment conditions. Of these, 85% of classrooms were assigned to the experimental groups (35% to Treatment 1 [T1], 30% to Treatment 2 [T2], and 20% to Treatment 3 [T3]), while 15% served as the control [C]. To maximize the number of classrooms receiving portable air purifiers, the percentage assigned to the control condition was reduced. Treatment 1 was given the highest percentage to increase the number of classrooms with HEPA (High-Efficiency Particulate Air) filters only, as many particle samples were planned. Following this, HEPA with activated carbon filters was assigned, and the fewest classrooms were allocated to Treatment 3, which included PAPs with HEPA, activated carbon, and GUV (Germicidal Ultraviolet) technology. The details about the treatment/control groups and the filter type/technology are listed in Figure 1.2.

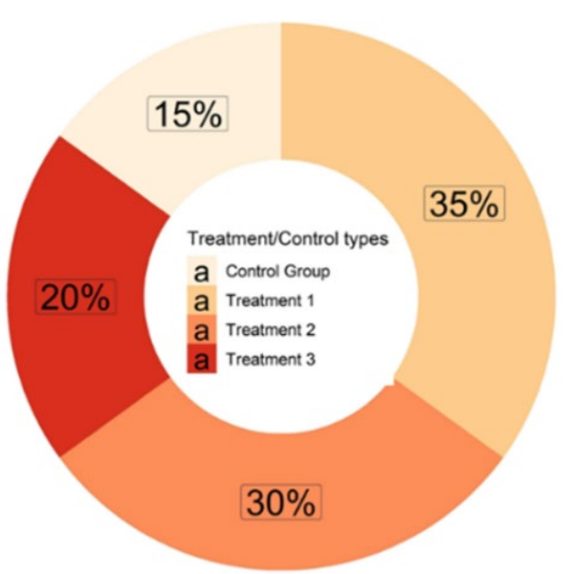

Figure 1.2. Percentage of classrooms in Treatment and Control groups

Randomization was performed at the school building level, ensuring that all four treatment and control conditions were included in each school. However, if a school had fewer than four classrooms available, the treatment and control conditions were randomly distributed across multiple school buildings. School-level differences in air quality due to the age of the buildings were also addressed by including all four treatment and control conditions in each building. Bioaerosol measurements were only taken in a very small sample (~11 classrooms) by collaborators from the University of Nebraska Medical Center with domain expertise, and the results are not presented in this report.

The details about the treatment/control conditions and the filter type/technology are listed in

Table **2.1**. The portable air purifiers installed in the classrooms are displayed in the

Figure **1.1**. From left to right, the units are Alen, Coway, Trioplus, and Okaysou air purifiers. A spreadsheet tool, "Harvard-CU Boulder Portable Air Cleaner Calculator for Schools v1.4" was utilized for guiding the selection of portable air purifiers in this research project (*Portable Air Cleaner Calculator for Schools by Harvard-CU Boulder*, 2021). Detailed specifications of twelve different brands of PAPs were obtained, and comparisons were made to select the best options based on higher CADR values, lower noise levels (ranging from 22-54 dB), and initial and annual filter costs. All PAPs included a HEPA filter at a minimum. The chosen air purifiers also did not include any ionization technology.

Table 2.1. Filtration Types, Brands, and Experimental Group

Sr.	Manufacturer	Company/Model	Filter type	Condition	CADR (cfm)
1	ALEN	Alen BreatheSmart 75i	☑ HEPA filter ☐ Activated Carbon filter ☐ GUV	Treatment Condition I	347
2	Coway Mega	Coway Airmega 400	☑ HEPA ☑ Activated Carbon filter ☐ GUV	Treatment condition II	328
3	Field Controls	Trioplus portable air purifier	☑ HEPA ☑Activated Carbon filter ☑ GUV	Treatment condition III	305
4	Okaysou	Okaysou AirMax8L	Purifier with fan only (Placebo device)	Placebo (Control condition)	125 (n/a)
5	-	-	Outdoor condition	Reference/Outside condition	-

Figure 1.1. Photos from some of the recruited classrooms with equipment.
Note. Pictured left to right: Alen, Cowey, Trioplus, Okaysou.

Procedure

The following measurements were conducted within the classrooms, including assessments of CO_2 levels, particle counts, TVOC, ozone concentration, relative humidity, and temperature. These measurements encompassed occupied and unoccupied periods. Occupied time was defined as the interval during which instructional activities were in session. Although there were minor variations across different school buildings, the schedule generally spanned approximately 08:00 am to 03:00 pm. The period outside of school hours, generally from 03:00 pm to 08:00 am, was categorized as unoccupied time. The details of all the air quality measuring instruments used in the research are mentioned in Table 1.2.

Particle Measurements. Particle count measurements were conducted over a single day at each school building for both fall and spring semesters, resulting in repeated classroom measurements. Logging started between 10:00 am and 11:00 am, with sensors recording data continuously for 24 hours. The loggers were then collected and moved to the next classroom the following day, ensuring a standardized measurement approach across all buildings.

Measurements were taken during both occupied and unoccupied times. Handheld 3016 particle counters from Lighthouse Worldwide Solutions (https://www.golighthouse.com/en) were used to log particle counts. These devices featured six channels for particle sizes of 0.3 µm, 0.5 µm, 1.0 µm, 2.5 µm, 5.0 µm, and 10.0 µm. Data collected from the 24-hour measurements was categorized into occupied and unoccupied periods. The typical classroom setup, including CO_2 loggers, portable air purifiers, and related measuring equipment, is shown in Figure 1.2.

Table 1.2. Indoor Air Quality Measurement Devices

Sr. #	Measurement Parameter	Sensor/Logger Model	Company	Specification
1	Carbon dioxide, Relative Humidity & Temperature	HOBO® MX CO_2 Logger (MX1102) data logger and HOBO® MX Gateway (MXGTW1)	Onset	CO2 (±50 ppm ±5% of reading at 25°C (77°F), less than 70% RH and 1,013 mbar), RH(1% to 70% RH when CO2 sensor is enabled), Temperature (+- 0.21 C from 0 to 50 C)
2	Particle Counts	Handheld 3016, Particle counter	Lighthouse Worldwide Solutions	Zero count level (< 1 count / 5 minutes (per ISO 21501-4))
3	Total Volatile Organic Compounds (Temperature & Relative Humidity)	Direct Sense II Probe	Graywolf Sensing Solutions, LLC	±2%RH <80%RH (±3%RH>80%RH)
5	Ozone	Ozone Monitor - Model 202, Sr. 1691.	2B Technologies, Inc.	The greater of 1.5 ppb or 2% of the reading

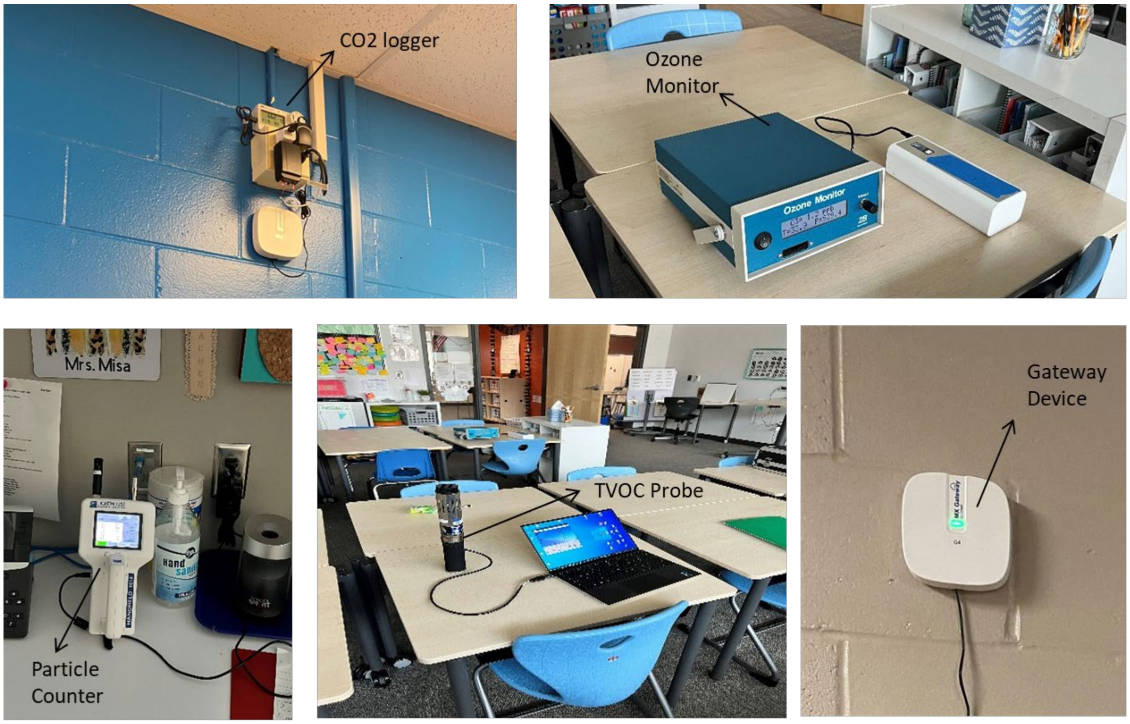

Figure 1.2. Measuring equipment used in classrooms

The particle data were downloaded from the particle counter in cumulative counts, with each particle size representing the total number of particles at that size and the count of all the particles larger than that size. For instance, $PN_{0.3}$ refers to cumulative counts for particles greater than 0.3 µm, $PN_{0.5}$ refers to cumulative counts for particles greater than 0.5 µm, and so on. We then converted the cumulative counts of each size bin to $PN_{2.5}$ and PN_{10}, representing the concentrations of particles with diameters of 2.5 µm or less and 10 µm or less, respectively, measured in counts per unit volume (also referred to as count concentrations). PN Coarse, on the other hand, describes the concentration of particles sized between 2.5 µm and 10 µm and can be derived as the difference between the total count concentrations for PN_{10} and $PN_{2.5}$.

For indoor measurements, all particle counters were set to 288 cycles, corresponding to a sampling time of 30 seconds and a hold time of 4.5 minutes, with a 30-second delay before the start of the first measurement. In each cycle, the particle counter processed a 30-second sample (corresponding to a sampling volume of 0.05 ft^3 or 1.42 Liters) and logged the particle count information. It then took another measurement after a 4.5-minute hold time. This hold time was chosen to prevent potential disturbances caused by the particle counter's noise during operation. On visits to each classroom, a location was selected to place the particle counter, which was positioned such that it could reflect an average condition of the room, taking care to ensure it was neither too close nor too far from the purifier, nor close to the supply/return grills, nor in the direction of any air drafts.

TVOC and Ozone Measurements. Total volatile organic compounds and ozone concentrations (TVOC) were measured in all classrooms for approximately 15 minutes during unoccupied periods. The ozone monitor produces noise, and the TVOC probe must be set up each time it is disconnected from the computer or power source. To minimize disruptions from researcher activities, it was decided to conduct these measurements when classrooms were unoccupied - either during outdoor activity sessions, breaks, or after school hours - while capturing near-occupied time conditions. During visits to each classroom, an appropriate location was selected for the measuring probe or meter. The probe was positioned to reflect an average room condition, ensuring it was neither too close nor too far from the purifier, and not near supply or return grills or in the path of any air drafts.

Measurement of Carbon Dioxide, Temperature, and Relative Humidity. The HOBO loggers (CO_2 loggers) were installed in all classrooms alongside gateway devices to continuously record Carbon dioxide (CO_2), Temperature (T), and Relative Humidity (RH) throughout the entire academic year. The CO_2 data logging was configured to log every 5 minutes.

Estimation of Ventilation Rates in Classrooms. Ventilation is one of the measures to improve indoor air quality; other measures include source control, air cleaning/filtration, and localized exhaust systems (Wargocki, 2013). Carbon dioxide is often used as a tracer gas to estimate ventilation rates in indoor environments (Coley & Beisteiner, 2002). The methods commonly used to estimate ventilation rates are concentration decay, steady state and transient mass balance equation method (Remion et al., 2019). The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) provides guidelines (Standard 62.1) for designing ventilation systems in buildings to maintain acceptable indoor air quality for humans and to minimize adverse health effects. The design outdoor air flow requirement for the Classrooms with students aged nine and over is 6.7 L/s-person at the default occupant density (*ANSI/ASHRAE Standard 62.1*, 2022). Previous studies have shown that classrooms in schools across USA (including Nebraska/ mid-west region) were under-ventilated (Daisey et al., 2003; Deng and Lau, 2019, Shaughnessy et al., 2006).

The steady state method was used to calculate ventilation rates using Equation 1.1 from the method (*ASTM D6245-18*, 2018). Previous research at the University of Nebraska found that the steady-state method is the most reliable for calculating ventilation rates due to its lowest uncertainty (Kabirikopaei & Lau, 2020). For the steady state, ventilation rate calculation, the CO_2 generation rate of 0.303 L/min was used for students, considering the average age range of the students involved in the study (Kabirikopaei and Lau 2020).

$$VR_{lps.person} = 10^6 * \frac{Generation\ Rate\ person\ [\frac{L}{s-per.}]}{C_{steadystate} - C_{outdoor}} \quad (1.1)$$

Where,

$VR_{lps,person}$ is the ventilation rate (L/s-person)

G is generation rate of CO_2 $(\frac{L}{s-per.})$

$C_{steady.state}$ is the zone steady state CO_2 concentration,

$C_{outdoor}$ is the outdoor CO_2 concentration.

Daily ventilation rates were estimated for all classrooms included in the study. There were 317 classrooms included in the study; however, due to faulty sensors and connectivity issues, 13 sensors were excluded and the data from 304 sensors was used to estimate daily ventilation rates. The ventilation rate information was aggregated to seasonal and yearly levels for analysis.

School Information, VR, and Illness-Related Absenteeism (IRA) Data Analysis.

The dataset collected over the course of the study encompassed identifiers for school districts, buildings, grade levels, classrooms, and the names of teachers assigned to each classroom. Additionally, the dimensions of all classrooms were obtained to estimate the design ventilation rates in accordance with ASHRAE Standard 62.1. Subsequently, an identifier for all classrooms was established based on the "Filter" assigned to each, referred to as the "Filter" identifier in the dataset, with levels designated as "Control," "T1," "T2," and "T3." All classroom identifiers within the dataset were anonymized, and a separate "sensor" identifier was utilized as a substitute for the classroom identifier. CO_2 data were employed to estimate daily ventilation rates in classrooms using steady-state methods, integrating all other identifiers acquired from the schools.

The absenteeism data were obtained from the Nebraska Department of Education (NDE). Utilizing the names of all teachers as identifiers, the absenteeism data was matched with the ventilation rate dataset. An identifier within this dataset was employed to filter the data for illness-related absenteeism. The NDE data did not contain classroom numbers as identifiers;

instead, classrooms were identified using the names of the assigned teachers. The dataset, however, contained information on school districts and school buildings. During the process of combining the two datasets, multiple issues were encountered: many teachers' names were spelled differently, some classrooms were identified by last name, others by first name, and others by full name. Consequently, it was necessary to manually review and correct the names in both datasets to enable proper matching based on teacher, school, and district identifiers across the two academic years.

The dataset obtained from the Nebraska Department of Education (NDE) included data from all classrooms in the participating schools. In the dataset, a significant number of students (about 40%) were associated with multiple classrooms within their respective schools, and entries corresponding to these students were excluded from the analysis. This led to the removal of a significant portion of the entries that could have distorted the dataset.

Data Analysis

Temperature and Relative Humidity in Classrooms. The temperature and relative humidity data were also logged by HOBOLOGGERS. Although portable air purifiers did not affect these variables, they are presented here to understand classroom conditions.

The comparison of the monthly average of the indoor air temperature throughout the academic year, along with the seasonal comparison, is shown in Figure 1.3. All the classrooms included in the study were mechanically ventilated, and the temperature of the classrooms was maintained at specific set points. The average temperature across the full sample shows that indoor temperatures were slightly lower in Winter than in Fall and Spring.

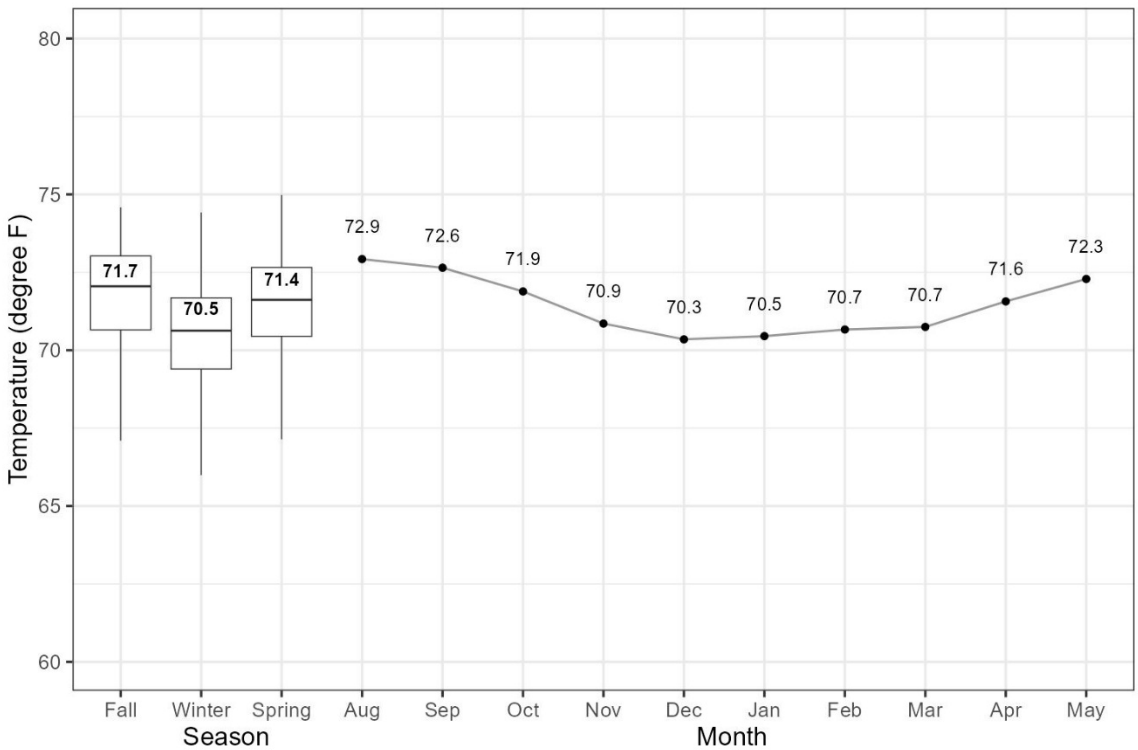

Figure 1.3. Seasonal and Monthly Variation in Temperature in the School Classrooms

Similarly, the monthly profile of the average relative humidity of the classrooms is shown in Figure 1.6. There was a significant difference in relative humidity during the winter months, when the humidity was lowest. The fall and spring seasons had a higher average relative humidity than the Winter season. The research team at the University of Nebraska has also found similar results in a previous large-scale measurement study. (Kabirikopaei, 2021).

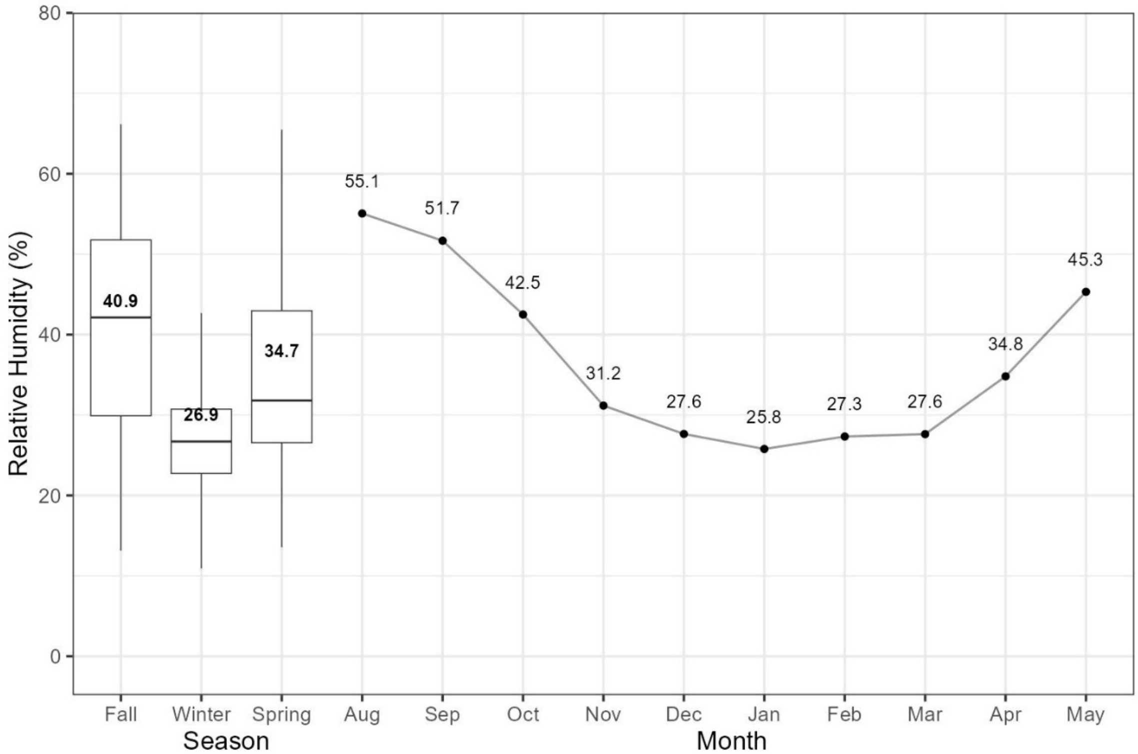

Figure 1.6. Seasonal and Monthly comparison of Relative Humidity in the School classrooms

Particle Data Results. The data from the 24-hour continuous measurement were separated based on occupied and unoccupied time. The raw cumulative particle counts were converted to cumulative counts/0.05ft^3 for each particle size. $PN_{0.3}$ refers to cumulative counts for particles greater than 0.3 µm, $PN_{0.5}$ refers to cumulative counts for particles greater than 0.5 µm, and so on. In our experimental setup, all the treatment types, T1, T2, and T3, had HEPA filters; although their CADR values varied slightly, for the final aggregated particle data analysis, all three treatments were considered as the same category (as all the filters performed particle filtration), referred to as "Treatment". Comparisons were then made against the "Control" condition.

The summary statistics of fine and coarse particle counts measured across all school classrooms throughout the study are presented in Table 1.3 and 1.5.

Table 1.3. Summary Statistics of Fine Particles (counts/0.05 ft3)

Occupancy	Filter	MIN	P25	P50	MEAN	P75	MAX
occupied	Control	642	2956	7360	9410	12244	35930
occupied	T1	470	2432	4671	7811	9213	31574
occupied	T2	494	2088	4326	8612	11423	56045
occupied	T3	546	3261	6255	10492	16592	46639
unoccupied	Control	703	2250	3953	6321	9239	29008
unoccupied	T1	297	1279	2205	4261	5252	34966
unoccupied	T2	179	987	2251	3462	4472	17244
unoccupied	T3	185	1924	3432	5334	6036	29359

Table 1.5. Summary Statistics of Coarse Particles (counts/0.05 ft3)

Occupancy	Filter	MIN	P25	P50	MEAN	P75	MAX
occupied	Control	18	150	244	330	364	2105
occupied	T1	8	151	223	276	335	854
occupied	T2	27	153	213	249	296	944
occupied	T3	12	162	224	278	302	880
unoccupied	Control	4	30	45	58	78	185
unoccupied	T1	1	21	35	45	50	355
unoccupied	T2	0	18	30	44	50	488
unoccupied	T3	2	20	35	42	60	185

In our study, the overall classroom-level ventilation ranged from 2.4 L/s-person to 12.8 L/s-person, with an average of 5.5 L/s-person. Classrooms within ±10% (i.e., 90% to 110% of the design value per ASHRAE Standard 62.1) were referred to as “At Design VR”. There were 50 classrooms out of 304 with ventilation rates at the design ventilation rate, while 208 classrooms had ventilation rates below the lower bound of the design VR range, and 46 classrooms had ventilation rates above the upper bound of the design VR range. In percent terms, as shown in Figure 1.7, 68 % classrooms were under-ventilated, 16% were at the design value, and 15% were over-ventilated.

Figure 1.7. Percentage of classrooms at, above and below design ventilation rate as per ASHRAE Standard 62.1.

The ventilation rates estimated using this steady-state method were then adjusted to the mean design ventilation rate for all classrooms (per ASHRAE Standard 62.1) to obtain a ventilation rate centered on the design rate, referred to as the Mean-Centered Ventilation Rate (VR_{CM}). This was done to interpret model results with reference to the design ventilation rate rather than an average value or zero. The design ventilation rates for the classrooms were constant and did not change daily. Using steady-state methods to calculate ventilation rates, it was assumed that the ventilation rate, outdoor CO2 levels, and the number of students remained constant throughout the day. The design ventilation rates and outdoor CO2 levels stayed nearly the same each day within the same classroom; however, classroom occupancy varied, leading to changes in CO2 concentrations and, consequently, different amounts of outdoor air available to each person (resulting in different calculated ventilation air each day). Although the computed ventilation rate is not directly related to occupancy, the steady-state CO2 concentration is. Therefore, the daily variation in estimated ventilation rates in our sample reflects changes in the outdoor air available per person, which depends on occupancy. See Figure 1.8 for the distribution of average ventilation rates across monitored classrooms.

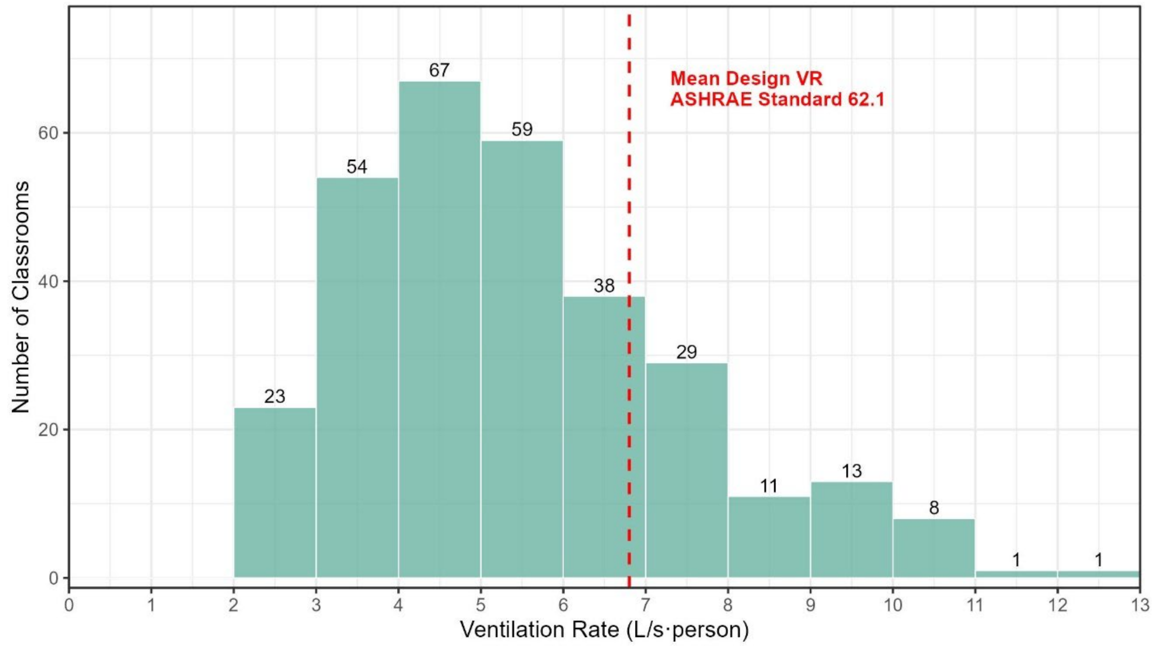

Figure 1.4. Distribution of average ventilation rates (L/s·person) across monitored classrooms

Statistical Model and Results from Particle Models

Two statistical models were developed for particle data, one for fine particles and the other for coarse particles.

Generalized Linear Mixed Effects Model for Fine Particles. A generalized linear mixed-effect model (GLMM) was used, estimated via maximum likelihood with a Laplace approximation. This approach suited the study because of the complex sampling process: districts were recruited to access buildings, and classrooms were sampled within these buildings. Variations among districts by building and HVAC standards, similarities within districts, and differences within buildings based on location introduce random variability at the district, building, and classroom levels. These random effects are modeled alongside fixed effects, such as treatment condition and ventilation rate. The GLMM also enables the analysis of non-normal response variables by assuming different distributions and incorporating suitable link functions.

These results suggest that differences between schools accounted for more of the variability in fine particles (PM2.5) than differences among sensors within the same school. This outcome is reasonable, as schools differ in factors such as geographical location, type of mechanical systems, and building age. In contrast, classrooms within the same school are likely to share similar conditions, leading to ventilation rates relatively close to each other within a building but greater variability across schools.

The response variable was $PN_{2.5}$, modeled using a negative binomial distribution, which is suitable for over-dispersed count data (where the variance exceeds the mean, with a dispersion parameter of 3.28). The fixed effects included the Filter type (Control, T_1, T2, T3), Centered Mean Ventilation Rate per person (VR_{CM}), Occupancy Status (occupied vs unoccupied), and the interaction between Filter type and Occupancy Status. Random intercepts were specified for School and Sensor nested within School to account for the hierarchical complex sampling structure.

The model equation is given by:

$$log(PN_{2.5}) = \beta_0 + \beta_{T_1} I_{T_1} + \beta_{T_2} I_{T_2} + \beta_{T_3} I_{T_3} + \beta_{VR_{CM}} x + \beta_{occ} I_{occ} + \beta_{T_1:occ}\left(I_{T_1} I_{occ}\right) + \beta_{T_2:occ}\left(I_{T_2} I_{occ}\right) + \beta_{T_3:occ}(I_{T_3} I_{occ}) + u_{sch} + u_{sch:class}$$

Where,

$I_{T_1}, I_{T_2}, I_{T_3}$ = the dummy variables for Filter categories T_1, T_2 and T_3, respectively

$I_{T_1}, I_{T_2}, I_{T_3}$ equal to 1 for filters T_1, T_2 and T_3 and 0 otherwise, respectively

I_{occ} = the dummy variable for occupancy (unoccupied = 0, occupied =1)

x = represents the centered mean ventilation rate value

β_0 = intercept (baseline: Class with Control filter during unoccupied time at VR_{CM}),

$\beta_{T_1}, \beta_{T_2}, \beta_{T_3}$ = coefficients for difference between Filters T_1, T_2, T_3 relative to Control during unoccupied periods,

$\beta_{VR_{CM}}$ = effect of the Mean Centered Ventilation rate (VR_{CM}),

β_{occ} = difference between coefficient for occupancy (occupied vs. unoccupied) under the Control filter,

$\beta_{T_1.occ}, \beta_{T_2.occ}, \beta_{T_3.occ}$ = difference between occupied vs. unoccupied additional occupancy effects specific to Filters T_1, T_2, and T_3, respectively

u_{sch} = school-level random effect capturing variation $PN_{2.5}$ across school buildings

$u_{sch:class}$ = sensor level random intercept capturing variation among classrooms nested within different school buildings

The fixed effects estimates are presented in Table 1.4. The intercept (β_0) which represents the expected log count of $PN_{2.5}$ under baseline conditions, was 8.65 ($p < 0.05$). Relative to the Control filter, $PN_{2.5}$ was significantly reduced under all filter conditions: T1 (-0.60, $p < 0.05$), T2 (-0.67, $p < 0.05$), and T3 (-0.36, $p <0.05$). The effect of Mean Centered Ventilation Rate (VR_{CM}) was positive but non-significant (0.03, $p = 0.222$). Occupied status was associated with a significant increase in $PN_{2.5}$ (0.37, $p < 0.05$). All filters showed significant positive interaction effects with occupancy, indicating that filter-related reductions in $PN_{2.5}$ were attenuated when classrooms were occupied.

The results demonstrate that all three tested filters (T1, T2, T3) significantly reduced $PN_{2.5}$ concentrations relative to the control, confirming their effectiveness in particle reduction under baseline (unoccupied) conditions. However, occupancy significantly increased $PN_{2.5}$ levels, and the positive interaction terms indicate that the particle-reducing benefits of filters were partially offset when classrooms were occupied. This likely reflects increased particle resuspension and human emissions during occupancy. Ventilation, while expected to influence indoor particle dynamics, did not show a significant association with $PN_{2.5}$ in this model. Overall, the modeling results highlight the importance of considering both filter technology and human occupancy patterns in evaluating indoor air quality interventions.

Table 1.4. Model output for the predicted log fine particles

Predictor	Estimate	Std. Error	z value	p-value
β_0	8.65	0.17	49.86	< 0.05 *
β_{T_1}	-0.60	0.14	-4.26	< 0.05 *
β_{T_2}	-0.67	0.14	-4.79	< 0.05 *
β_{T_3}	-0.36	0.15	-2.41	<0.05 *
$\beta_{VR_{CM}}$	0.04	0.03	1.22	0.222
β_{occ}	0.37	0.12	3.14	<0.05 *
$\beta_{T_1.occ}$	0.45	0.15	3.05	<0.05 *
$\beta_{T_2.occ}$	0.52	0.15	3.50	< 0.05 *
$\beta_{T_3.occ}$	0.40	0.16	2.57	<0.05 *

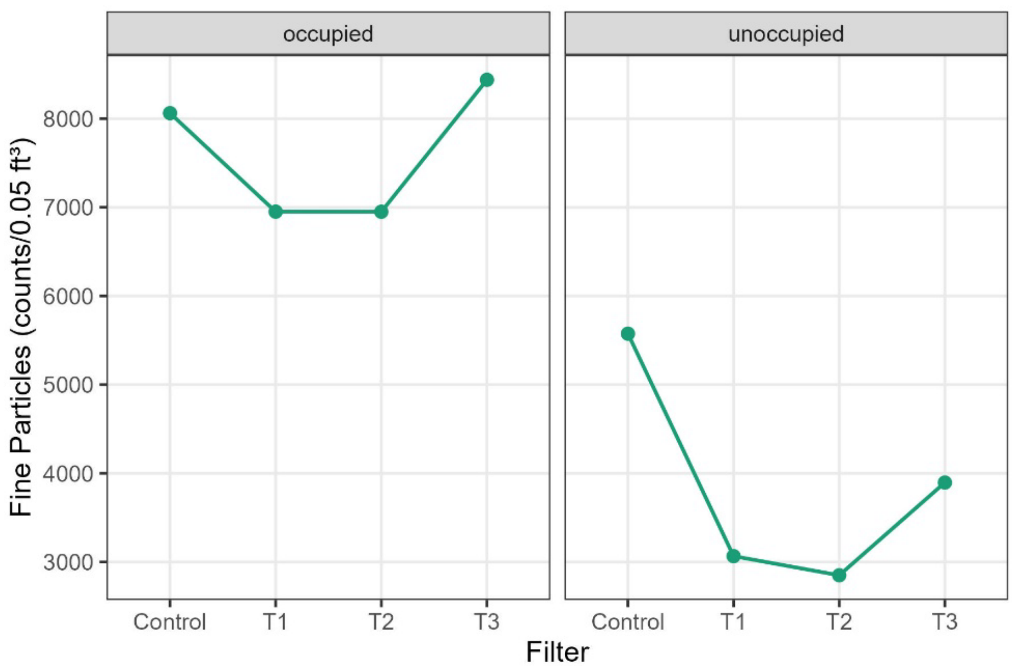

Figure 1.5. Mean predicted Fine particles (counts/0.05 ft3) from GLMM

Generalized Linear Mixed Effects Model for Coarse Particles. A generalized linear mixed-effect model (GLMM) was fitted to coarse particle number concentrations (PN_{Coarse}) using the same justification and specifications described in the previous section. A negative binomial distribution with log-link was employed (dispersion parameter = 2.54) to account for overdispersion. The fixed and random effect specifications were identical to the prior model.

The model equation is given by:

$$\begin{aligned} log(PN_{coarse}) = \beta_0 + \beta_{T_1} I_{T_1} + \beta_{T_2} I_{T_2} + \beta_{T_3} I_{T_3} + \beta_{VR_{CM}} x + \beta_{occ} I_{occ} + \beta_{T_1:VR_{CM}} I_{T_1} \\ + \beta_{T_2:VR_{CM}} I_{T_2} + \beta_{T_3:VR_{CM}} I_{T_3} + \beta_{T_1:occ} \left(I_{T_1} I_{occ} \right) + \beta_{T_2:occ} \left(I_{T_2} I_{occ} \right) \\ + \beta_{T_3:occ} (I_{T_3} I_{occ}) + u_{sch} + u_{sch:class} \end{aligned}$$

Where all variables and parameters were identical to those described in the previous section. The fitted model demonstrated satisfactory convergence. The deviance was 5486.4, with an AIC of 5516.4 and a BIC of 5580.3. Scaled residuals ranged from -1.50 to 7.90, with most near zero, indicating adequate model fit despite a few high-positive residuals. The random intercept variance for School was 0.047 (SD = 0.216), while Sensor within School accounted for 0.026 (SD = 0.160). Thus, variability among schools was slightly higher than among sensors within schools.

Table **1.7** shows the model output for the fixed effects in the coarse particle model.

All filters (T1, T2, T3) significantly reduced coarse particles compared with the control under baseline conditions i.e. unoccupied time and at Mean Design Ventilation Rate (MDVR). The Treatment condition (T1) had the highest reduction (β_{T_1}=-0.44, $p < 0.05$) followed by T2 (β_{T_2}=-0.40, $p < 0.05$) and T3 (β_{T_2}=-0.40, $p < 0.05$) The main effect of ventilation rate was marginally non-significant ($\beta_{VR_{CM}}$=-0.09, $p > 0.05$), suggesting a tendency for higher ventilation to reduce coarse particles. Notably, the interaction of T2 and VRCM was significant ($\beta_{T_2:VR_{CM}}$= 0.11, p < 0.05), indicating that the reduction in coarse particles is offset as ventilation increased. Occupancy was the most influential factor, associated with a dramatic increase in coarse particle concentrations ($\beta_{occupied}$= 1.90, p < 0.05), consistent with human activity and resuspension as dominant contributors to coarse particles. All filters (treatment conditions) showed positive interaction effects with occupancy, implying that their particle-reducing benefits were diminished when classrooms were occupied. This effect was most substantial for T1 ($\beta_{T_1:occ}$=0.44 p < 0.05) followed by T2 ($\beta_{T_2:occ}$= 0.36, p < 0.05) and T3 ($\beta_{T_3:occ}$= 0.33, p < 0.05).

Table 1.7. Model output for the predicted log coarse particles

Predictor	*Estimate*	*Std. Error*	*z value*	*p-value*
β_0	3.54	0.12	28.97	< 0.05 *
β_{T_1}	-0.44	0.14	-3.15	< 0.05 *
β_{T_2}	-0.40	0.14	-2.85	< 0.05 *
β_{T_3}	-0.33	0.15	-2.28	< 0.05 *
$\beta_{VR_{CM}}$	-0.09	0.05	-1.84	0.07
$\beta_{occupied}$	1.90	0.13	14.13	< 0.05 *
$\beta_{T_1:VR_{CM}}$	0.07	0.06	1.30	0.195
$\beta_{T_2:VR_{CM}}$	0.11	0.05	1.99	< 0.05 *
$\beta_{T_3:VR_{CM}}$	0.09	0.06	1.53	0.127
$\beta_{T_1:occ}$	0.44	0.17	2.55	< 0.05 *
$\beta_{T_2:occ}$	0.36	0.17	2.08	< 0.05 *
$\beta_{T_3:occ}$	0.33	0.18	1.84	< 0.05 *

Figure 1.6 displays predicted coarse particle concentrations under different filter conditions (Control, T1, T2, T3), broken down by occupancy status. Each colored line represents a different ventilation level: orange indicates the mean design ventilation rate (MDVR) for all classrooms according to ASHRAE Standard 62.1. Green lines show rates 20% higher than

MDVR, while purple lines represent rates 20% lower than MDVR for all classrooms in the study.

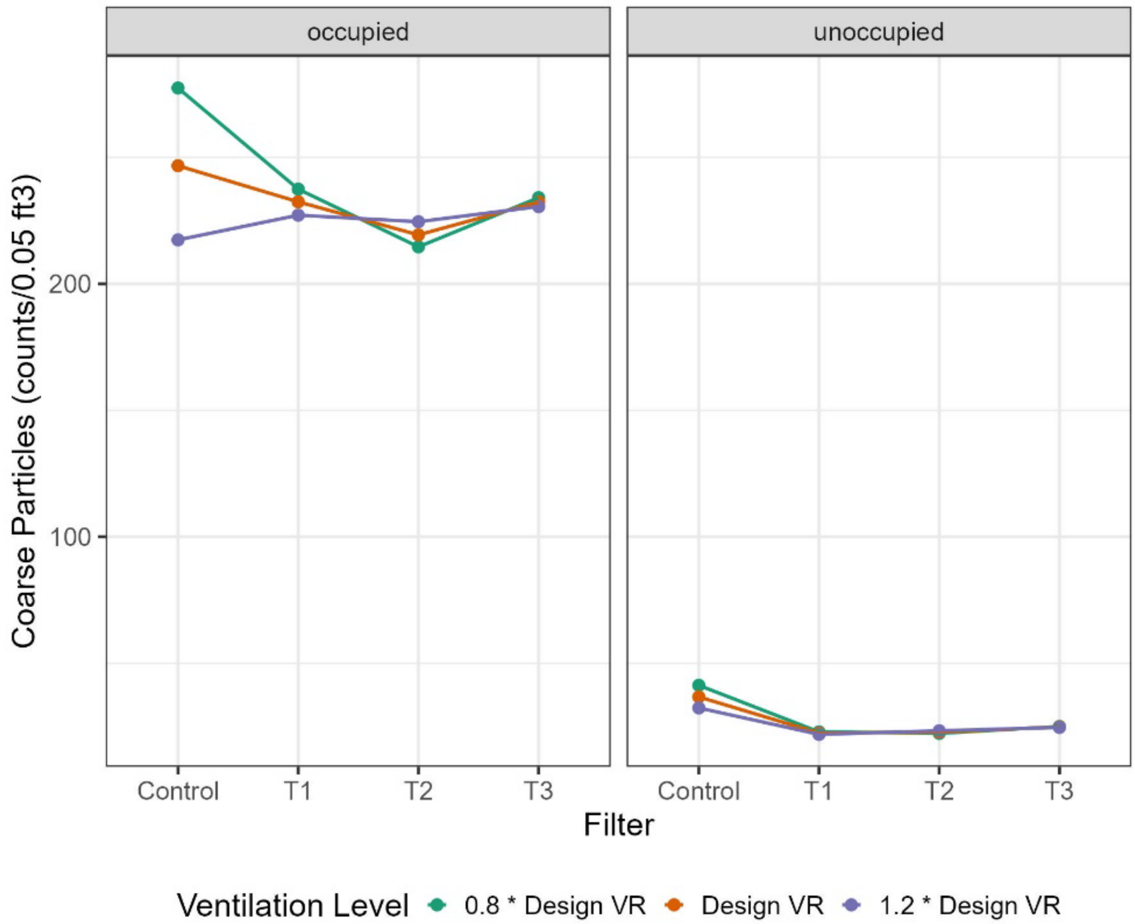

Figure 1.6. Mean predicted Coarse particles (counts/0.05 ft3) from GLMM

During occupied periods, particle concentrations were consistently higher across all treatment and control conditions compared to unoccupied times, which is expected since occupancy leads to particle generation and dispersion. At MDVR and at a ventilation rate 20% lower than MDVR, predicted particle counts were lower for all treatment conditions than for control conditions. However, when the ventilation rate was 20% higher than MDVR, no treatment effect was observed. During unoccupied times, predicted averages showed a significant decrease in coarse particles in the treatment groups compared to the control. Overall, the model indicates that both filter performance and ventilation help reduce coarse particles, but these gains are mitigated by occupancy-related resuspension and emissions.

Summary of Particulate Matter Results. The statistical modeling results showed that for coarse particles, there was a significant reduction in particle count during unoccupied time at each ventilation rate (20% lower than MDVR, at MDVR, and 20% higher than MDVR). During occupied time, there were significant reductions in coarse particles at a ventilation rate 20% lower than MDVR and at MDVR, but a minimal increase (practically no increase) in coarse particles at a ventilation rate 20% higher than MDVR. For the control condition, the predicted coarse particles were higher at lower ventilation (20% lower than MDVR) and lower at higher ventilation (20% higher than MDVR). This shows a negative association of ventilation rate and coarse particles.

For fine particles, significant reductions were observed during unoccupied time across all treatments, whereas during occupied time, reductions were observed for T1 & T2 but not for T3. The particle counts were, in fact, higher in T3 than in the control. Occupancy is also an influential factor for both particle size ranges, significantly increasing particle concentration and diminishing filter benefits. The filters in treatment conditions T1 and T2 consistently produced the most significant reductions in both fine and coarse particles (except at a ventilation rate 20% higher than MDVR during occupied time, where coarse particles increased), while T3 showed weaker or inconsistent performance, particularly during occupied time.

Ventilation rates had no significant effect on fine particles, but ventilation affected filter performance for coarse particles. Finally, the variability in particle counts was more strongly attributable to differences between schools than between classrooms within schools, highlighting the importance of building-specific factors.

TVOC and Ozone Data

Total Volatile Organic Compounds (TVOC) and Ozone Concentrations were also measured in this study. Details of the measurements and results of the data analysis are presented in this section.

TVOC Measurements. The research project included 317 classrooms, and TVOC measurements were conducted in 149 (about 47%). Specifically, 28 classrooms were measured in the Control category, 41 in Treatment 1, 41 in Treatment 2, and 39 in Treatment 3. Additionally, measurements were carried out outside some of the school buildings for the same duration, referred to as "Outdoor" measurements. Outdoor measurements were obtained from 28 different school buildings. Certain schools were in close geographic proximity to each other; therefore, representative measurements were obtained at one school and used as reference measurements for nearby schools. The summary of the total number of classrooms measured is presented in Table .

Table 1.8. Number of TVOC measurements from each category

Category	Number of Classrooms
Outdoor	28
Control	69 (C=28, T1=41)
Treatment	80 (T2=41, T3=39)

The measurements commenced in the Fall of 2022 and were recorded as 15-minute samples collected from various school districts over 2 years. Each school building was surveyed using four measurements, each corresponding to a classroom assigned to a Treatment condition (T1, T2, or T3) or a Control condition. In our experimental design, treatments T2 and T3 used gas-phase filters containing activated carbon, whereas treatment T1 did not. For overall analysis, treatments T2 and T3—with activated carbon filters—were consolidated into a single treatment condition, while the Control condition and T1 were similarly combined into a single Control condition.

Ozone Measurements. Ozone measurements were conducted in 128 classrooms (about 40% of the total 317 participating classrooms). Specifically, 28 classrooms were measured in the Control category, 35 in Treatment 1, 33 in Treatment 2, and 34 in Treatment 3. Additionally, measurements were carried out outside some of the school buildings for the same duration, referred to as "Outdoor" measurements. Outdoor measurements were obtained from 28 different school buildings. Certain schools were in close geographic proximity to each other; therefore, representative measurements were obtained at one school and used as reference measurements for nearby schools. The condition wise summary of the number of classrooms is presented in Table 1.9.

Table 1.9. Number of Ozone measurements from each category

Category	Number of Classrooms
Outdoor	28
Control	61 (C=26, T1=35)
Treatment	67 (T2=33, T3=34)

Ozone concentrations were measured for 15 minutes during unoccupied classroom time, at the same time as TVOC readings were acquired. The 15-minute means of ozone concentration ranged from 1.0 ppb to 25.8 ppb in Control classrooms (C and T1) while the concentrations ranged from 1.8 ppb to 22.4 ppb in treatment classrooms (T2 & T3). Ozone concentrations were also measured outside the school buildings for the same time period and the average ozone concentration outdoors ranged from 2.6 ppb to 47.1 ppb. The indoor ozone levels in all treatment and control conditions were within acceptable limits by the National Institute for Occupational Safety and Health (NIOSH) & Occupational Safety and Health Administration (OSHA) in both treatment and control conditions. The NIOSH recommended exposure level (REL) is C (ceiling) 0.1 ppm, or 100 ppb and the OSHA permissible exposure limit (PEL) is TWA (time weighted average) 0.1 ppm (*CDC - NIOSH*, 2019). All classrooms had ozone concentrations below 100 ppb. The average indoor ozone concentration in classrooms in this study was 8.6 ppb, with a standard deviation of 5.8 ppb. Conversely, the overall outdoor average ozone concentration was 31.9 ppb, with a standard deviation of 12.5 ppb.

A study conducted at Lawrence Berkeley National Laboratory found that activated carbon filters were effective in reducing ozone concentration over long periods (Gundel et al., 2002). The ozone concentrations in the experiment ranged from 100 to 126 ppb. In our experimental setup, the T2 and T3 conditions had activated carbon filters in addition to the HEPA filters and were expected to reduce classroom ozone concentrations. The results of the raw data analysis did not show that the treatment conditions (T2 & T3) consistently had lower concentrations than the Control conditions (C and T1).

Summary of TVOC and Ozone Results. The portable air purifiers did not significantly reduce TVOC or ozone levels in the classrooms we tested, likely because those classrooms had low pollution levels. However, this analysis did not account for variations in classroom ventilation rates, which may contribute to differences in classroom air quality and filter performance.

Study 2: Impact of Air Filtration on Student Illness-Related Absenteeism

Method

A generalized linear mixed-effects model was used, as described in the particle model. Daily absenteeism was modeled with a negative binomial distribution. The distribution of the total number of students absents in all classrooms involved in the study in the academic years 2022-23 and 2023-24 is presented in Figure 2.1. Because some models did not converge with this distribution, the absenteeism data were eventually modeled using a binomial distribution. The results from all models that converged with the negative binomial distribution were compared to those obtained with a Poisson distribution, and the coefficients were found to be very similar. Classroom-level daily ventilation rates, calculated as described in Study 1, were used to compute moving averages. These averages were calculated over 3, 5, 7, 10, 14, 21, and 30 days. The goal was to understand how ventilation rates influence illness-related absenteeism in classrooms. The impact of various moving-average ventilation rates was modeled to assess whether ventilation rates with portable air purifiers installed in classrooms affect student absenteeism. To prepare the dataset, the design ventilation rate per ASHRAE Standard 62.1 for each classroom was subtracted from the daily ventilation rates (estimated using the steady-state method). This allows interpretation of ventilation rates relative to the design ventilation rate for each classroom. All moving averages of the design ventilation rates remained constant across classrooms, since these rates (calculated per ASHRAE Standard 62.1) represent the system's designed values, which did not change during the study.

This ventilation rate was referred to as the Adjusted Ventilation Rate (aVR), and all moving averages (3, 5, 7, 10, 14, 21, and 30 days) were computed for the aVR. Then, classroom-level averages were calculated for all moving averages of Adjusted Ventilation Rates and referred to as the Adjusted Mean Classroom Ventilation Rate (aVR_{MC}). Similarly, all school and district level averages were calculated for all moving averages (for 3, 5, 7, 10, 14, 21, and 30 days) of Adjusted Ventilation Rates (aVR) and referred to as Adjusted Mean School Ventilation Rate (aVR_{MS}) and Adjusted Mean District Ventilation Rate (aVR_{MD}).

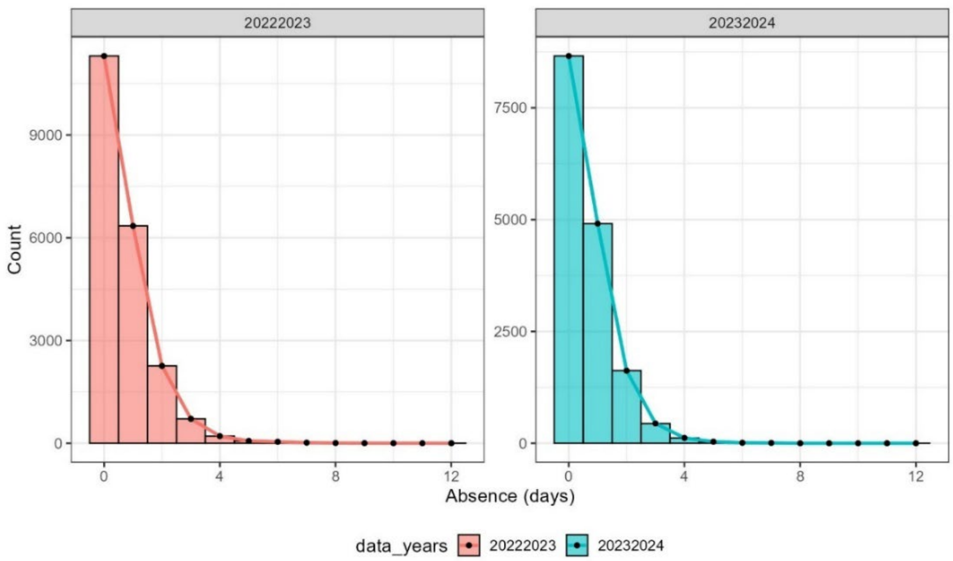

Figure 2.1. The distribution of the total number of students absent in all classrooms involved in the study in the academic years 2022-23 and 2023-24

R programming was used for all data analysis and statistical modeling. The *glmmTMB* function from the "glmmTMB" package in R was used to fit a generalized linear mixed model (GLMM) with absenteeism modelled as a negative binomial distribution for the yearly analysis. Daily absenteeism was modelled using Treatment (i.e., Filter) and ventilation rate variables (i.e., aVR, aVRMC, aVRMS) as fixed effects, while District, Schools, and Classrooms were modelled as random effects.

Statistical Model and Results

As a first step, the model was fitted using daily absence information for the whole study duration. The following model formula was used:

$$\begin{aligned} Daily\ IRA \sim Filter * \ & Adjusted\ Ventilation\ Rate\ (aVR) \\ & * Adjusted\ Mean\ Classroom\ Ventlation\ Rate\ (aVR_{MC}) \\ & * Adjusted\ Mean\ School\ Ventilation\ Rate (aVR_{MS}) \\ & + 1\ |\ School\ Random\ Effects\ /\ Sensor\ Random\ Effects \end{aligned}$$

Full-Yearly Absenteeism Model (FYAM). The complete model included six main effects. Twelve 2-way interactions, ten 3-way interactions, and three 4-way interactions, leading to a total of 31 terms in the model.

Reduced Model 1. All 4-way interactions in the model were non-significant and were therefore removed.

Reduced Model 2. One 3-way interaction term among adjusted ventilation rates (aVR, aVR_{MC}, aVR_{MC}) was significant in only one of eight models and was therefore removed from the model.

Reduced Model 3. The three 3-way interaction terms involving Filter, aVR_{MC}, and aVR_{MS} were non-significant, and hence were removed from the model.

Reduced Model 4. Six 3-way interaction terms in five out of eight models were non-significant (filter, aVR and aVR_{MC}) and were eliminated from the model.

Reduced Model 5. The three 2-way interactions of aVR:aVR_{MC}, aVR:aVR_{MS} and aVR_{MS}:aVR_{MD} were also non-significant in five out of eight models. The ventilation rate in schools was also not manipulated in the school buildings but instead measured; therefore, these two terms were also eliminated from the model.

Reduced Model 6. This model had six main effects and nine terms for 2-way interactions of filter with aVR, aVR_{MC} and aVR_{MS}. The interaction of filters and aVR_{MS} was non-significant in 7 out of 8 models, and the interaction of filters and aVR_{MC} was non-significant in all 8 models, resulting in 6 interaction terms, with the majority non-significant. These six 2-way interaction terms were removed after calculating the Chi-Square test on the difference in -2 log-likelihood (-2LL) values between the model with and without these interaction terms. The results of the Chi-Square test are provided in

Table . All p-values from the Chi-Square test were non-significant, indicating no statistically significant difference between the two models (with and without these six interaction terms). The final model obtained is being referred to as the Reduced Yearly Model (RYM).

Table 2.1. χ^2-Square test to compare model fit for the Full Yearly model vs the Reduced Yearly Model

Moving Average of Ventilation Rate	-2 Log-Likelihood for Full Model (FM_{-2LL})	-2 Log-Likelihood for Reduced Model (RM_{-2LL})	Difference = FM_{-2LL} - RM_{-2LL}	df	p-value
One-day	46310.2	46318.5	-8.3	6	0.21
3-day MA	46141.3	46151.0	-9.7	6	0.13
5-day MA	46103.4	46111.7	-8.3	6	0.21
7-day MA	45945.9	45955.3	-9.4	6	0.15
10-day MA	45587.0	45592.1	-5.1	6	0.23
14-day MA	45523.4	45531.2	-7.8	6	0.25
21-day MA	44989.2	44999.5	-10.3	6	0.11
30-day MA	44266.7	44273.5	-6.8	6	0.33

Reduced Yearly Absenteeism Model (RYM). This model included all six main effects, and the interaction between filters and the adjusted ventilation rate was retained since it was the primary variable of interest. This model was fitted for the filter types in Treatment/Control conditions and all calculated moving averages (for 3, 5, 7, 10, 14, 21, and 30 days) of Adjusted

Ventilation Rate (aVR), adjusted Mean Classroom Ventilation Rate (aVR_{MC}), and adjusted Mean School Ventilation Rate (aVR_{MS}). The Reduced Yearly Model (RYM) for daily absenteeism is given by:

$$
\begin{aligned}
log(Daily\ IRA) &= \beta_{0,\mathrm{MA}} + \beta_{T_1,MA} I_{T_1} + \beta_{T_2,MA} I_{T_2} + \beta_{T_3,MA} I_{T_3} + \beta_{aVR,MA} x + \beta_{aVR_{MC},MA} I_{aVR_{MC}} \\
&+ \beta_{aVR_{MS},MA} I_{aVR_{MS}} + \beta_{T_1:\mathrm{aVR},MA} I_{T_1} + \beta_{T_2:\mathrm{aVR},MA} I_{T_2} + \beta_{T_3:\mathrm{aVR},MA} I_{T_3} + u_{sch} \\
&+ u_{sch:class}
\end{aligned}
$$

Where MA represents the variable specifying the moving average used in the model. The modelling was performed for one-day, 3-day, 5-day, 7-day, 10-day, 14-day, 21-day, and 30-day moving averages of ventilation rate variables (i.e., aVR, aVR_{MC}, aVR_{MS}). The coefficients for one-day, three, five, seven, ten, fourteen, twenty-one, and thirty-day moving averages are presented in Figure 2.2 where the first facet of rows shows the intercepts $\beta_{0,\mathrm{MA}}$ ($\beta_{0,1}$, $\beta_{0,3}$, $\beta_{0,5}$, $\beta_{0,7}$, $\beta_{0,10}$, $\beta_{0,14}$, $\beta_{0,21}$, $\beta_{0,30}$) for one-day, three, five, seven, ten, fourteen, twenty-one, and thirty-day moving average respectively. The facets 2, 3, and 4 represent the coefficients and their significance levels for the main effects of Treatment 1 ($\beta_{T_1,MA}$) i.e. $\beta_{T_1,1}$, $\beta_{T_1,3}$, $\beta_{T_1,5}$, $\beta_{T_1,7}$, $\beta_{T_1,10}$, $\beta_{T_1,14}$, $\beta_{T_1,21}$, $\beta_{T_1,30}$, Treatment 2 ($\beta_{T_2,MA}$) i.e. $\beta_{T_2,1}$, $\beta_{T_2,3}$, $\beta_{T_2,5}$, $\beta_{T_2,7}$, $\beta_{T_2,10}$, $\beta_{T_2,14}$, $\beta_{T_2,21}$, $\beta_{T_2,30}$ and Treatment 3 ($\beta_{T_3,MA}$) i.e. $\beta_{T_3,1}$, $\beta_{T_3,3}$, $\beta_{T_3,5}$, $\beta_{T_3,7}$, $\beta_{T_3,10}$, $\beta_{T_3,14}$, $\beta_{T_3,21}$, $\beta_{T_3,30}$ respectively for one-day, three, five, seven, ten, fourteen, twenty-one, and thirty-day moving averages. The facet 5 represents the coefficients for all moving averages of adjusted ventilation rates ($\beta_{aVR,MA}$) i.e. $\beta_{aVR,1}$, $\beta_{aVR,3}$, $\beta_{aVR,5}$, $\beta_{aVR,7}$, $\beta_{aVR,10}$, $\beta_{aVR,14A}$, $\beta_{aVR,21}$, $\beta_{aVR,30}$ whereas facet 6 represents the coefficients for all moving averages of Adjusted Mean Classroom Ventilation Rate (aVR_{MC}) i.e. $\beta_{aVR_{MC},1}$, $\beta_{aVR_{MC},3}$, $\beta_{aVR_{MC},5}$, $\beta_{aVR_{MC},7}$, $\beta_{aVR_{MC},10}$, $\beta_{aVR_{MC},14A}$, $\beta_{aVR_{MC},21}$, $\beta_{aVR_{MC},30}$. The facet 7 represents the coefficients for all moving averages of Adjusted Mean School Ventilation Rate (aVR$_{MS}$) i.e. $\beta_{aVR_{MS},1}$, $\beta_{aVR_{MS},3}$, $\beta_{aVR_{MS},5}$, $\beta_{aVR_{MS},7}$, $\beta_{aVR_{MS},10}$, $\beta_{aVR_{MS},14A}$, $\beta_{aVR_{MS},21}$, $\beta_{aVR_{MS},30}$. The facets 8, 9, and 10 represent the coefficients (($\beta_{T_1:\mathrm{aVR},MA}$, $\beta_{T_2:\mathrm{aVR},MA}$, $\beta_{T_3:\mathrm{aVR},MA}$) for the interaction effects of Filters T1, T2, and T3 for one-day, three, five, seven, ten, fourteen, twenty one and thirty-day moving averages of aVR, aVR$_{MC}$ and aVR$_{MS}$.

The model outputs for RYM were plotted in Figure 2.2 which shows the magnitude of all the coefficients. All statistically significant terms are shown in red and green bars, whereas those that were not are shown in grey. The red color shows negative coefficients, and the green shows positive coefficients.

There was no main effect of filters on absenteeism throughout the year. The interaction effects of filters with adjusted ventilation rates (aVR, aVR$_{MC}$, aVR$_{MC}$) were all non-significant, indicating no evidence of filters interacting with daily changes in ventilation rates or with variation in classroom- or school-wide ventilation rates. The effects of classroom-wide and school-wide ventilation rates on students' classroom illness-related absenteeism (IRA) were also non-significant.

However, the model coefficients for the adjusted ventilation rates for one-day, three-day, and five-day moving averages indicate a positive effect on absenteeism, suggesting an increase in absenteeism with ventilation rates above the design ventilation rate. This result was not as expected, and increased ventilation should improve classroom air quality, provided the outdoor air is clean, and potentially lead to lower classroom absenteeism. To further investigate this, models were developed to examine the seasonal effect of ventilation rate on absenteeism.

Seasonal IRA analysis

A testing of over fifty-two thousand respiratory samples over six years determined seasonality for the highest number of active cases for a range of respiratory viruses. (Price et al., 2019). Based on the reported month of the year with the highest number of active cases, the seasons corresponding to each virus in Nebraska's climate were determined.

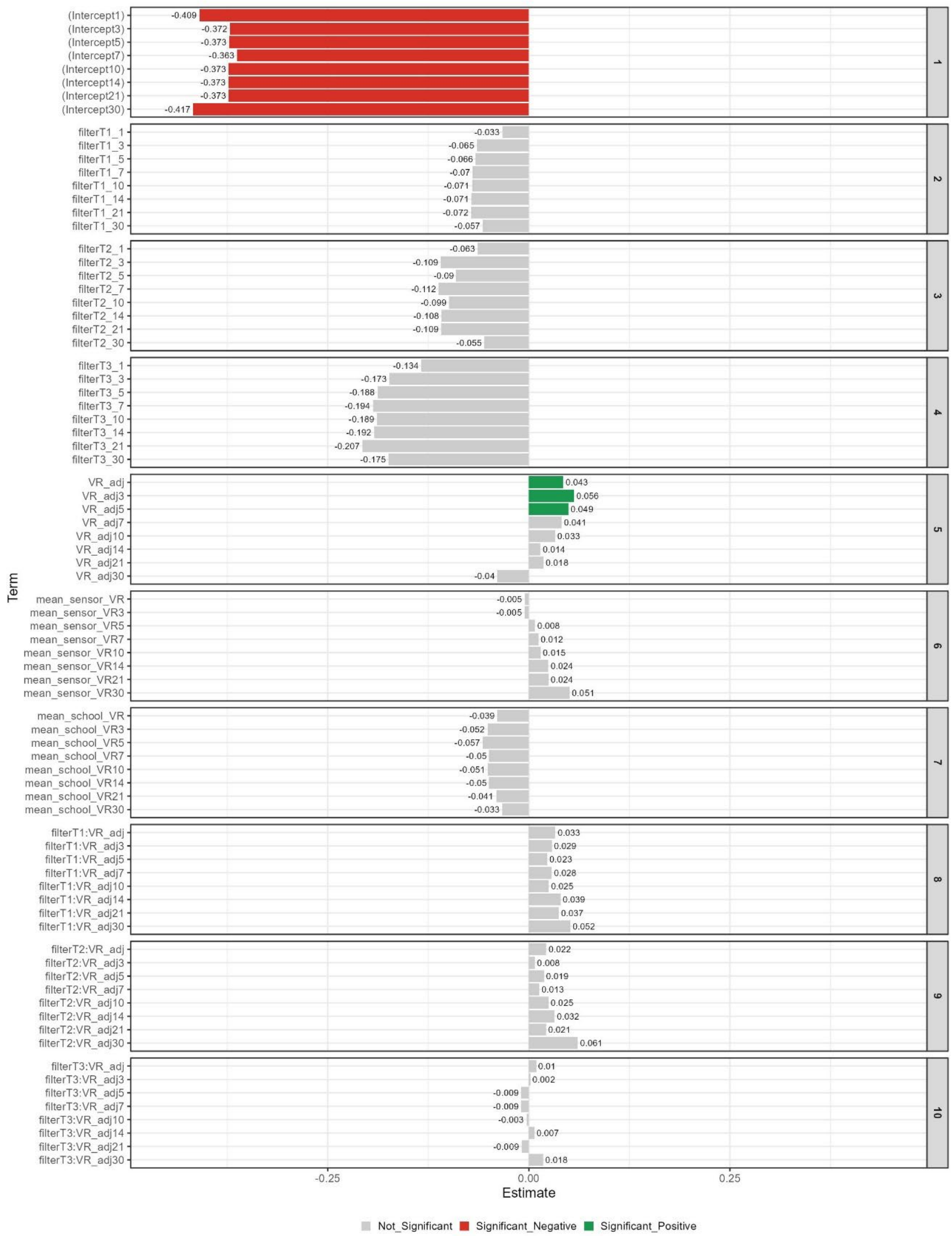

Figure 2.2. Model outputs from the final reduced yearly model for the absenteeism data

Respiratory syncytial virus (RSV), influenza A (IAV) and influenza (IBV) were the most prevalent viruses in Winter season (CDC, 2025a; Hamid, 2023; Neumann & Kawaoka, 2022; Price et al., 2019; Read et al., 2021). Human metapneumovirus (HMPV) and adenovirus were most prevalent in early spring (Price et al., 2019) although adenovirus spreads year round (CDC, 2025b). The Human parainfluenza 3 (HIPV-3) virus was the most prevalent in late spring. Rhinovirus (common cold), Human parainfluenza virus 1 & 2 (HPIV-1 and HIPV-2) were the most active in Fall season (CDC, 2025b; Price et al., 2019). Streptococcal Pharyngitis (commonly called Strep throat) is also common in students and peaks in early spring and winter season (Mc et al., 2024). See Table 2.2 for a summary.

Table 2.2. Seasonal distribution of respiratory viruses Based on Nebraska's climate

Season	Illness
Year round	Adenovirus, Rhinovirus, Whooping cough (pertussis)
Fall	Mycoplasma pneumoniae (year-round), Common human coronaviruses (year-round), HIPV-1, HIPV-2, Rhinovirus (late fall)
Winter	Group A Strep, Pneumococcal disease, Influenza, RSV
Spring	Pneumococcal disease & Group A Strep (early spring), HMPV, HIPV-3 (late spring),

Lessler et al. (2009) compiled the range of mean/median incubation period of majority of these infectious agents and the central tendencies ranged from two to ten days. 7-day moving average and 10-day moving average models predicting the highest absenteeism were selected for Fall and Winter season while 1-day moving average model predicted the highest absenteeism in Spring season.

A longitudinal study conducted over 20 years showed that the asthma-related emergency department visit peak in spring season (K et al., 2023) and pollens are linked to allergic responses in this season (Berezhanskiy et al., 2025). The early-phase reaction to the allergen can occur immediately, while the late-phase response can take up to 9 hours to fully develop after allergen exposure (Galli et al., 2008). The daily-absenteeism model for the spring season was therefore selected to predict the absenteeism.

Reduced Seasonal Models (RSM)

To examine the impact of ventilation on student illness-related absenteeism in classrooms across the Fall, Winter, and Spring seasons, a "Season" identifier was added to the dataset to filter rows for each season. The study was conducted in Nebraska, and a season identifier was therefore created to categorize August through November as the Fall Season, December through February as the Winter Season, and March through May as the Spring Season.

The Seasonal Model (SM) was developed similarly to the Full Yearly Absenteeism Model (FYAM). The Seasonal Model had a total of 32 terms in the model, from main effects to the four-way interaction term. The same methodology was used to get to a Partially Reduced Seasonal Model (pRSM) with six main effects and nine two-way interaction terms from the Seasonal Model (SM). The six two-way interaction terms in pRSM were statistically non-significant across most of the variants of moving averages, and therefore, Chi-Square tests were performed on all the seasonal models to remove the six two-way interaction terms of Filter with adjusted ventilation rates (aVR, aVR_{MC} , aVR_{MC}). The results of the Chi-Square test for Fall, Winter, and Spring Reduced Seasonal Models are provided in Table , Table and Table respectively. After removing the six interaction terms from the pRSM, a final reduced seasonal model (RSM) was obtained for each season.

Table 2.3. Chi-Square test to compare model fit for the Reduced Seasonal model (RSM) vs Partially Reduced Seasonal Model (pRSM) for the Fall Season

Ventilation Rate	-2 Log-Likelihood for Full Model (FM_{-2LL})	-2 Log-Likelihood for Reduced Model (RM_{-2LL})	Difference = FM_{-2LL} - RM_{-2LL}	df	p-value
One-day	12612.3	12618.3	6.0	6	0.42
3-day MA	12546.1	12550.8	4.7	6	0.58
5-day MA	12611.3	12614.2	2.9	6	0.82
7-day MA	12571.0	12575.4	4.4	6	0.62
10-day MA	12480.8	12485.2	4.4	6	0.62
14-day MA	12554.8	12558.1	3.3	6	0.77
21-day MA	12366.9	12375.9	9.0	6	0.17
30-day MA	12160.2	12163.1	2.9	6	0.82

The Chi-Square test (as shown in Table the -2 Log Likelihood (-2LL) values of RSM and pRSM for the Fall Season were statistically non-significant ($p > 0.05$) for the one-day ventilation rate and all the ventilation rate moving averages, thereby showing that there was no significant difference in the model fit with and without the six 2-way interaction terms in the model.

The Chi-Square test performed (as shown in Table) on the -2 Log Likelihood (-2LL) values of RSM and pRSM for Winter Season was statistically non-significant ($p > 0.05$) for the one-day ventilation rate and all the ventilation rate moving averages except the 30-day moving average thereby showing that there was no significant difference in the model fit with and without the six 2-way interaction terms in all the model variants for varying moving averages except the 30-day moving average. Overall, to maintain consistency, the RSM for the Winter season was used for further analysis, with the six 2-way interaction terms removed from the model.

The Chi-Square test was performed (as shown in Table) on the -2 Log Likelihood (-2LL) values of RSM and pRSM for Spring Season was statistically non-significant ($p > 0.05$) for the one-day ventilation rate and all the ventilation rate moving averages except the 1-day and 3-day moving average thereby showing that there was no significant difference in the model fits with and without the six 2-way interaction terms in all the model variants for varying moving averages except the 1-day and 3-day moving average. Overall, to maintain consistency, the RSM for the Spring season was used for further analysis, with the six 2-way interaction terms removed from the model.

Table 2.4. Chi-Square test to compare model fit for the Reduced Seasonal model (RSM) vs Partially Reduced Seasonal Model (pRSM) for the Winter Season

Ventilation Rate	-2 Log-Likelihood for Full Model (FM_{-2LL})	-2 Log-Likelihood for Reduced Model (RM_{-2LL})	Difference = FM_{-2LL} - RM_{-2LL}	df	p-value
One-day	17186.4	17193	6.6	6	0.36
3-day MA	17113.9	17122.6	8.7	6	0.19
5-day MA	17001.4	17011.2	9.8	6	0.13
7-day MA	16914.8	16925.4	10.6	6	0.10
10-day MA	16683.1	16692.3	9.2	6	0.16
14-day MA	16544.5	16555.9	11.4	6	0.08
21-day MA	16191.3	16202.7	11.4	6	0.08
30-day MA	15836.2	15855.2	19.0	6	<0.05 *

Table 2.5. Chi-Square test to compare model fit for the Reduced Seasonal model (RSM) vs Partially Reduced Seasonal Model (pRSM) for Spring Season

Ventilation Rate	-2 Log-Likelihood for Full Model (FM_{-2LL})	-2 Log-Likelihood for Reduced Model (RM_{-2LL})	Difference = FM_{-2LL} - RM_{-2LL}	df	p-value
One-day	16473.5	16487.6	14.1	6	<0.05 *
3-day MA	16448.2	16462.8	14.6	6	<0.05 *
5-day MA	16444.4	16455.3	10.9	6	0.09
7-day MA	16424.3	16433.6	9.3	6	0.16
10-day MA	16373.9	16382.1	8.2	6	0.22
14-day MA	16362.1	16368	5.9	6	0.43
21-day MA	16318.8	16323.8	5.0	6	0.54
30-day MA	16165.7	16170.5	4.8	6	0.57

As already mentioned, separate models were created for one-day ventilation rate, three-, five-, seven-, ten-, fourteen-, twenty-one-, and thirty-day ventilation rate moving averages, resulting in 8 models for each season. This led to a total of 24 Reduced Seasonal Models (RSMs), with eight models for each Fall, Winter, and Spring Season.

The model output for the one-day ventilation rate for the Fall Season is presented in Table . The coefficients for all the main effects were negative, indicating the tendency of the installation of filters in the classrooms leading to a decrease in absenteeism, but the decrease was statistically non-significant ($p > 0.05$), thereby indicating no significant effect of filtration on the illness-related absenteeism in comparison to the control condition in our study. The daily adjusted ventilation rate had a positive coefficient, indicating a tendency toward increased absenteeism when the daily ventilation rate exceeded the classroom's design ventilation rate. In contrast, the adjusted mean classroom ventilation rate had a negative coefficient, indicating a tendency toward decreased absenteeism at ventilation rates above the design ventilation rate. This makes sense, as the majority (68%, as shown in Figure 1.7) of the classrooms in the study were under-ventilated and could benefit from increased ventilation rates. Similarly, the adjusted mean school ventilation rates had negative coefficients, indicating a decrease in absenteeism with increases in school-level ventilation rates above the design value. However, although these terms had positive or negative coefficients indicating an effect on absenteeism, they were not statistically significant. The two-way interactions between filters with adjusted ventilation rate were also not significant.

These results, presented in Table were for one-day ventilation rate for the Fall Seasons only. As there were 24 models in total, covering all moving averages of ventilation rates across all three seasons (Fall, Winter, and Spring), it is tedious to present all outputs individually and discuss the results. Therefore, the model outputs from all the models were combined into one visual and presented in

Figure **2.3**.

Table 2.6. One-day ventilation rate RSM output for Fall Season

Predictor	Estimate	Std. Error	z value	p-value
$\boldsymbol{\beta_0}$	-0.48168	0.14722	-3.272	< 0.05 ***
$\boldsymbol{\beta_{T_1}}$	-0.07327	0.139459	-0.525	0.60
$\boldsymbol{\beta_{T_2}}$	-0.03037	0.146098	-0.208	0.84
$\boldsymbol{\beta_{T_3}}$	-0.05366	0.15954	-0.336	0.74
$\boldsymbol{\beta_{aVR}}$	0.014752	0.027981	0.527	0.60
$\boldsymbol{\beta_{aVR_{MC}}}$	-0.00238	0.039793	-0.06	0.95
$\boldsymbol{\beta_{aVR_{MS}}}$	-0.06255	0.061636	-1.015	0.31
$\boldsymbol{\beta_{T_1:aVR}}$	0.058358	0.033871	1.723	0.08
$\boldsymbol{\beta_{T_2:aVR}}$	0.052401	0.032924	1.592	0.11
$\boldsymbol{\beta_{T_3:aVR}}$	0.036341	0.032992	1.102	0.27

The three columns compare model outputs for each Season (Fall, Winter, and Spring). Facet 1, on the right, shows the intercepts for all moving averages. Facets 2, 3, and 4 show the main effects of Filters in the Treatment condition T1, T2, and T3, respectively. The reference condition is the Control condition at MDVR for Adjusted Ventilation Rate, adjusted Mean Classroom Ventilation Rate and adjusted mean School Ventilation Rate. The Facets 4, 5, and 6 show the main effects of adjusted Ventilation Rate, adjusted Mean Classroom Ventilation Rate, and adjusted Mean School Ventilation Rate, respectively, and the Facets 8, 9, and 10 represent the interaction terms for Filters (T1, T2, T3) with aVR, aVR_{MC}, aVR_{MS}.

Fall Season. In the Fall Season, the main effect of all treatments (T1, T2, and T3) had non-significant coefficients across all moving averages of ventilation rate. The daily adjusted ventilation rate (aVR) in the 7-day model variant had a positive association with IRA, indicating increase in absenteeism with an increase in daily ventilation rate beyond the design ventilation rate (VR_D). However, the three-, five-, seven-, and ten-day model variants showed adjusted mean school ventilation rates with negative coefficients, indicating that increases in school-wide ventilation rates were associated with decreases in absenteeism. All interactions between filters and the daily adjusted ventilation rate (aVR) were statistically non-significant, except in the 30-day model variant.

Figure 2.3. Model coefficients for Reduced Seasonal Models (RSMs)

The central tendency (mean or median) of the incubation periods for respiratory viruses (Adenovirus, Coronavirus, Influenza, Human metapneumovirus, Measles, Parainfluenza, Respiratory Syncytial Virus, and Rhinovirus) range from two to ten days (Lessler et al., 2009). In the Fall Season, the 7-day model had the highest predicted IRA among all model variants and covers the incubation period for the majority of respiratory viruses. The model also had the largest main effects of filters and adjusted ventilation rates. The predictions from the model are presented in

Figure **2.3** where the levels “Low”, “Medium”, and “High” correspond to ventilation rates “20% lower than MDVR”, “at MDVR”, and “20% higher than MDVR”, where MDVR is the mean of design ventilation rates of all classrooms. The predictions from the 7-day model, however, also indicate a significant decrease in IRA with increases in school-level average ventilation rates. However, there was an increase in IRA with increases in daily ventilation rates, and a small increase in absenteeism with increases in classroom average ventilation rates. The filtration effect on IRA (i.e., reduction in IRA in Treatment conditions compared to the Control condition) increased with higher daily ventilation rates. It remained approximately constant with higher school-level and classroom-level ventilation rates.

Winter Season. In the Winter Season, the main effect of all treatments (T1, T2, and T3) were statistically non-significant across all model variants, although the coefficients had a positive effect on student absenteeism in the model (shown in Figure 2.4). The 1-day model showed that the daily adjusted ventilation rate (aVR) had a positive coefficient, indicating an increase in absenteeism with an increase in daily ventilation rate beyond the design ventilation rate (VR_D). One day aVR_{MC}, and three-, five-, seven-, ten-, and fourteen-day moving averages of adjusted mean classroom ventilation rates had negative coefficients, indicating a decrease in IRA with increasing classroom-wide ventilation rates beyond the design value. The coefficients corresponding to school-wide ventilation rates were all negative, indicating a decrease in IRA with increasing school-wide ventilation rates beyond the design value. The increase in daily ventilation rates in Treatment 1 classrooms was associated with increased IRA; however, the coefficients for these terms were only significant for the three-, five-, seven-, and ten-day moving averages of adjusted ventilation rates (aVR). Similarly, there was a positive association between the interaction of adjusted ventilation rate and Treatment 2, indicating that the increase in ventilation in T2 classrooms was associated with higher daily absenteeism. There was also a positive association of ventilation rate in one-day model classrooms associated with the T3 condition. Overall, during the Winter Season, there was no statistically significant decrease in IRA associated with the installation and operation of portable air purifiers in classrooms. In fact, an increase in the daily adjusted ventilation rate (for all moving averages) tended to be associated with an increase in student absenteeism. However, none of the terms were statistically significant except for the one-day moving average. The effect of classroom (sensor) level ventilation rate was also significant, and higher ventilation rates were negatively associated with IRA, suggesting that higher ventilation rates were associated with lower absenteeism.

Among all the model variants for the Winter Season, the 1-day, 10-day, and 14-day models had the highest predicted IRA percentages, with the 10-day and 14-day models covering incubation periods for the majority of respiratory viruses. Additionally, the 10-day moving average of ventilation rates showed the largest main effects for filters and adjusted ventilation rates. The predictions from these models are presented in Figure 2.4 exhibiting a significant decrease in absenteeism with the increase in classroom-level mean ventilation rates; however, there was an increase in student absenteeism with the increase in daily ventilation rates. There was a very small decrease in absenteeism associated with increases in school-level mean ventilation rates.

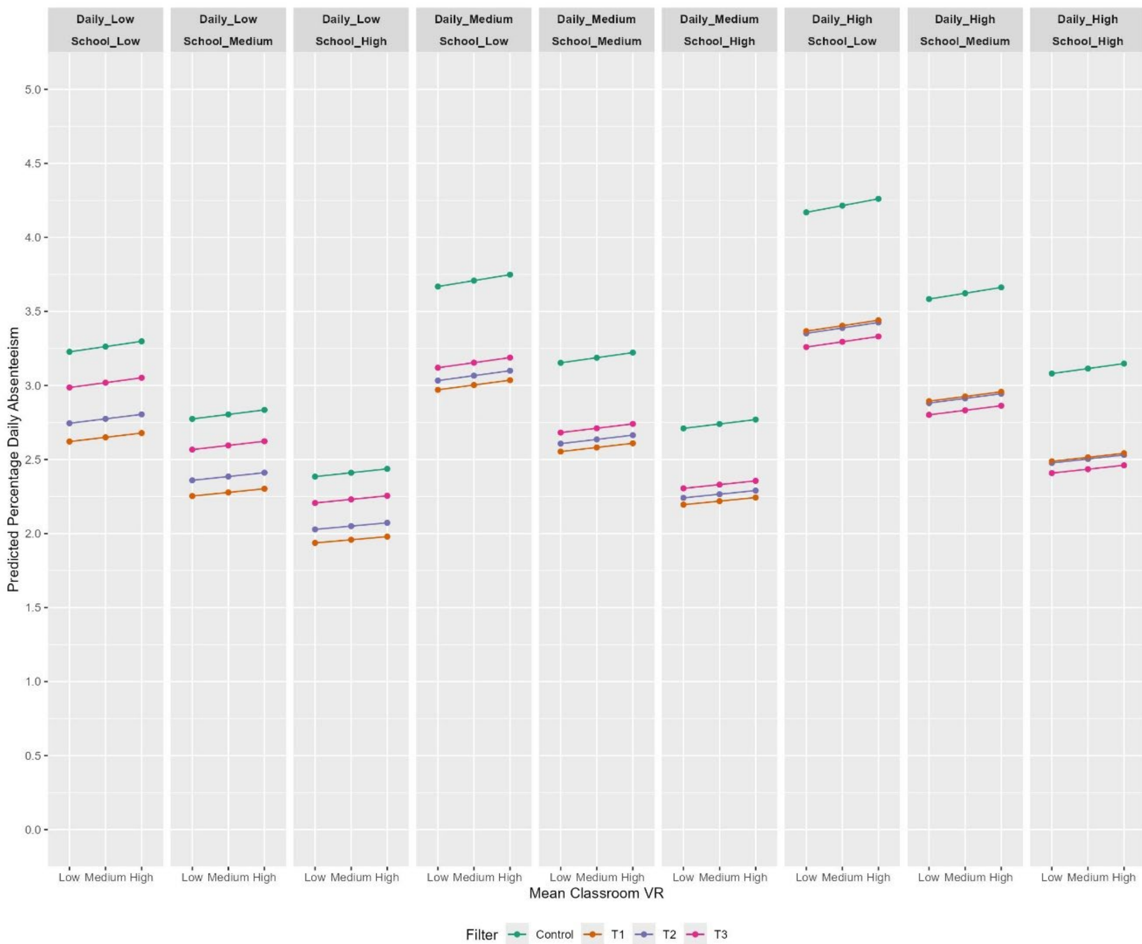

Figure 2.4. Reduced Seasonal Model (RSM) for the Fall Season for a 7-day moving average of ventilation rates

The filtration effect on IRA (i.e., reduction in IRA in Treatment conditions relative to the Control condition) remained almost constant as mean classroom ventilation rates increased. There was a reduction in the IRA in treatment conditions in comparison to the control conditions at daily ventilation rates 20% lower than MDVR. However, there was an increase in absenteeism in the Treatment conditions as compared to the control condition at daily ventilation rates at

MDVR and 20% higher than MDVR, which needs further evaluation, as the hypothesis of this study was that an increase in ventilation rate is associated with a reduction in indoor air contaminants and bioaerosols. Hence, at higher ventilation rates, the student absenteeism was expected to decrease.

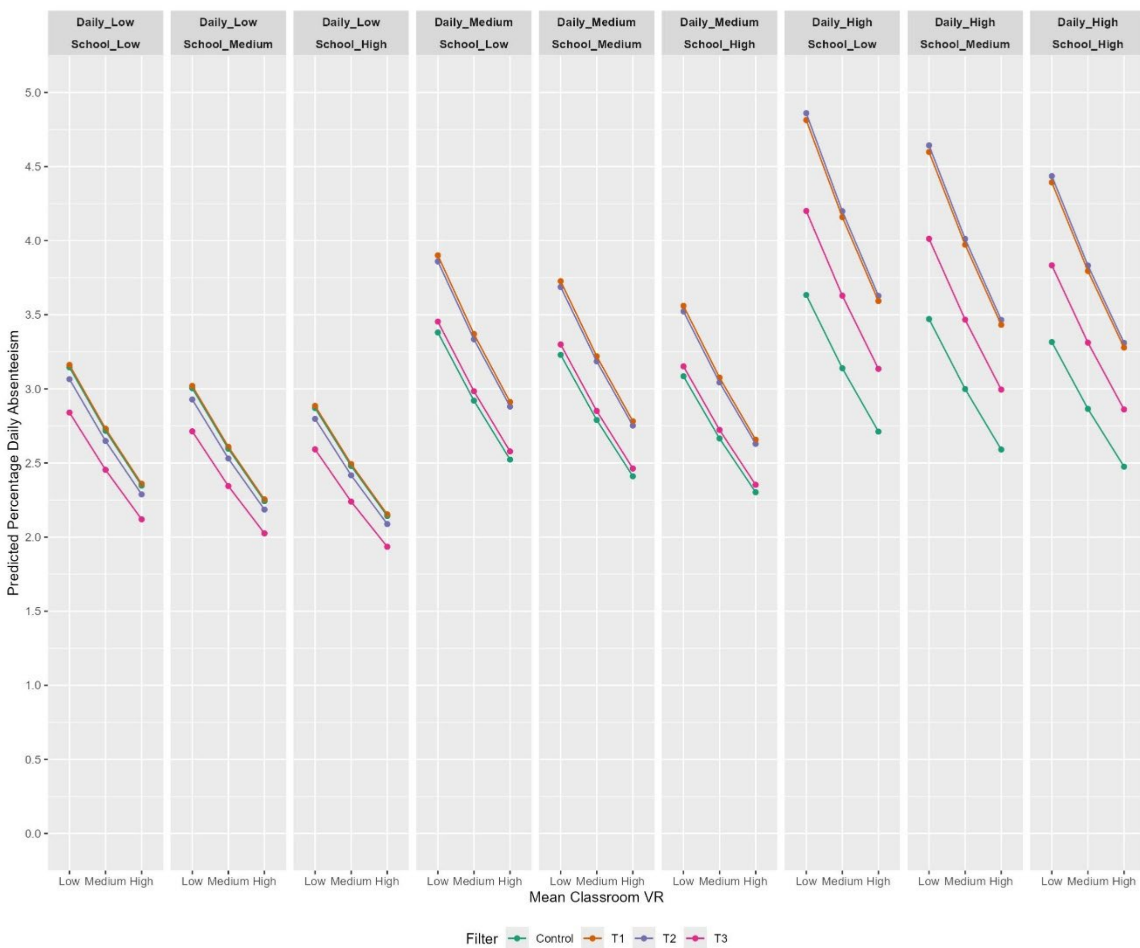

Figure 2.4. Reduced Seasonal Model (RSM) for the Winter Season for a 10-day moving average of ventilation rates

Spring Season. In the Spring Season for all model variants, the main effect (Treatment 1) had a negative relation with daily IRA, i.e. the Treatment condition (T1) was associated with lower IRA when compared to the control condition (as shown in

Figure **2.3**) although the main effect of Treatment 1 was statistically non-significant in all the model variants except the one-day model. The coefficients for filter effects (in Treatment 2) were significant across all other models in the one-day and two-day model variants. However, all variants showed negative associations with IRA, indicating that Treatment 2 was associated with a decrease in classroom illness-related absenteeism. For Treatment 3, the main-effect coefficients were negative across all model variants for the Spring season, indicating a reduction in absenteeism in Treatment 3 classrooms. The adjusted ventilation rate (aVR) had a positive coefficient in all model variants. In contrast, only the one-day, three-day, five-day, and seven-day model variants had these coefficients statistically significant. The sensor and school ventilation rates for all model variants had negative associations with IRA; however, these coefficients were not statistically significant. The coefficients for the interaction effects of Filters with aVR showed a negative relationship with IRA in the majority of the model variants.

The predicted percentage IRA was highest for the one-day model, followed by the 3-day model variant in the Spring season. The 1-day model also shows the most substantial main effects, and most terms were statistically significant. The results of the one-day model variant are presented in Figure 2.6. The predicted IRA shows a decrease in absenteeism with increases in average School-level and Classroom-level ventilation rates. However, the predicted IRA increased with rising daily ventilation rates.

The predicted values show a reduction in IRA in the treatment conditions compared to the control condition. This reduction further increases at higher daily ventilation rates due to the positive association between daily ventilation rate and daily IRA; however, the net daily IRA percentage increased.

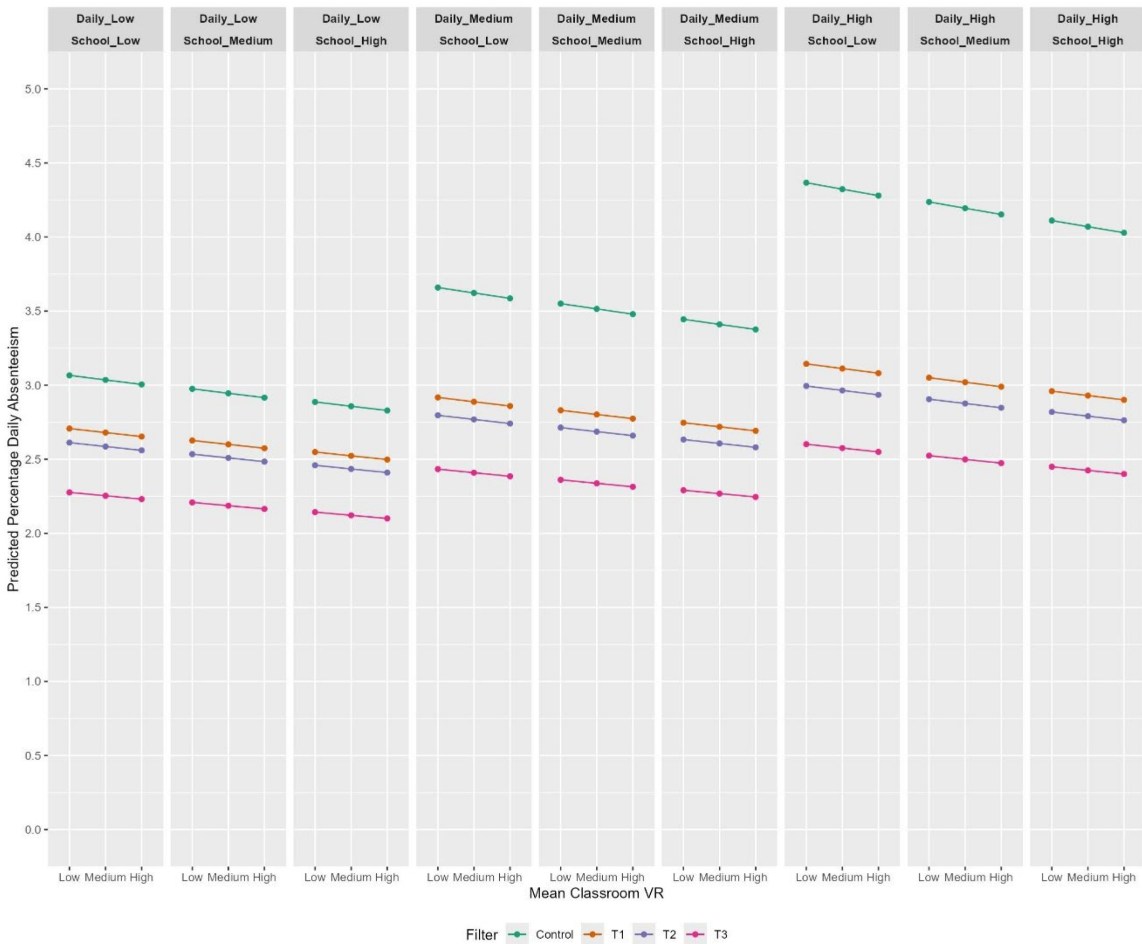

Figure 2.6. Reduced Seasonal Model (RSM) for the Spring Season for daily ventilation rates

Summary of Results

The IRA reduction in Treatment conditions relative to the Control condition increased with increasing daily ventilation rate in the Fall and Spring seasons. However, there was no IRA reduction in the Winter season in the Treatment conditions as compared to the control condition, as shown in Figure 2.5. There was no change in IRA reduction with changes in average school and classroom ventilation rates across seasons.

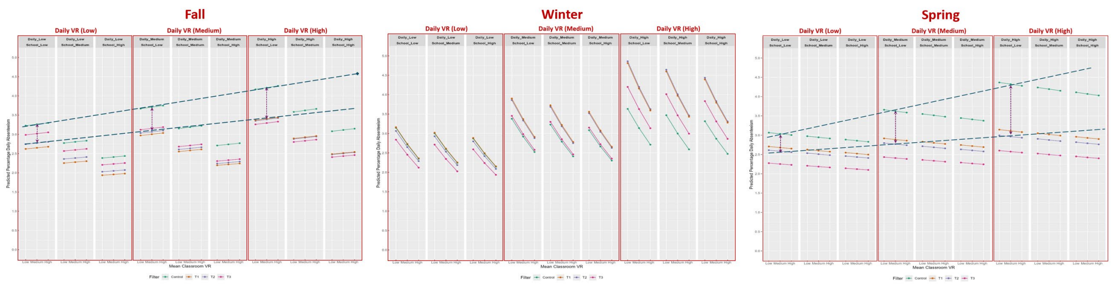

Figure 2.5. Comparison of IRA reduction in Treatment conditions as compared to Control conditions at varying ventilation rates

The summarized results of the causal impact of PAP on IRA reduction are provided in Table 2.1.

Table 2.1. Causal impact of PAPs on IRA reduction in Treatment conditions as compared to Control condition

		Ventilation Rate		
	Season	Daily VR	Average School VR	Average Classroom VR
IRA reduction in Treatment conditions as compared to Control condition (Causal effect of PAPs)	Fall	Increased	No Change	No change
	Winter	Reduction at low VR for T2 & T3 only No reduction at and above design VR (instead, an increase in IRA)	No change	No change
	Spring	Increased	No Change	No change

Study 3: Impact of PAPs on Elementary Student Academic Outcomes

This study addresses the third primary research question addressed in the overall research project, ***"After controlling student demographics, grade, school district, rurality, etc., do students in classrooms with PAPs achieve higher academic and learning outcomes than students in the control condition?"*** This portion of the research study was operationalized as a cluster randomized control trial (CRCT) where classrooms were randomly assigned to PAP intervention condition. Evaluation of the PAP intervention consisted of three components:

1) Assessment of direct effects of the PAP intervention on student academic outcomes and attendance, controlling for student demographics and school characteristics
2) Assessment of the potential mediating role of classroom attendance in the effect of the PAP intervention on student outcomes
3) Assessment of the role of student demographics and school characteristics as potential moderators of the effect of the PAP intervention on student outcomes

Methods

Analytic Frameworks. Empirical evaluations of the PAP intervention on academic outcomes were operationalized in two general frameworks. First, a longitudinal generalized linear mixed model (GLMM) framework was used to evaluate direct effects of the PAP intervention on academic outcomes and student attendance, controlling for student demographic information and school location through propensity scores as a covariate. A similar GLMM framework was also used to address potential moderation of PAP intervention effects by assessing differences in effects across categorically defined levels of relevant student demographic and school characteristics.

Second, longitudinal multilevel mediation modeling (MLM) was implemented to examine whether classroom attendance mediated the effects of the PAP intervention on academic outcomes. The theory of change suggests that the classroom-level PAP intervention can indirectly improve academic outcomes by increasing classroom attendance. The longitudinal multilevel mediation modeling framework is an extension of the GLMM framework to allow cleaner evaluation of indirect, and thus potential mediation, effects through the structural equation modeling environment.

Participants. The initial dataset provided by the Nebraska Department of Education (NDE) contained 4,684 3^{rd}-6^{th} grade student records for $J = 158$ classrooms located in $K = 27$ school buildings across $M = 5$ publicly-funded districts during the 2022-2023 academic year. Two districts were considered to be representative of an urban Nebraska environment, and three districts were characteristic of rural Nebraska. All five districts are publicly-funded. Three small private schools participated in the study; however, as private schools, they did not administer the annual Nebraska statewide assessment system, nor did they all administer an annual assessment that could be linked or compared to public schools. Consequently, data from private schools were not used in this study. However, 880 students had between two to five duplicate records in the dataset. Duplicate records occurred when the same de-identified student identifier within a school was attached to 2 or more different teachers and the multiple teachers were in classrooms participating in different intervention conditions (e.g. student 555 was duplicated to be in both teacher A's control classroom and teacher B's T2 classroom). Such duplication confounds estimation of the treatment effects, so all students with duplicate records were excluded from all analyses. This resulted in a final analyzable dataset of $N = 2{,}604$ students nested within $J = 135$ classrooms located in $K = 27$ schools across $M = 5$ districts.

Student level demographic information was considered, including gender, race or ethnicity, English language learner (ELL) status, and free/reduced lunch eligibility (FRLE). Gender, ELL, and FRLE were reported dichotomously. Race or ethnicity was reported with multiple categories; however, due to small sample sizes in all categories other than white/Caucasian and Black, all non-white race and ethnicity categories were combined into a single category. Consequently, race or ethnicity was also operationalized as a dichotomous variable contrasting white and non-white/multiracial.

Complex Sampling Structure. Academic and attendance data was provided by NDE. This study used academic outcome and attendance data from the 2022-2023 academic year as the primary outcome information. The prior year (2021-2022 academic year) tests scores and attendance data were obtained when available and used as control information to account for outcome levels prior to participation in the PAP intervention in 2022-2023. This resulted in two repeated observations (prior year and current year) for each student. The two repeated testing measures (Level 1) were considered nested within each student (Level 2), students were nested within their participation year classroom (Level 3), and participating classrooms were nested within their respective schools (Level 4). With only five participating school districts and minimal variability between districts, district was not considered as a fifth nesting level and treated as a fixed effect at the school level. Random assignment to the experimental PAP condition occurred at the classroom level (Level 3) resulting in the number of participating classrooms as the key sample size for evaluating intervention effects.

Measures. The primary outcomes in this study were the Nebraska Student-Centered Assessment System (NSCAS) and total attendance expressed as a percentage (or proportion) of school days attended. Three subtests from the NSCAS were evaluated as separate outcomes:

English Language Arts (ELA), Mathematics (MAT), and Science (SCI). For each content area, both the Achievement Level and Scale Score scalings were evaluated. Achievement level is operationalized as an ordinal scale with three levels: Developing, On Track, and Advanced. Scale scores are continuous measurements, varying in overall range based on content area: ELA 2220 – 2890, MAT 1000 – 1550, and SCI 3000 – 3250. Scale scores, conditional on grade, are used to determine achievement level classifications. Total attendance (ATT) was calculated as the proportion of attendance over the course of the 2022-2023 academic year. All outcomes were measured at the student level (Level 2) with the two repeated observations as the current intervention year data and the prior year outcome, when available. In both the GLMM and longitudinal multilevel mediation modeling frameworks, the Level 1 repeated measures were modeled as the change in outcomes between successive years.

The NSCAS tests for English Language Arts (ELA) and Mathematics (MAT) are administered annually in third through eighth grade. While students in a third-grade classroom during the intervention year did not have a prior year assessment on the ELA and MAT tests, they did generally have prior attendance information available unless they were new to the respective district. In contrast to the annual administration of the ELA and MAT assessments, the Science (SCI) assessment is only administered in fifth and eighth grades. Consequently, only current fifth grade students in the 2022-23 academic year were administered the SCI assessment with no prior year data available (SCI was not administered in 4^{th} grade), and only current sixth grade students had prior year SCI data but not data during the intervention year (SCI was not administered in 8^{th} grade). Due to the absence of any overlapping SCI test data, SCI was dropped from this study. The planned state assessment schedule and the missing prior year data for current third grade (ELA and MAT) and fifth grade (SCI) students resulted in data that can be considered missing completely at random (MCAR) due to the intentional nature of the assessment schedule (Graham et al., 2001). The GLMM and MLM estimation and modeling framework utilize Full Information Maximum Likelihood (FIML) to adjust model parameter estimates in the presence of missing outcome information.

Assignment to Condition and Operationalization of Comparisons. Assignment to condition occurred at the classroom level (Level 3). Random assignment was used within school buildings to ensure that building-level covariate effects - such as the central HVAC system and ventilation rate - were dispersed across all conditions within the building. Assignment to condition was operationalized in the analytic framework as three Helmert contrasts comparing:

1) The control condition (C) to the average of the three treatment conditions (T1/T2/T3)
2) T1 versus the average of T2/T3, and
3) T2 versus T3.

Where:

1) The control condition (C) is a PAP without any filtration providing only air circulation,
2) T1 were classrooms with a High-Efficiency Particulate Air (HEPA) PAPs,
3) T2 were classrooms with HEPA and activated carbon PAPs, and
4) T3 were classrooms with HEPA, activated carbon, and GUV (Germicidal Ultraviolet) PAPs.

Helmert contrasts were chosen because they allow determination of "value-added" effects in this context: PAP filtration regardless of filtration type (T1/T2/T3; but all providing HEPA filtration) compared to no filtration (C), the value added of activated carbon (T2/T3) versus only HEPA particle filtration, and the value added of biological contaminant filtration (T3; GUV - germicidal ultraviolet) above and beyond activated carbon (T2).

Schools (Level 4) were determined to be either (a) city/urban or (b) non-city/town/rural based on the National Center for Education Statics (NCES) Locale Classifications and Criteria (Geverdt, 2019). Due to the small number of participating districts (five), school district was initially considered as a fixed effect at the school level, but eventually dropped due to the small sample size and lack of statistical impact.

Covariates. All covariates regardless of level – gender, ELL, FRLE, race/ethnicity, grade district, urban/rural were used to calculate a propensity score which was then entered into models as a covariate to account for potential confounding influences that were not at the classroom level. Classroom level confounding effects are generally considered to be addressed through the random assignment process.

Direct Effect of PAPs on Academic Outcomes and Attendance

First, a four-level longitudinal generalized linear mixed model (GLMM) framework was used to evaluate direct effects of the PAP intervention on academic outcomes and student attendance, controlling for student demographic information and school location through propensity scores as a covariate. Subgroup analyses by demographic characteristic groupings were conducted as exploratory follow-up analyses. Parameters were estimated through restricted maximum likelihood (REML; Patterson & Thompson, 1971) using the MIXED procedure in the SAS environment (SAS Institute Inc., 2023). Degrees of freedom were computed using the Kenward–Roger method (Kenward & Roger, 1997).

Year was coded 0 for the prior school year (pre-intervention) and 1 for the intervention year. The three orthogonal Helmert contrast simple effects then represent condition differences in the prior year, and the contrast X year interaction terms test differential improvement between contrast conditions from the prior year to the intervention year. Thus, the focal parameters to evaluate the effect of the PAP intervention were the Helmert contrast X year interactions.

Random intercepts were included to adjust for the random variability in outcomes between students within a classroom, classrooms within a school building, and between schools. A residual term was also included to model the variable within a student due to the repeated measures. Random slopes were not included because they would be confounded with the within-student residual term due to only two repeated observations. Variability between schools within districts or between districts were not included due to the small number of participating districts. Random effects are variances and must be positive non-zero values by definition. On occasion, due to the model estimation process, random effect estimates may be estimated at the lower boundary of zero. Random effects and/or variance components estimated at or near zero are common in multilevel models. Constraining random effects to be zero or positive during the estimation process avoids negative estimates, but boundary estimates pose special inferential considerations (Pinheiro & Bates, 1995; Self & Liang, 1987). When variance components are near zero or at the boundary, fixed effect estimates and their standard errors may be affected, particularly in small samples, motivating careful degrees-of-freedom adjustment (Kenward & Roger, 1997; Gelman, 2006). This phenomenon further supports usage of the Kenward–Roger method for degree of freedom determination (Kenward & Roger, 1997). Consequently, these boundary estimates, when they occurred, were left in the model, especially when at the classroom level (Level 3), to ensure correct degree of freedom determination as classroom was the unit of randomization.

Attendance. Random effect estimates and intraclass correlations (ICCs) can be found in Table 3.1, and hypothesis test results can be found in Table 3.2. On average, students in this sample attended school on 94.86% of available school days in the 2021-22 academic and significantly improved to an attendance rate of 95.15% in the 2022-23 academic year. There were no statistically significant baseline differences among conditions (H1: $b = 0.05$, $p > .05$; H2: $b = 0.14$, $p > .05$; H3: $b = -0.17$, $p > .05$), thus, attendance rates in the prior year did not differ significantly across experimental conditions indicating no evidence of pre-intervention imbalance in attendance. While there was a significant simple effect of year ($b = 0.28$, $p < .05$), indicating that attendance increased modestly from the prior year to the intervention year when averaging across all conditions, none of the year by contrast interactions were statistically significant (year × H1: $b = 0.06$, $p > .05$, ES[1] = .06 [-0.06,0.17]; year × H2: $b = -0.04$, $p > .05$, ES = -.03 [-0.13,0.07]; year × H3: $b = 0.12$, $p > .05$, ES = 0.06 [-0.09,0.20]). Thus, there was no evidence that any treatment condition demonstrated greater improvement in attendance relative to the control condition or relative to one another.

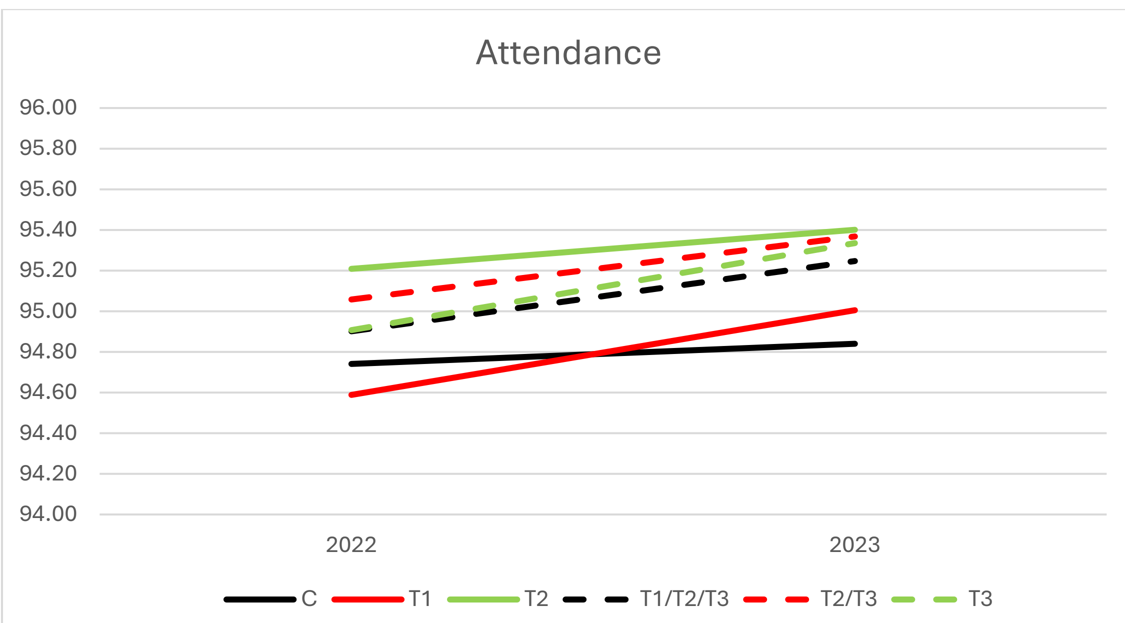

Figure 3.1. Attendance Percentage by Helmert Condition

[1] "ES" is a model-based effect size calculated based on methods provided by Feingold (2013) and Hedges (2007). Values in brackets [,] reflect the 95% confidence interval for the effect size.

Table 3.1. Empty model random effects, fixed effects, and intraclass correlations

	Attendance			ELA			Mathematics		
SCALE SCORE				Random Effects					
Parameter	Est	*ICC*		Est	*ICC*		Est	*ICC*	
School	0.82	0.05	*	1005.3	0.13	*	1484.8	0.19	*
Classroom	0.00	0		732.0	0.09	*	593.2	0.08	*
Student	8.40	0.50	*	4364.7	0.55	*	4141.7	0.53	*
Residual	7.44	0.45	*	1827.0	0.23	*	1631.7	0.21	*
				Fixed Effects					
Effect	Est	SE		Est	SE		Est	SE	
Intercept	95.06	[0.19]	*	2501	[6.89]	*	1223	[7.99]	*
ACHIEVEMENT LEVEL					Random Effects				
Parameter				Est	*ICC*		Est	*ICC*	
School				0.06	0.10	*	0.07	0.14	*
Classroom				0.03	0.06	*	0.02	0.05	*
Student				0.30	0.50	*	0.25	0.50	*
Residual				0.20	0.34	*	0.16	0.32	*
					Fixed Effects				
Effect				Est	SE		Est	SE	
Intercept				1.92	[0.05]	*	1.81	[0.06]	*

Note. * indicates statistical significance at the $p < .05$ level.

Table 3.2. Full model random effects, fixed effects, and conditional intraclass correlations

	Attendance			ELA			MAT		
SCALE SCORE				Random Effects					
Effect	Est	**ICC**		Est	**ICC**		Est	**ICC**	
School	0.82	0.05	*	996.51	0.12	*	1513.55	0.19	*
Classroom	0.00	0.00		921.27	0.11	*	824.06	0.10	*
Student	8.38	0.50	*	4555.14	0.57	*	4487.16	0.56	*
Residual	7.41	0.45	*	1550.90	0.19	*	1130.80	0.14	*
				Fixed Effects					
Effect	Est	SE		Est	SE		Est	SE	
Intercept	94.85	0.21	*	2484.89	7.13	*	1200.20	8.29	*
Year	0.28	0.10	*	22.40	1.49	*	31.20	1.28	*
H1	0.05	0.06		1.45	2.28		0.51	2.17	
H2	0.14	0.07		-1.31	2.44		-1.90	2.30	
H3	-0.17	0.15		1.31	5.02		-2.65	4.76	

Year*H1	0.06	0.06	-2.77	0.91	*	-2.37	0.78	*
Year*H2	-0.04	0.07	-0.52	1.09		0.21	0.93	
Year*H3	0.12	0.15	-3.82	2.20		-1.85	1.89	
ACHIEVEMENT LEVEL			Random Effects					
Effect			Est	**ICC**		Est	**ICC**	
School			0.06	0.11	*	0.08	0.15	*
Classroom			0.03	0.05	*	0.02	0.05	*
Student			0.31	0.52	*	0.26	0.51	*
Residual			0.19	0.32	*	0.15	0.29	*
			Fixed Effects					
Effect			Est	SE		Est	SE	
Intercept			1.80	0.06	*	1.69	0.06	*
Year			0.17	0.02	*	0.17	0.01	*
H1			-0.01	0.02		-0.01	0.01	
H2			0.00	0.02		-0.01	0.02	
H3			0.02	0.04		-0.02	0.03	
Year*H1			0.00	0.01		0.00	0.01	
Year*H2			0.00	0.01		0.00	0.01	
Year*H3			-0.01	0.02		0.01	0.02	

Note. * indicates statistical significance at the $p < .05$ level.

English Language Arts.

Scale Score. Random effect estimates and intraclass correlations (ICCs) can be found in Table 3.1, and hypothesis test results can be found in Table 3.2. On average, students in this sample had an average ELA scale score of 2485.94 in the 2021-22 academic year and significantly improved to an scale score of 2508.36 in the 2022-23 academic year. There were no statistically significant baseline differences among conditions (H1: $b = 0.44$, $p > .05$; H2: $b =$ 0.0.25, $p > .05$; H3: $b = 2.88$, $p > .05$), thus, ELA scale scores in the prior year did not differ significantly across experimental conditions indicating no evidence of pre-intervention imbalance. There was a significant simple effect of year ($b = 22.42$, $p < .05$), indicating that ELA scale scores increased from the prior year to the intervention year when averaging across all conditions; however, all three year by contrast interactions suggested that the treatment conditions' rates of improvement were lower in the PAP conditions than in the control condition, but still indicating overall improvement as shown in Figure 3.2. Of these interactions, the year by H1 was statistically significant (b = -2.77, p < .05, ES = -0.12 [-0.20,-0.04]), the year by H2 interaction was not (b = -0.51, p > .05, ES = -0.02 [-0.09,0.05]), and the year by H3 interaction was trending (b = -3.82, p > .05, ES = -0.09 [-0.18,0.01]). Thus, there was no evidence that any treatment condition demonstrated greater improvement in ELA scale scores relative to the control condition or relative to one another.

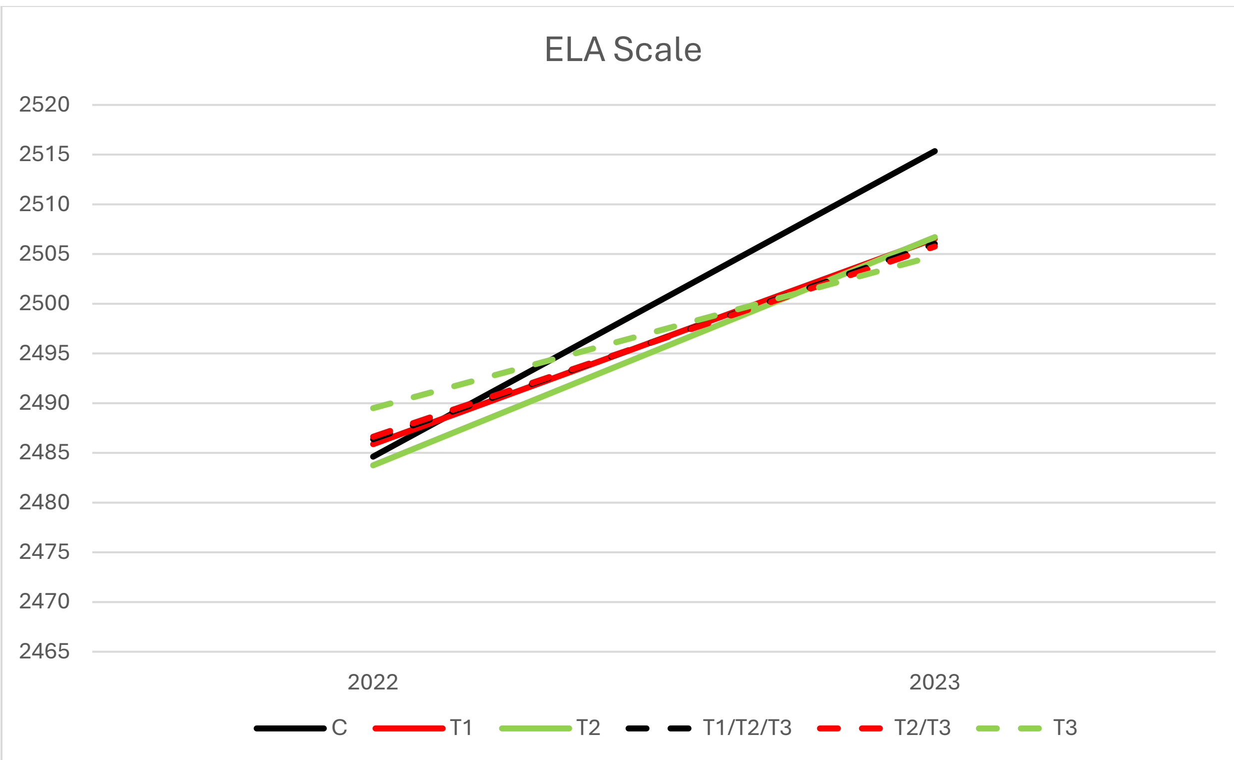

Figure 3.2. English Language Arts Scale Scores by Helmert Condition.

Achievement Level. Random effect estimates and intraclass correlations (ICCs) can be found in Table 3.1, and hypothesis test results can be found in Table 3.2. had an average ELA achievement level of 1.80 in the 2021-22 academic and significantly improved to an average achievement level of 1.98 in the 2022-23 academic year, with a score of "2" indicating that students were "On Track" on average. There was a significant simple effect of year (b = 0.17, p <

.05), indicating that ELA achievement levels significantly increased from the prior year to the intervention year when averaging across all conditions. As was the case with prior outcomes, there were no statistically significant baseline differences among conditions (H1: b = -0.0099, p > .05; H2: b = -0.0033, p > .05; H3: b = 0.017, p > .05), thus, ELA achievement level in the prior year did not differ significantly across experimental conditions indicating no evidence of pre-intervention imbalance. All three year by contrast interactions suggested that the treatment conditions' rates of improvement were statistically the same in the PAP conditions as compared to the control condition but still indicating overall improvement as shown in Figure 3.3 (year x H1: b = 0.0027, p > .05, ES = 0.01 [-0.09,0.12]), year x H2: b = -0.0047, p > .05, ES = -0.02 [-0.11,0.07]), year x H3: b = -0.0056, p > .05, ES = -0.01 [-0.14,0.11]). Thus, there was no evidence that any treatment condition demonstrated greater improvement in ELA achievement level relative to the control condition or relative to one another.

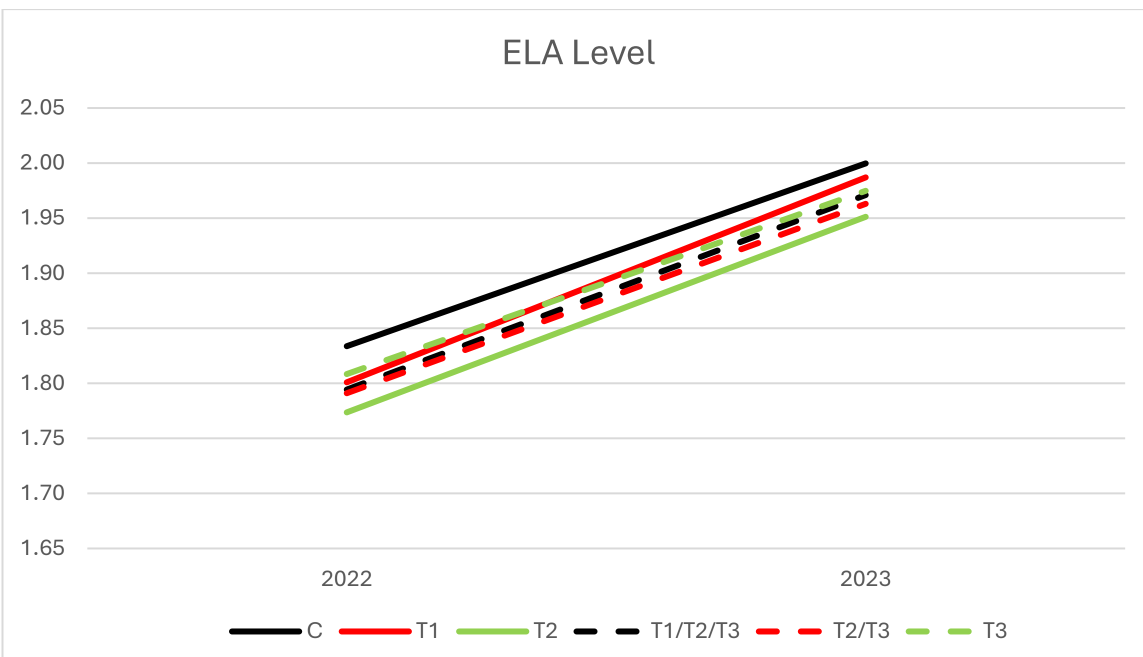

Figure 3.3. English Language Arts Achievement Levels by Helmert Condition

Mathematics

Scale Score. Random effect estimates and intraclass correlations (ICCs) can be found in Table 3.1, and hypothesis test results can be found in Table 3.2. On average, students in this sample had an average Mathematics scale score of 1201.35 in the 2021-22 academic year and significantly improved to a Mathematics scale score of 1232.56 in the 2022-23 academic year. There were no statistically significant baseline differences among conditions (H1: $b = -0.21$, $p > .05$; H2: $b = -0.80$, $p > .05$; H3: $b = -1.60$, $p > .05$), thus, Mathematics scale scores in the prior year did not differ significantly across experimental conditions indicating no evidence of pre-intervention imbalance. There was a significant simple effect of year ($b = 31.21$, $p < .05$), indicating that Mathematics scale scores increased from the prior year to the intervention year when averaging across all conditions; however, all three year by contrast interactions suggested that the treatment conditions' rates of improvement were lower in the PAP conditions than in the control condition or no different than, but still indicating overall improvement as shown in Figure 3.4. Of these interactions, the year by H1 was statistically significant ($b = -2.37$, $p < .05$, ES = -0.11 [-0.17,-0.04]), the year by H2 interaction was not ($b = 0.22$, $p > .05$, ES = 0.01 [-0.05,0.07]), and the year by H3 interaction also not significant ($b = -1.85$, $p > .05$, ES = -0.04 [-0.12,0.04]). Thus, there was no evidence that any treatment condition demonstrated greater improvement in Mathematics scale scores relative to the control condition or relative to one another.

Achievement Level. Random effect estimates and intraclass correlations (ICCs) can be found in Table 3.1, and hypothesis test results can be found in Table 3.2. On average, students in this sample had an average Mathematics achievement level of 1.69 in the 2021-22 academic and significantly improved to an average achievement level of 1.85 in the 2022-23 academic year, with a score of "2" indicating that students were "On Track" on average. There was a significant simple effect of year ($b = 0.17$, $p < .05$), indicating that Mathematics achievement levels significantly increased from the prior year to the intervention year when averaging across all conditions. As was the case with prior outcomes, there were no statistically significant baseline differences among conditions (H1: $b = -0.0063$, $p > .05$; H2: $b = -0.018$, $p > .05$; H3: $b = -0.027$, $p > .05$), thus, Mathematics achievement level in the prior year did not differ significantly across experimental conditions indicating no evidence of pre-intervention imbalance. All three year by contrast interactions suggested that the treatment conditions' rates of improvement were statistically the same in the PAP conditions as compared to the control condition but still indicating overall improvement as shown in Figure 3.5 (year x H1: $b = 0.0048$, $p > .05$, ES = 0.03 [-0.07,0.12]), year x H2: $b = 0.0041$, $p > .05$, ES = 0.02 [-0.07,0.10]), year x H3: $b = 0.0062$, $p > .05$, ES = 0.02 [-0.10,0.13]). Thus, there was no evidence that any treatment condition demonstrated greater improvement in Mathematics achievement level relative to the control condition or relative to one another.

Summary

All five outcomes (attendance, ELA scale score, ELA achievement level, MAT scale score, MAT achievement level) increased slightly from the prior year to the intervention year across all conditions. However, controlling for baseline differences among conditions along with student and school level covariates, there was no statistical evidence of differential improvement in academic outcomes or attendance that was attributable to the PAP intervention. Most between-unit variability in attendance occurred at the student and assessment year levels, with smaller but significant variation across schools, and very little variability at the classroom level itself.

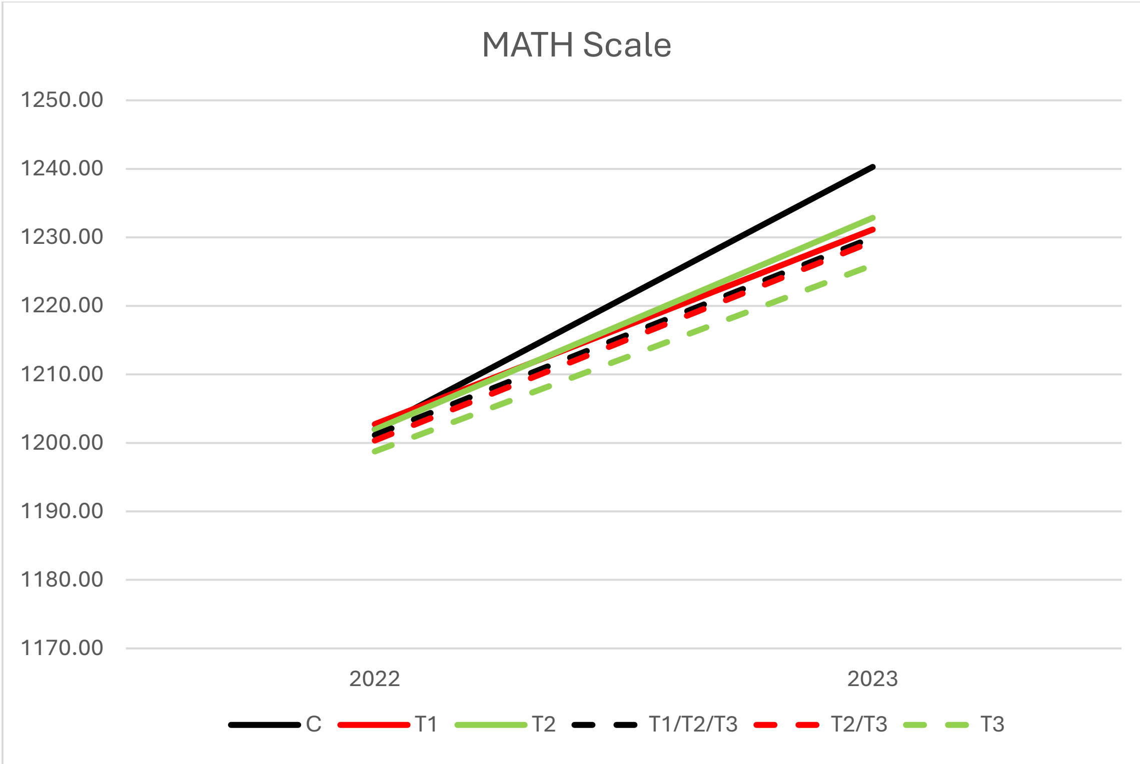

Figure 3.4. Mathematics Scale Scores by Helmert Condition

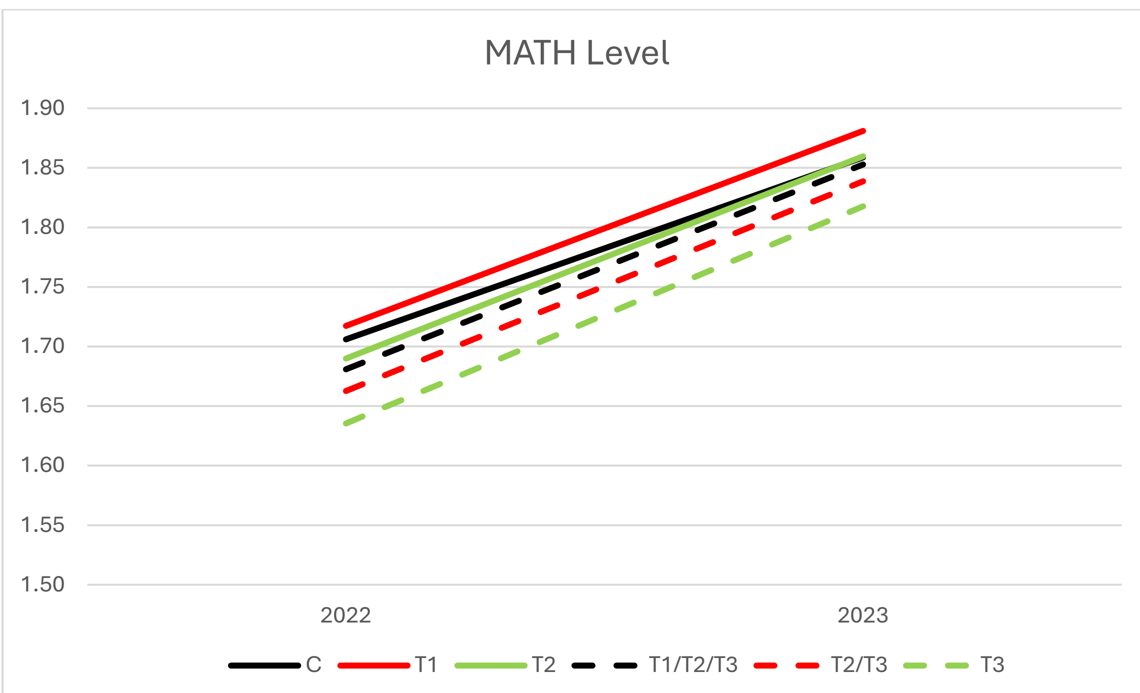

Figure 3.5. Mathematics Achievement Levels by Helmert Condition

Longitudinal Multilevel Mediation Models

Longitudinal multilevel mediation models were estimated to examine whether the classroom-level PAP intervention potentially caused improved academic outcomes indirectly by improving classroom attendance. Consistent with the prior direct effect models, the multilevel mediation models also had a four-level structure, with two repeated testing measures (Level 1) considered nested within each student (Level 2), students were nested within their participation year classroom (Level 3), and participating classrooms were nested within their respective schools (Level 4). For purposes of reducing model complexity and assisting in the efficient estimation of all models, the repeated testing measure level (prior year, current intervention year) was controlled for with a fixed effect of time at the student level rather than being explicitly modeled as an additional nesting level. Thus, computationally, Level 1 was the repeated observations, with student differences within classrooms effectively folded into this level; Level 2 was the classroom; and Level 3 was the school. Because there were not separate nesting levels for repeated observations and students, the Level-1 residual combines within-student change across years, and between-student differences within classrooms. The within-classroom-level effect of attendance is more accurately a within-classroom association at the observation level, blending repeated-measure and student-within-class variation.

Each model included classroom-level intervention contrasts (H1: Control vs. T1/T2/T3; H2: T1 vs. T2/T3; H3: T2 vs. T3) as predictors of classroom mean attendance, and classroom mean attendance as a predictor of the academic outcome. Four outcomes were examined: ELA achievement level (ELA_L), ELA scale score (ELA_S), mathematics achievement level (MAT_L), and mathematics scale score (MAT_S). All models were estimated in Mplus 8.11 (Muthén & Muthén, 1998–2023) using Bayesian Markov chain Monte Carlo (MCMC) estimation with 60,000 iterations and two chains. Posterior medians are reported as point estimates, and 95% credible intervals (CrIs) were used for inference (Asparouhov & Muthén, 2010).

Centering and Level Decomposition. These models included explicit centering, decomposing the attendance measure into two distinct components: the within-classroom observational/student deviation in attendance after classroom mean centering (ATT) and the classroom mean attendance at the classroom level (ATT_M). This decomposition means that the within-classroom level path coefficient reflects whether occasions/students with relatively higher attendance than their classroom mean also tended to show higher outcomes, whereas the between-classroom-level path coefficient reflects whether classrooms with higher mean attendance tended to show higher average academic outcomes. Because the intervention contrasts (H1–H3) were specified at the classroom level, the indirect effect is strictly a classroom-level mediation effect, consistent with the multilevel mediation framework described by Krull and MacKinnon (2001) and by Preacher, Zyphur, and Zhang (2010).

Model Fit. Across all four models, posterior predictive p-values were very close to .50 (.491 to .494), which is generally consistent with adequate Bayesian model fit (Asparouhov & Muthén, 2010).

Table 3.3. Unconditional longitudinal mediation model random effects, fixed effect, and intraclass correlations

	Attendance			ELA			Mathematics	
SCALE SCORE	Random Effects							
Parameter	Est	*ICC*		Est	*ICC*		Est	*ICC*
School	1.224	0.07	*	1053.3	0.15	*	1835.2	0.24
Classroom	0.151	0.01	*	485.7	0.07	*	551.3	0.07
Student	15.9	0.92	*	5424.4	0.78	*	5189.9	0.69

Posterior Predictive p-value	0.483			0.475			0.477		
	Fixed Effects								
Effect	Est	SE		Est	SE		Est	SE	
Intercept	94.89	[0.27]	*	2500.8	[7.80]	*	1218.21	[9.87]	*
ACHIEVEMENT LEVEL				Random Effects					
Parameter				Est	*ICC*		Est	*ICC*	
School				0.08	0.14	*	0.11	0.21	*
Classroom				0.01	0.02	*	0.01	0.02	*
Student				0.48	0.84	*	0.42	0.77	*
Posterior Predictive p-value				0.477			0.477		
				Fixed Effects					
Effect				Est	SE	df	Est	SE	
Intercept				1.80	[0.07]	*	1.73	[0.08]	*

Note. * indicates statistical significance at the $p < .05$ level. Ideal posterior predictive p-values should approach 0.50.

Random Effects

As shown in Table 3.3, there is nontrivial school-level variation in all four outcomes. Classroom-level variation is smaller than school-level variation, but still present. Mathematics outcomes show somewhat more overall higher-level (classroom and school combined) clustering than ELA outcomes.

English Language Arts

Scale Score. Classroom-mean-centered attendance positively predicted ELA when measured as a scale score at the observational/student level, $b = 1.273$, 95% CrI $[0.344, 2.188]$, reflecting a within-classroom observational/student association rather than a pure within-student change effect. Year did not credibly predict ELA scale score, $b = 11.489$, 95% CrI $[-10.592, 33.960]$, nor did it credibly predict attendance, $b = -0.043$, 95% CrI $[-0.557, 0.469]$.

At the classroom level, the intervention contrasts did not credibly predict classroom mean attendance. Classroom mean attendance, however, significantly predicted classroom mean ELA scale score, $b = 6.549$, 95% CrI [$0.747, 9.388$]. Direct intervention effects on ELA scale score were not credible, and none of the credible intervals for the indirect effects through classroom mean attendance excluded zero.

Achievement Level. Classroom-mean-centered attendance was positively associated with ELA at the observational/student level, $b = 0.012$, 95% CrI [$0.003, 0.020$], reflecting a within-classroom observational/student association, not a pure within-student longitudinal effect. The effect of year on ELA performance level was not credible, $b = 0.099$, 95% CrI [$-0.066, 0.272$], and year did not credibly predict attendance, $b = -0.043$, 95% CrI [$-0.557, 0.468$], indicating no significant change from prior year to current year attendance and ELA as operationalized as an Achievement Level.

At the classroom level, none of the intervention contrasts credibly predicted classroom mean attendance: H1, $b = 0.206$, 95% CrI [$-0.070, 0.480$]; H2, $b = 0.026$, 95% CrI [$-0.282, 0.336$]; H3, $b = -0.362$, 95% CrI [$-0.992, 0.272$]. However, classroom mean attendance significantly predicted classroom mean ELA performance level, $b = 0.040$, 95% CrI [$0.020, 0.059$]. Direct classroom-level intervention effects on ELA performance level were not credible, and none of the credible intervals for the indirect effects through classroom mean attendance excluded zero.

Mathematics

Scale Score. Classroom-mean-centered attendance positively predicted mathematics scale score at the observational/student level, $b = 2.777$, 95% CrI [$1.877, 3.664$]. The year effect on mathematics scale score was not clearly credible, $b = 19.112$, 95% CrI [$-4.568, 43.063$], and year did not credibly predict attendance, $b = -0.043$, 95% CrI [$-0.556, 0.469$].

At the classroom level, classroom mean attendance significantly predicted classroom mean mathematics scale score, $b = 7.109$, 95% CrI $[1.973, 10.651]$, but none of the intervention contrasts credibly predicted classroom mean attendance. Direct intervention effects and indirect effects were not credible.

Achievement Level. Classroom-mean-centered attendance positively predicted mathematics performance level at the observational/student level, $b = 0.017$, 95% CrI [0.009, 0.025]. Year did not credibly predict attendance, $b = -0.043$, 95% CrI $[-0.556, 0.468]$, nor did it credibly predict mathematics performance level, $b = 0.136$, 95% CrI $[-0.029, 0.307]$.

Classroom mean attendance significantly predicted classroom mean mathematics performance level, $b = 0.034$, 95% CrI $[0.015, 0.053]$; however, the intervention contrasts did not credibly predict classroom mean attendance, and neither the direct nor indirect classroom-level intervention effects were credible.

Summary. Across all four outcomes, the pattern is consistent. Classroom-mean-centered attendance was positively related to each outcome at the within classroom levels, indicating that students who attend class more, perform better. Classroom mean attendance was also positively related to each outcome at the classroom level indicating that classrooms with higher attendance rates tend to have higher performing students. Unfortunately, the intervention contrasts did not credibly predict classroom mean attendance indicating that the PAP intervention did not credibly lead to improved attendance or academic outcomes. Therefore, the classroom-level indirect effects through attendance were not supported.

Table 3.4. Multilevel Mediation Path Estimates by Outcome

	English Language Arts				*Mathematics*			
	Scale Score		Achievement Level		Scale Score		Achievement Level	
Path	**Mdn**	**95% CrI**	**Mdn**	**95% CrI**	**Mdn**	**95% CrI**	**Mdn**	**95% CrI**
Observational/Student Level								
Attendance → Outcome	1.27	[0.34, 2.19]	0.01	[0.00, 0.02]	2.78	[1.88, 3.66]	0.02	[0.01, 0.03]
Year → Outcome	11.49	[-10.59, 33.96]	0.10	[-0.07, 0.27]	19.11	[-4.57, 43.06]	0.14	[-0.03, 0.31]
Year → Attendance	-0.04	[-0.56, 0.47]	-0.04	[-0.56, 0.47]	-0.04	[-0.56, 0.47]	-0.04	[-0.56, 0.47]
Classroom level								
H1 → mean attendance	0.21	[-0.07, 0.48]	0.21	[-0.07, 0.48]	0.21	[-0.07, 0.48]	0.21	[-0.07, 0.48]
H2 → mean attendance	0.03	[-0.28, 0.34]	0.03	[-0.28, 0.34]	0.03	[-0.28, 0.34]	0.03	[-0.28, 0.34]
H3 → mean attendance	-0.36	[-0.99, 0.27]	-0.36	[-0.99, 0.27]	-0.36	[-1.00, 0.27]	-0.36	[-0.99, 0.27]
Mean attendance → Outcome	6.55	[0.75, 9.39]	0.04	[0.02, 0.06]	7.11	[1.97, 10.65]	0.03	[0.02, 0.05]
H1 → Outcome	2.22	[-2.36, 6.90]	0.00	[-0.04, 0.03]	1.51	[-3.37, 6.45]	-0.01	[-0.04, 0.03]
H2 → Outcome	-1.48	[-6.59, 3.73]	-0.02	[-0.06, 0.02]	-0.58	[-5.99, 4.92]	-0.01	[-0.04, 0.03]
H3 → Outcome	3.14	[-7.29, 13.45]	0.01	[-0.07, 0.08]	3.49	[-7.53, 14.52]	0.03	[-0.04, 0.10]
Indirect effects								
H1 indirect	1.13	[-0.40, 3.44]	0.01	[-0.00, 0.02]	1.34	[-0.49, 4.04]	0.01	[-0.00, 0.02]
H2 indirect	0.10	[-1.88, 2.31]	0.00	[-0.01, 0.02]	0.15	[-2.20, 2.66]	0.00	[-0.01, 0.01]
H3 indirect	-1.92	[-7.12, 1.65]	-0.01	[-0.05, 0.01]	-2.33	[-8.35, 1.96]	-0.01	[-0.04, 0.01]

H1: Control (no filter) versus the average of T1 (dust), T2 (dust + chemical), and T3 (dust + chemical + biological)

H2: T2 versus the average of T2, and T3

H3: T2 versus T3

Mdn: Median of the posterior distribution

95% CrI: Bayesian 95% Credible interval

Student and School Characteristics as Potential Moderating Effects

As an exploratory follow-up to the primary evaluation of the PAP intervention, a series of 25 four-level generalized linear mixed models were estimated to evaluate the potential moderating impact of five demographic variables on the PAP intervention effect involving each of five outcomes: attendance, ELA scale score, ELA achievement level, mathematics scale score, and mathematics achievement level. Separate models were fit to evaluate whether treatment effects varied by each of the five dichotomously-scaled student (gender [female], race/ethnicity [minoritized], English learner [ELL] status, free/reduced-price lunch eligibility [FRLE]) and school (rural status) characteristics. Consistent with direct evaluation of treatment effects and mediation models of the indirect effect of intervention on attendance to positively impact achievement, all models were structured to consider repeated observations nested within students, students within classrooms, and classrooms within schools, with random intercepts specified for schools, classrooms, and students.

Variance Components. Across models, most variability occurred at the student level. For example, after accounting for year, intervention condition, and the respective potential moderator (gender, race, etc.), the student-level variability component was large ($\sigma^2 = 8.38$, $p < .05$) while school-level variance was smaller but significant ($\sigma^2 = 0.82$, $p < .05$), and classroom variance was negligible. Similar patterns emerged across academic outcomes, where student-level variance consistently accounted for the largest proportion of total variance, followed by smaller contributions from schools and classrooms. This distribution of variance was highly consistent across the demographic moderation models. See Table 3.5 for variance component estimates and intraclass correlations.

Attendance. There is limited evidence that Attendance improved in the intervention year relative to the prior year. In most models, the intervention condition-specific change coefficients (C × Year, T1 × Year, etc.) were not statistically significant, indicating little pre–post change for the reference subgroup (Gender: male, Race: white, ELL: fluent, FRLE: paid; Rural: urban) within conditions. Baseline subgroup differences were modest but present for some moderator groups. For example, FRLE eligibility was associated with significantly lower baseline attendance across intervention conditions (e.g., $b = -2.35$, $p < .05$ for C × FRLE). Likewise, minoritized students in T1 classrooms had lower baseline attendance ($b = -1.20$, $p < .05$).

Evidence of subgroup differences in change over time was limited. The only notable moderation effect occurred with rurality as the moderator, where the interaction for T2 × Year × Rural indicated a differential pre–post change for rural versus urban students ($b = 0.78$, $p < .05$) with rural students having a larger improvement in attendance compared to urban students. No significant gender-, race-, ELL-, or FRLE-based differences in change over time were detected.

Parameter estimates and inferential decisions are reported in Table 3.6, and Figures 3.6 and 3.11 present change graphs organized by intervention condition and moderator.

English Language Arts.

Scale Score. ELA scale scores were significantly higher in the intervention year than they were in the prior year regardless of intervention condition. Positive Year Intervention (C, T1-T3) × Year coefficients indicated significant gains for the reference subgroup in each condition (e.g., [Female] C × Year: $b = 34.79$, $p < .05$; [Race] T1 × Year: $b = 19.34$, $p < .05$, etc.).

Several demographic characteristics were associated with baseline disparities. Minoritized, ELL, and FRLE students had significantly lower baseline ELA scores compared to their reference groups (white, fluent, paid) in several conditions (e.g., T1 × Race: $b = -28.98$, $p <$

.05; C × ELL: $b = -113.98$, $p < .05$; C × FRLE: $b = -27.17$, $p < .05$). Despite these baseline differences, most subgroup characteristics did not significantly moderate growth over time. One exception occurred in the FRLE model, where T3 × Year × FRLE was negative and statistically significant ($b = -22.39$, $p < .05$), indicating smaller ELA gains among FRLE-eligible students in the T3 condition. In addition, the rural model showed significant negative interactions for T1 × Year × Rural ($b = -14.59$, $p < .05$) and T2 × Year × Rural ($b = -16.32$, $p < .05$), suggesting smaller improvements among rural students in those treatment conditions.

Parameter estimates and inferential decisions are reported in Table 3.6, and Figures 3.7 and 3.11 present change graphs organized by intervention condition and moderator.

Achievement Level. ELA performance also improved significantly from prior year to the intervention year – when measured as an achievement level - across conditions (e.g., [ELL] C × Year: $b = 0.17$, $p < .05$; [rural] T2 × Year: $b = 0.19$, $p < .05$). Baseline disparities were again evident. FRLE students had lower baseline ELA performance levels in all conditions (e.g., C × FRLE: $b = -0.27$, $p < .05$). ELL was similarly associated with lower baseline performance levels in C, T1, and T2 conditions (e.g., C × ELL: $b = -0.45$, $p < .05$). Race differences were present in some conditions, with minoritized students showing lower baseline performance levels in T1 and T2. Few subgroup differences emerged for change over time. However, FRLE significantly moderated change in two treatment conditions. Both T2 × Year × FRLE ($b = -0.13$, $p < .05$) and T3 × Year × FRLE ($b = -0.18$, $p < .05$) indicated smaller improvements in ELA achievement levels among FRLE-eligible students relative to non-eligible students. Rural students in the T1 condition had smaller improvements in ELA achievement levels compared to improvements made by urban students in the T1 condition (T1 × Year × Rural: ($b = -0.12$, $p < .05$).

Parameter estimates and inferential decisions are reported in Table 3.6, and Figures 3.8 and 3.11 present change graphs organized by intervention condition and moderator.

Mathematics

Scale Score. Mathematics scale scores showed strong and consistent pre–post improvement across conditions (e.g., [Race] C × Year: $b = 38.81.74$, $p < .05$; [ELL] T1 × Year: $b = 28.31$, $p < .05$). Baseline differences by demographic characteristics were again apparent. Minoritized students had significantly lower prior year mathematics scores across conditions (e.g., C × Race: $b = -30.55$, $p < .05$). ELL students also had substantially lower prior year scores (e.g., C × ELL: $b = -70.91$, $p < .05$). FRLE eligibility was similarly associated with lower baseline mathematics scores (e.g., C × FRLE: $b = -25.99$, $p < .05$). A small number of moderation effects were observed. When race was included as a potential moderator, the T1 × Year × Race interaction was significant ($b = 13.79$, $p < .05$), indicating larger mathematics gains for minoritized students in T1 relative to White students (but they also had lower scores in the year). With rurality as a moderator, T1 × Year × Rural ($b = -22.04$, $p < .05$) and T3 × Year × Rural ($b = -21.90$, $p < .05$) indicated smaller mathematics gains among rural students compared to urban students in those conditions.

Parameter estimates and inferential decisions are reported in Table 3.6, and Figures 3.9 and 3.11 present change graphs organized by intervention condition and moderator.

Achievement Level. Mathematics achievement levels also improved significantly over time across all conditions and in all moderator model variations (e.g., [ELL] C × Year: $b = 0.16$, $p < .05$; [Rural] T1 × Year: $b = 0.18$, $p < .05$). Baseline subgroup differences mirrored those observed for scale scores. Minoritized and FRLE-eligible students had lower baseline mathematics achievement levels across all conditions (all *ps* < .05), and female and Ell students also had lower mathematics achievement levels in at least two conditions (all ps < .05). Rural students in the T1 and T3 conditions had higher prior year achievement levels than urban students (see Table XXX). Only one potential moderation effect emerged. The only statistically significant differential growth effect was observed with rurality as the moderator, where T3 × Year × Rural was negative ($b = -0.29$, $p < .05$), indicating smaller gains in mathematics performance level among rural students in the T3 condition.

Parameter estimates and inferential decisions are reported in Table 3.6, and Figures 3.10 and 3.11 present change graphs organized by intervention condition and moderator.

Summary. Across outcomes, ELA and mathematics scores and performance levels generally improved from pretest to posttest in all intervention conditions, whereas attendance showed little change regardless of intervention condition. Baseline demographic disparities were common, particularly for race, ELL status, and FRLE eligibility, which were consistently associated with lower academic outcomes in the prior year. In contrast, subgroup differences in prior-year-to-intervention-year change were relatively limited. When present, moderation effects most frequently involved FRLE or rural students and tended to indicate smaller gains for those groups in specific treatment conditions.

Study 3 Summary

Direct Effects of Air Purifiers

Attendance. Average student attendance increased slightly across the sample with 94.86% average attendance in 2021–2022 and 95.15% attendance in 2022–2023. This improvement was statistically significant overall, indicating a modest general increase in attendance from the prior year. However, no differential improvement was observed between the control classrooms and the PAP intervention classrooms. Therefore, classrooms with functioning PAPs did not show greater improvement in attendance than classrooms with a placebo PAP with no filter. Attendance increased slightly across all classrooms, but the improvement cannot be attributed to the air purifier intervention.

English Language Arts (ELA). ELA scale scores increased from an average of approximately 2,486 in 2021-2022 to an approximate average of 2,508 in the intervention year of 2022-2023. This was a statistically significant increase indicating general academic improvement from the prior year. However, treatment classrooms did not improve more than control classrooms. In fact, results suggest that there were slightly smaller gains in treatment classrooms compared to control classrooms, though the differences were small. Thus, while students improved overall, air purifier conditions did not produce additional gains in ELA performance. When using Achievement Level as the outcome, average level increased from 1.80 to 1.98, where a score of 2 indicates a student is "On Track." No treatment condition showed significantly greater year-to-year improvement when compared to control, indicating that improvements occurred equally across all conditions.

Mathematics. Mathematics scale scores increased from an average of approximately 1,201 in the prior 2021-2022 academic year to an average of approximately 1,233 in the intervention year, again representing a statistically significant overall improvement. However, no treatment condition improved more than the control condition. Similar to results of intervention effects on English language arts outcomes, results suggest that there were slightly smaller gains in treatment classrooms compared to control classrooms, though the differences were again small. Thus, while students improved overall, air purifier conditions did not produce additional gains in mathematics performance. When using mathematics achievement level as the outcome, average level increased from 1.69 to 1.85, where a score of 2 again indicates a student is "On Track." None of the treatment conditions showed significantly greater year-to-year improvement when compared to control, indicating that improvements occurred equally across all conditions.

Overall Direct Effect Conclusions. Across all five outcomes, students improved from the prior year to the intervention year; however, no statistically significant improvement was attributable to the portable air purifier intervention.

Mediation Analysis: Does Attendance Explain Academic Outcomes? The study also tested whether PAPs might improve outcomes indirectly through improved attendance, hypothesizing that the PAP intervention would lead to higher attendance which would in turn lead to better academic performance. Higher attendance was found to be positively associated with improved academic performance where students who attended school more frequently tended to have higher ELA and mathematics scores and achievement levels. This held at both the student and the classroom levels where students with better attendance performed better academically and classrooms with higher average attendance had higher overall performance. However, the critical mediation pathway failed as the PAP intervention did not statistically increase attendance, therefore PAPs of any type did not improve attendance over the control condition. Because PAPs did not affect attendance, the mediation hypothesis was not supported, thus the PAP intervention did not positively influence academic outcomes either directly or indirectly through attendance.

Moderation Analysis: Do Effects Differ Across Student Groups?. The study also examined whether PAP effects varied across demographic groups with potential moderators including student gender, race or ethnicity, English learner status, and free or reduced lunch eligibility and rural vs urban school location. Significant baseline academic disparities were observed across many demographic groups. Students who were minoritized, English learners, and eligible for free/reduced lunch generally had lower academic outcomes in the prior year, and these disparities were consistent across conditions. There was very little evidence of differential change in outcomes due to potential moderation, however, although a few demographic interactions were observed. Rural students in certain treatment conditions showed smaller academic gains than urban students, and free or reduced lunch eligible students showed smaller ELA gains in the PAP condition with highest filtration (T3: HEPA + activated carbon + germicidal ultraviolet). However, these effects were isolated and inconsistent, and the overall pattern indicated limited moderation.

Variability in Outcomes Across Contextual Levels. Across nearly all models, most variability in outcomes occurred at the student level with smaller but meaningful variability occurring at the school level. Classroom-level variance was minimal, particularly for attendance. This pattern suggests that individual differences between students explain most variation in outcomes, school context matters somewhat, but classroom-level variation beyond school effects was relatively small.

Final Conclusions. The cluster randomized trial found minimal evidence that portable air purifiers in the classroom improved elementary student attendance or academic achievement. Although attendance and academic outcomes improved slightly from the prior year, these improvements occurred equally across treatment and control classrooms, suggesting they were due to broader factors unrelated to the intervention. Attendance was positively related to academic performance, but because the PAP intervention did not increase attendance, it also did not indirectly affect student achievement. Overall, the findings indicate that installing portable air purifiers in classrooms did not produce measurable academic or attendance benefits within the timeframe of this study.

Table 3.5. Variance Components and Intraclass Correlations Across Outcomes

	Female			Race			ELL			FRLE			Rural		
							Attendance								
Effect	**Est**	**ICC**		**Est**	**ICC**		**Est**	**ICC**		**Est**	**ICC**		**Est**	**ICC**	
School	0.82	0.05	*	0.67	0.04	*	0.84	0.05	*	0.33	0.02	*	0.76	0.05	*
Classroom	0.00	--		0.00	--		0.00	--		0.00	--		0.00	--	
Student	8.38	0.50	*	8.36	0.51	*	8.35	0.50	*	7.83	0.50	*	8.42	0.51	*
Residual	7.41	0.45	*	7.40	0.45	*	7.41	0.45	*	7.40	0.48	*	7.39	0.45	*
							ELA Scale Score								
Effect	**Est**	**ICC**		**Est**	**ICC**		**Est**	**ICC**		**Est**	**ICC**		**Est**	**ICC**	
School	999.11	0.12	*	857.25	0.11	*	862.69	0.11	*	545.71	0.08	*	994.46	0.12	*
Classroom	931.18	0.12	*	906.41	0.12	*	873.16	0.11	*	850.34	0.12	*	949.30	0.12	*
Student	4527.49	0.57	*	4468.16	0.57	*	4343.38	0.57	*	4292.86	0.59	*	4566.59	0.57	*
Residual	1549.74	0.19	*	1545.43	0.20	*	1546.72	0.20	*	1540.82	0.21	*	1534.81	0.19	*
							ELA Level								
Effect	**Est**	**ICC**		**Est**	**ICC**		**Est**	**ICC**		**Est**	**ICC**		**Est**	**ICC**	
School	0.06	0.11	*	0.06	0.10	*	0.06	0.10	*	0.04	0.06	*	0.06	0.11	*
Classroom	0.03	0.05	*	0.03	0.05	*	0.03	0.05	*	0.03	0.05	*	0.03	0.05	*
Student	0.31	0.52	*	0.30	0.52	*	0.30	0.52	*	0.29	0.54	*	0.31	0.52	*
Residual	0.19	0.32	*	0.19	0.33	*	0.19	0.33	*	0.19	0.35	*	0.19	0.32	*
							MATH Scale Score								
Effect	**Est**	**ICC**		**Est**	**ICC**		**Est**	**ICC**		**Est**	**ICC**		**Est**	**ICC**	
School	1506.40	0.19	*	1252.58	0.17	*	1351.56	0.18	*	927.87	0.13	*	1288.85	0.17	*
Classroom	822.47	0.10	*	813.05	0.11	*	808.02	0.11	*	737.39	0.11	*	862.52	0.11	*
Student	4438.28	0.56	*	4349.08	0.58	*	4343.37	0.57	*	4197.53	0.60	*	4510.96	0.58	*
Residual	1131.65	0.14	*	1124.13	0.15	*	1131.68	0.15	*	1127.27	0.16	*	1098.39	0.14	*
							MATH Level								
Effect	**Est**	**ICC**		**Est**	**ICC**		**Est**	**ICC**		**Est**	**ICC**		**Est**	**ICC**	
School	0.07	0.15	*	0.06	0.13	*	0.07	0.14	*	0.04	0.10	*	0.07	0.14	*
Classroom	0.02	0.05	*	0.02	0.05	*	0.02	0.05	*	0.02	0.04	*	0.03	0.05	*
Student	0.26	0.51	*	0.26	0.52	*	0.26	0.52	*	0.25	0.54	*	0.26	0.52	*
Residual	0.15	0.29	*	0.15	0.30	*	0.15	0.30	*	0.15	0.32	*	0.15	0.29	*

Note. Est = variance estimate (σ^2); ICC = Intraclass correlation; "*" indicates statistical significance at the $p < .05$ level

Table 3.6. Fixed Effects Estimates for PAP Intervention Effects by Moderator

	Female			***Race***			***ELL***			***FRLE***			***Rural***		
							Attendance								
Effect	**Est**	**SE**		**Est**	**SE**		**Est**	**SE**		**Est**	**SE**		**Est**	**SE**	
C	94.89	[0.37]	*	94.76	[0.30]	*	94.62	[0.30]	*	95.64	[0.31]	*	94.54	[0.34]	*
T1	94.87	[0.29]	*	94.96	[0.25]	*	94.58	[0.25]	*	95.52	[0.24]	*	94.41	[0.29]	*
T2	95.25	[0.31]	*	95.26	[0.27]	*	95.16	[0.26]	*	95.68	[0.25]	*	95.19	[0.30]	*
T3	94.78	[0.37]	*	95.08	[0.32]	*	94.87	[0.30]	*	95.69	[0.31]	*	94.99	[0.36]	*
C*Year	-0.20	[0.31]		0.08	[0.24]		0.09	[0.22]		-0.09	[0.28]		0.02	[0.25]	
T1*Year	0.37	[0.22]		0.31	[0.19]		0.44	[0.16]	*	0.29	[0.20]		0.43	[0.20]	*
T2*Year	0.25	[0.25]		0.20	[0.21]		0.22	[0.18]		0.22	[0.21]		-0.05	[0.21]	
T3*Year	0.45	[0.31]		0.51	[0.27]	*	0.45	[0.23]	*	0.35	[0.29]		0.15	[0.30]	
C*MOD	-0.38	[0.43]		-0.25	[0.55]		2.41	[1.27]		-2.35	[0.44]	*	0.64	[0.65]	
T1*MOD	-0.50	[0.32]		-1.20	[0.37]	*	2.08	[1.10]		-2.33	[0.33]	*	0.77	[0.52]	
T2*MOD	-0.07	[0.36]		-0.10	[0.41]		1.11	[0.88]		-1.15	[0.39]	*	0.23	[0.56]	
T3*MOD	0.20	[0.46]		-0.73	[0.53]		0.42	[1.40]		-2.06	[0.49]	*	-0.04	[0.63]	
C*Year*MOD	0.59	[0.43]		0.07	[0.54]		0.09	[1.24]		0.43	[0.43]		0.33	[0.49]	
T1*Year*MOD	0.10	[0.32]		0.36	[0.35]		-1.18	[1.10]		0.27	[0.33]		-0.01	[0.33]	
T2*Year*MOD	-0.12	[0.36]		-0.06	[0.40]		-0.65	[0.87]		-0.14	[0.38]		0.78	[0.39]	*
T3*Year*MOD	-0.05	[0.46]		-0.35	[0.52]		-0.95	[1.37]		0.25	[0.48]		0.69	[0.47]	
							ELA Scale Score								
Effect	**Est**	**SE**		**Est**	**SE**		**Est**	**SE**		**Est**	**SE**		**Est**	**SE**	
C	2474.06	[11.12]	*	2488.07	[10.27]	*	2484.59	[9.96]	*	2490.86	[9.84]	*	2478.24	[12.11]	*
T1	2485.45	[8.87]	*	2496.79	[8.23]	*	2490.46	[7.97]	*	2505.46	[7.50]	*	2479.24	[9.83]	*
T2	2477.09	[9.53]	*	2492.88	[8.82]	*	2488.38	[8.53]	*	2496.48	[8.07]	*	2479.15	[10.46]	*
T3	2483.73	[10.61]	*	2490.83	[9.82]	*	2488.98	[9.42]	*	2496.27	[9.32]	*	2480.36	[11.65]	*
C*Year	34.79	[4.59]	*	28.34	[3.58]	*	29.95	[3.29]	*	33.72	[4.18]	*	33.36	[3.76]	*
T1*Year	21.65	[3.34]	*	19.34	[2.82]	*	20.36	[2.43]	*	21.51	[3.04]	*	26.18	[3.02]	*
T2*Year	18.17	[3.71]	*	20.13	[3.10]	*	22.42	[2.73]	*	25.96	[3.17]	*	28.13	[3.22]	*
T3*Year	14.08	[4.78]	*	17.97	[4.04]	*	15.92	[3.55]	*	23.15	[4.31]	*	15.85	[4.55]	*
C*MOD	12.93	[8.07]		-34.97	[10.33]	*	-113.98	[23.37]	*	-27.17	[8.51]	*	7.48	[23.65]	
T1*MOD	7.30	[6.00]		-28.98	[6.97]]	*	-79.66	[20.38]	*	-44.85	[6.55]	*	31.61	[19.00]	
T2*MOD	13.26	[6.78]	*	-32.08	[7.80]	*	-99.80	[16.33]	*	-32.24	[7.55]	*	13.52	[20.22]	
T3*MOD	5.60	[8.39]		-16.91	[10.03]		-90.92	[25.25]	*	-23.08	[9.46]	*	22.33	[21.99]	
C*Year*MOD	-7.96	[6.35]		12.64	[8.10]		26.24	[18.31]		-7.33	[6.45]		-10.18	[7.33]	

T1*Year*MOD	-1.97	[4.72]		4.66	[5.25]		12.85	[16.33]		-2.66	[4.85]		-14.59	[4.96]	*
T2*Year*MOD	9.72	[5.26]		10.50	[5.97]		10.45	[12.96]		-10.25	[5.71]		-16.32	[5.71]	*
T3*Year*MOD	2.59	[6.84]		-10.24	[7.82]		-13.41	[20.51]		-22.39	[7.17]	*	-1.11	[7.08]	
ELA Achievement Level															
Effect	**Est**	**SE**		**Est**	**SE**		**Est**	**SE**		**Est**	**SE**		**Est**	**SE**	
C	1.74	[0.09]	*	1.87	[0.08]	*	1.85	[0.07]	*	1.94	[0.07]	*	1.86	[0.09]	*
T1	1.78	[0.07]	*	1.87	[0.06]	*	1.81	[0.06]	*	1.93	[0.06]	*	1.77	[0.08]	*
T2	1.72	[0.07]	*	1.85	[0.07]	*	1.80	[0.07]	*	1.89	[0.06]	*	1.79	[0.08]	*
T3	1.79	[0.08]	*	1.84	[0.08]	*	1.82	[0.07]	*	1.89	[0.07]	*	1.78	[0.09]	*
C*Year	0.22	[0.05]	*	0.17	[0.04]	*	0.17	[0.04]	*	0.18	[0.05]	*	0.18	[0.04]	*
T1*Year	0.20	[0.04]	*	0.19	[0.03]	*	0.19	[0.03]	*	0.19	[0.03]	*	0.23	[0.03]	*
T2*Year	0.13	[0.04]	*	0.17	[0.03]	*	0.18	[0.03]	*	0.22	[0.03]	*	0.19	[0.04]	*
T3*Year	0.16	[0.05]	*	0.19	[0.04]	*	0.18	[0.04]	*	0.23	[0.05]	*	0.17	[0.05]	*
C*MOD	0.18	[0.08]	*	-0.15	[0.10]		-0.45	[0.22]	*	-0.27	[0.08]	*	-0.10	[0.17]	
T1*MOD	0.04	[0.06]		-0.26	[0.07]	*	-0.53	[0.19]	*	-0.35	[0.06]	*	0.07	[0.14]	
T2*MOD	0.11	[0.06]		-0.26	[0.07]	*	-0.63	[0.15]	*	-0.31	[0.07]	*	-0.09	[0.15]	
T3*MOD	0.03	[0.08]		-0.13	[0.10]		-0.34	[0.25]		-0.19	[0.09]	*	0.09	[0.16]	
C*Year*MOD	-0.11	[0.07]		-0.03	[0.09]		-0.07	[0.20]		-0.04	[0.07]		-0.07	[0.08]	
T1*Year*MOD	-0.03	[0.05]		0.00	[0.06]		0.01	[0.18]		-0.02	[0.05]		-0.12	[0.05]	*
T2*Year*MOD	0.10	[0.06]		0.04	[0.07]		-0.07	[0.14]		-0.13	[0.06]	*	-0.03	[0.06]	
T3*Year*MOD	0.02	[0.07]		-0.09	[0.09]		-0.23	[0.22]		-0.18	[0.08]	*	-0.01	[0.08]	
MATH Scale Score															
Effect	**Est**	**SE**		**Est**	**SE**		**Est**	**SE**		**Est**	**SE**		**Est**	**SE**	
C	1205.67	[11.53]	*	1205.79	[10.62]	*	1201.32	[10.60]	*	1208.66	[10.10]	*	1192.94	[12.34]	*
T1	1215.12	[9.65]	*	1215.96	[8.88]	*	1205.71	[8.92]	*	1222.82	[8.16]	*	1185.77	[10.35]	*
T2	1206.15	[10.19]	*	1210.54	[9.38]	*	1204.84	[9.38]	*	1216.87	[8.63]	*	1193.20	[10.90]	*
T3	1202.87	[11.06]	*	1205.40	[10.19]	*	1198.99	[10.10]	*	1214.69	[9.63]	*	1178.19	[11.88]	*
C*Year	40.91	[3.94]	*	38.81	[3.06]	*	38.40	[2.82]	*	40.46	[3.59]	*	35.67	[3.19]	*
T1*Year	26.36	[2.87]	*	24.50	[2.41]	*	28.31	[2.08]	*	27.30	[2.61]	*	36.71	[2.56]	*
T2*Year	28.80	[3.18]	*	30.10	[2.65]	*	30.52	[2.34]	*	33.31	[2.72]	*	32.72	[2.73]	*
T3*Year	24.76	[4.10]	*	24.54	[3.46]	*	27.35	[3.04]	*	23.53	[3.70]	*	36.35	[3.86]	*
C*MOD	-14.39	[7.58]		-30.55	[9.62]	*	-70.91	[22.00]	*	-25.99	[7.99]	*	22.14	[24.16]	
T1*MOD	-21.87	[5.62]	*	-42.07	[6.53]	*	-64.65	[19.25]	*	-49.30	[6.16]	*	63.22	[20.08]	*
T2*MOD	-9.60	[6.37]		-31.14	[7.31]	*	-72.62	[15.41]	*	-40.54	[7.08]	*	30.10	[21.13]	
T3*MOD	-14.14	[7.79]		-34.47	[9.31]	*	-96.67	[23.43]	*	-47.66	[8.80]	*	58.01	[22.64]	*
C*Year*MOD	-5.13	[5.46]		-2.77	[6.96]		-2.45	[15.76]		-5.40	[5.54]		10.04	[6.21]	

T1*Year*MOD	4.11	[4.06]		13.79	[4.50]	*	4.14	[14.08]		2.46	[4.17]		-22.04	[4.20]	*
T2*Year*MOD	4.29	[4.51]		2.90	[5.11]		8.09	[11.17]		-8.14	[4.90]		-5.69	[4.84]	
T3*Year*MOD	5.09	[5.89]		10.29	[6.71]		0.87	[17.69]		10.19	[6.17]		-21.90	[6.00]	*
MATH Achievement Level															
Effect	**Est**	**SE**		**Est**	**SE**		**Est**	**SE**		**Est**	**SE**		**Est**	**SE**	
C	1.82	[0.08]	*	1.77	[0.07]	*	1.74	[0.07]	*	1.83	[0.07]	*	1.68	[0.09]	*
T1	1.78	[0.07]	*	1.78	[0.06]	*	1.70	[0.06]	*	1.83	[0.06]	*	1.61	[0.07]	*
T2	1.74	[0.07]	*	1.75	[0.07]	*	1.71	[0.07]	*	1.82	[0.06]	*	1.65	[0.08]	*
T3	1.74	[0.08]	*	1.70	[0.07]	*	1.66	[0.07]	*	1.78	[0.07]	*	1.50	[0.09]	*
C*Year	0.13	[0.04]	*	0.16	[0.03]	*	0.16	[0.03]	*	0.13	[0.04]	*	0.15	[0.04]	*
T1*Year	0.15	[0.03]	*	0.14	[0.03]	*	0.17	[0.02]	*	0.16	[0.03]	*	0.18	[0.03]	*
T2*Year	0.12	[0.04]	*	0.17	[0.03]	*	0.17	[0.03]	*	0.17	[0.03]	*	0.17	[0.03]	*
T3*Year	0.15	[0.05]	*	0.19	[0.04]	*	0.19	[0.03]	*	0.17	[0.04]	*	0.30	[0.04]	*
C*MOD	-0.19	[0.07]	*	-0.17	[0.09]	*	-0.39	[0.20]	*	-0.27	[0.07]	*	0.16	[0.17]	
T1*MOD	-0.17	[0.05]	*	-0.31	[0.06]	*	-0.33	[0.17]		-0.36	[0.05]	*	0.29	[0.14]	*
T2*MOD	-0.11	[0.06]		-0.23	[0.07]	*	-0.49	[0.14]	*	-0.37	[0.06]	*	0.14	[0.15]	
T3*MOD	-0.18	[0.07]	*	-0.18	[0.09]	*	-0.19	[0.22]		-0.33	[0.08]	*	0.43	[0.16]	*
C*Year*MOD	0.05	[0.06]		-0.06	[0.08]		-0.09	[0.18]		0.05	[0.06]		0.02	[0.07]	
T1*Year*MOD	0.04	[0.05]		0.09	[0.05]		-0.09	[0.16]		-0.01	[0.05]		-0.05	[0.05]	
T2*Year*MOD	0.09	[0.05]		0.01	[0.06]		-0.01	[0.13]		0.01	[0.06]		0.01	[0.06]	
T3*Year*MOD	0.07	[0.07]		-0.02	[0.08]		-0.36	[0.20]		0.04	[0.07]		-0.29	[0.07]	*

Note. C = control condition, T1 = HEPA only, T2 = HEPA + activated carbon, T3 = HEPA, activated carbon, germicidal ultraviolet; year = 0/prior & 1/current; MOD = dichotomous moderator coded 0/1 where moderator is the variable name of the column, 1 = variable name category, 0 = not the variable name category (i.e. “female”: 0 = male, 1 = female). * indicates statistical significance at the $p < .05$ level.

“C-T3” reflect initial levels for the moderator coded “0” during the prior year, for the respective intervention condition.
“C-T3 * Year” reflect the change in outcome for moderator = 0 from prior to current year, for the respective intervention condition.
“C-T3 * MOD” reflect difference between moderator = 0 and moderator = 1 during the prior year, for the respective intervention condition.
“C-T3 * Year * MOD” reflect difference in year-to-year change between moderator = 0 and moderator = 1, for the respective intervention condition.

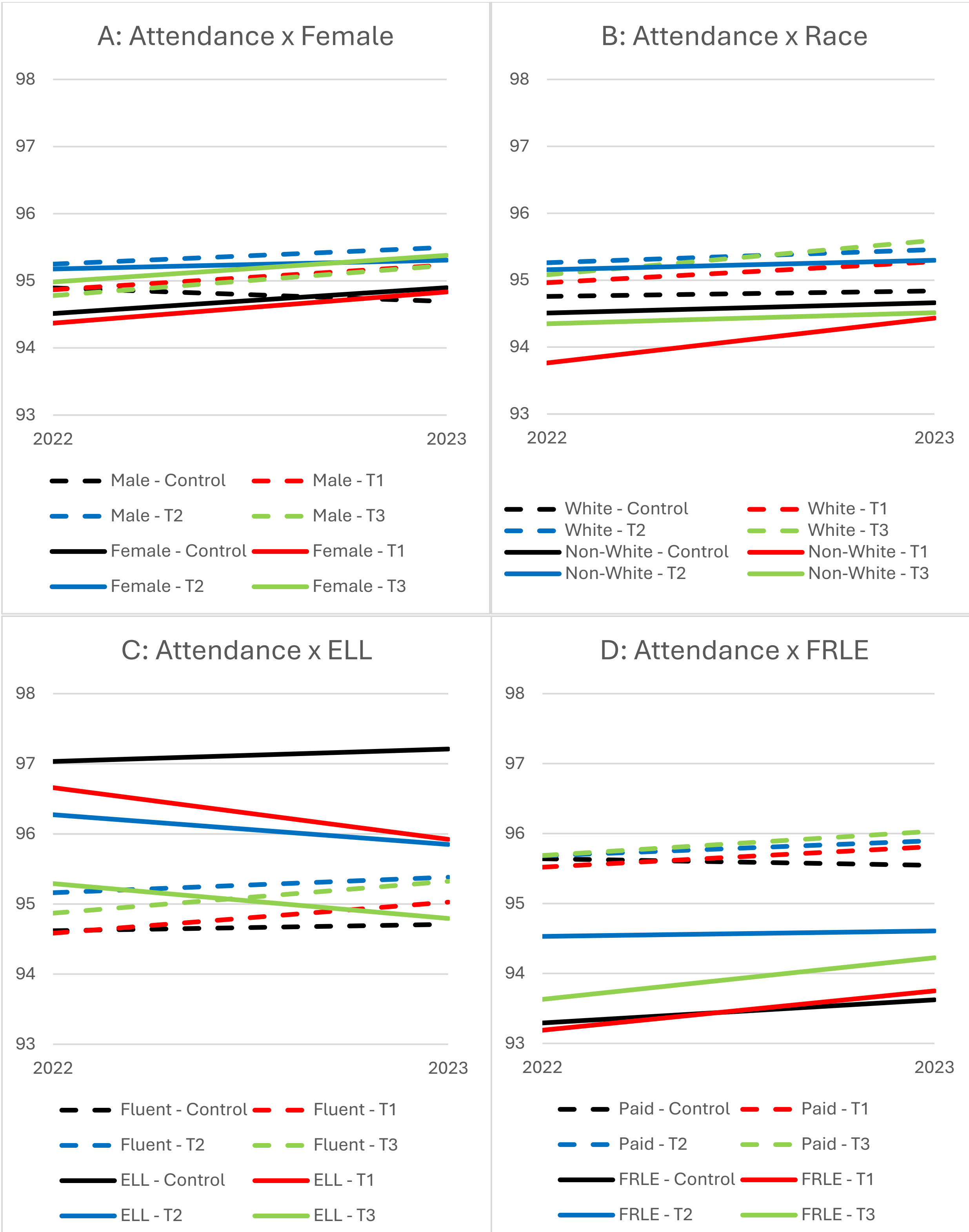

Figure 3.6. Attendance by student-level moderator.

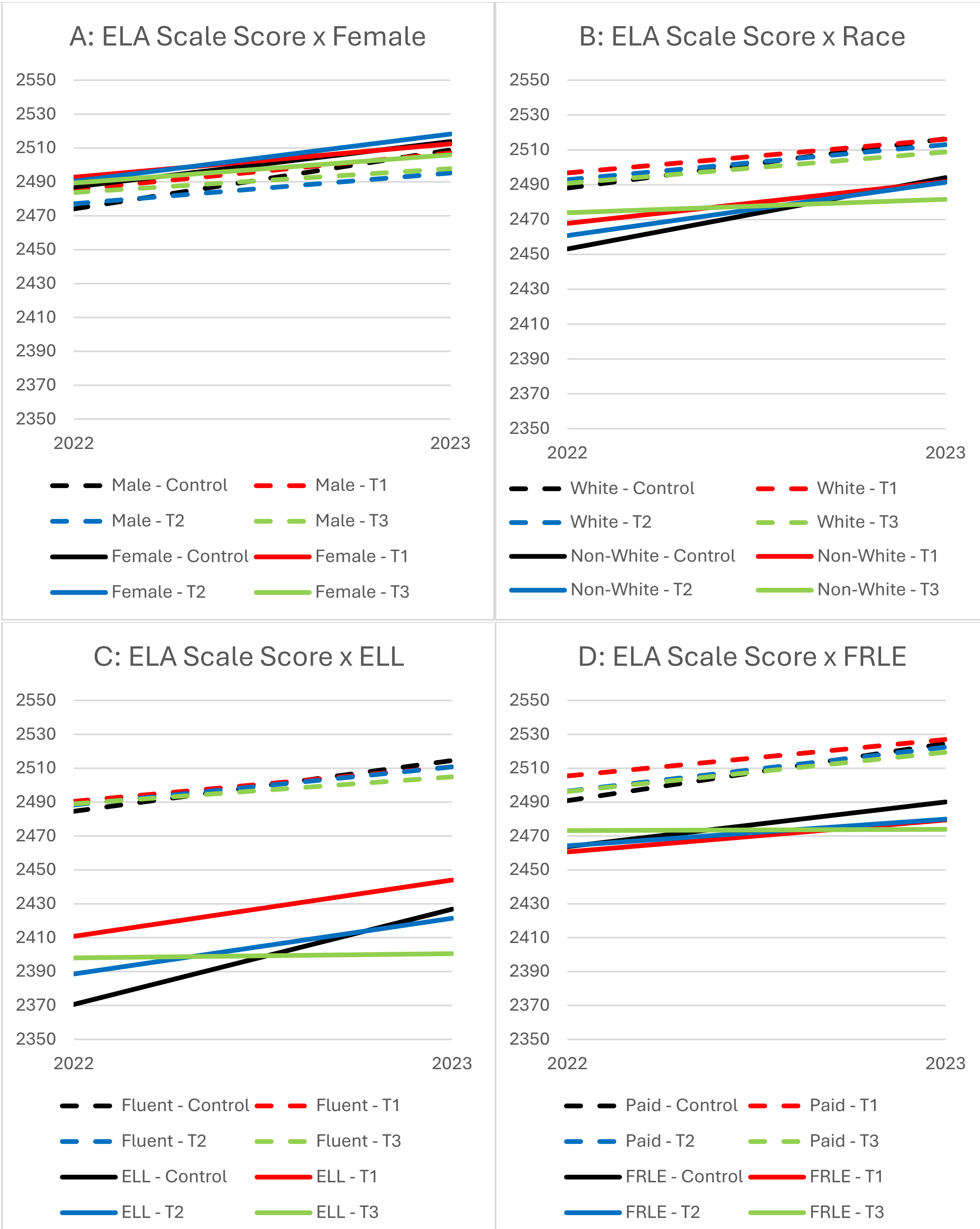

Figure 3.7. ELA Scale Score by student-level moderator.

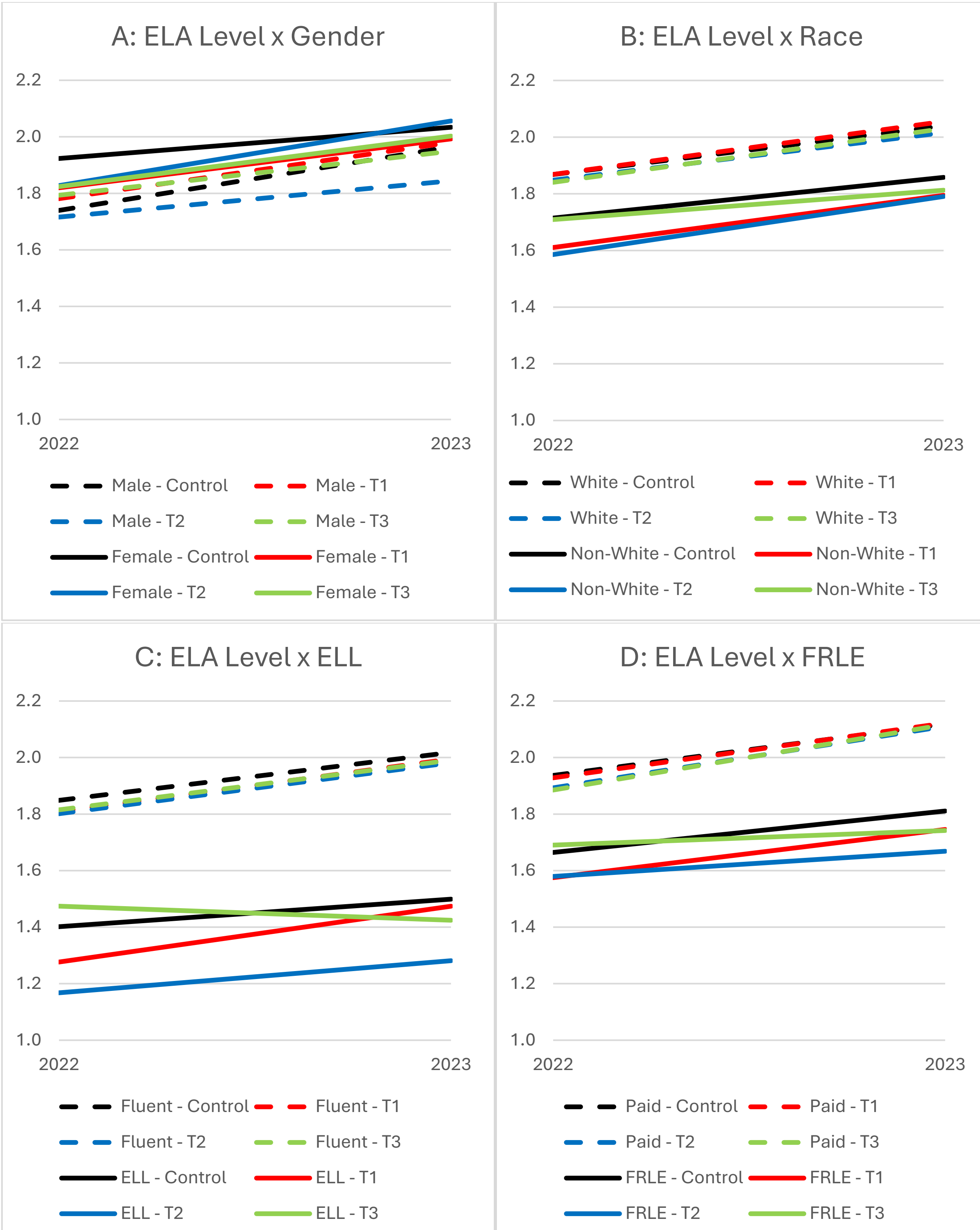

Figure 3.8. ELA Achievement Level by student-level moderator.

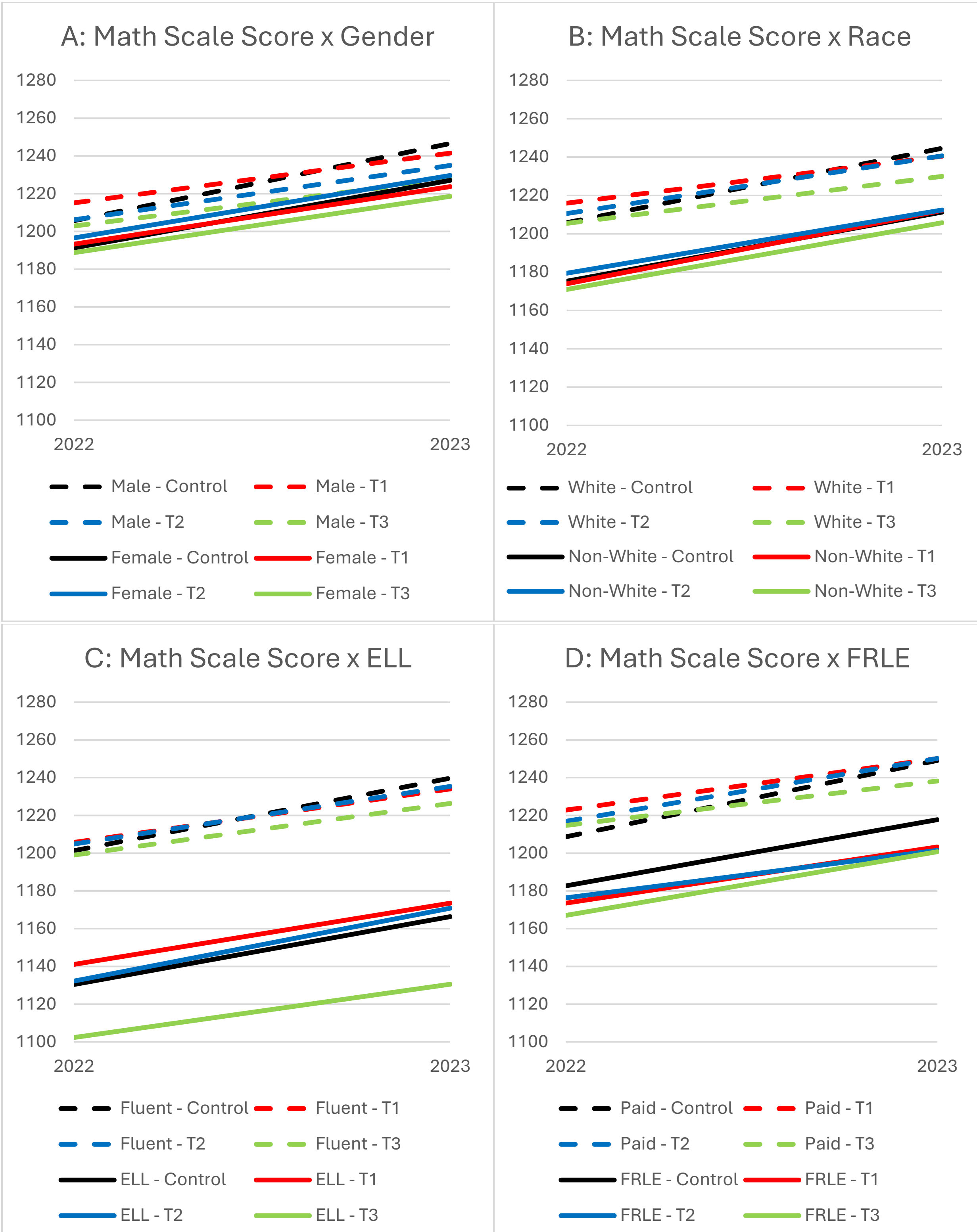

Figure 3.9. Mathematics Scale Score by student-level moderator.

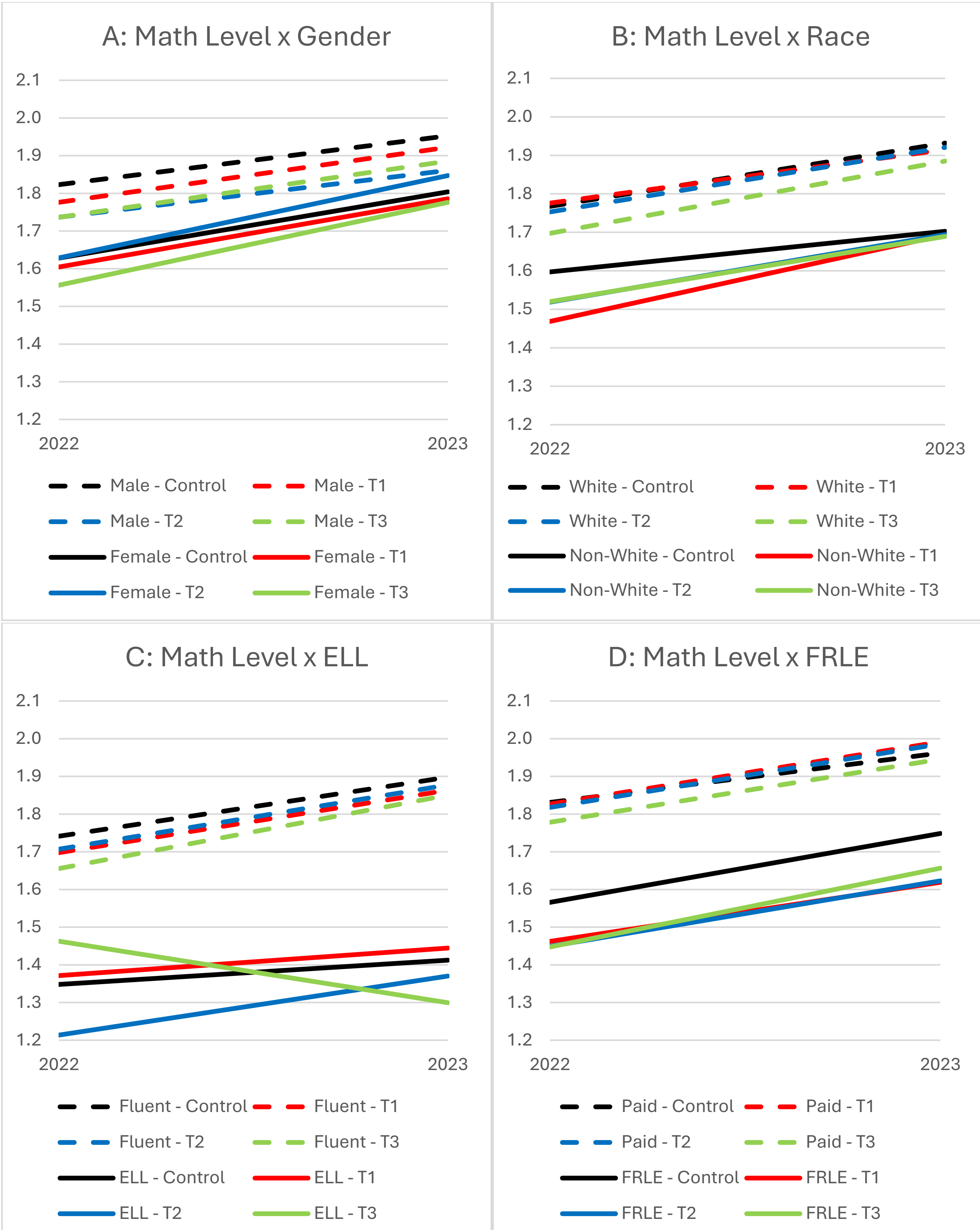

Figure 3.10. Mathematics Achievement Level by student-level moderator.

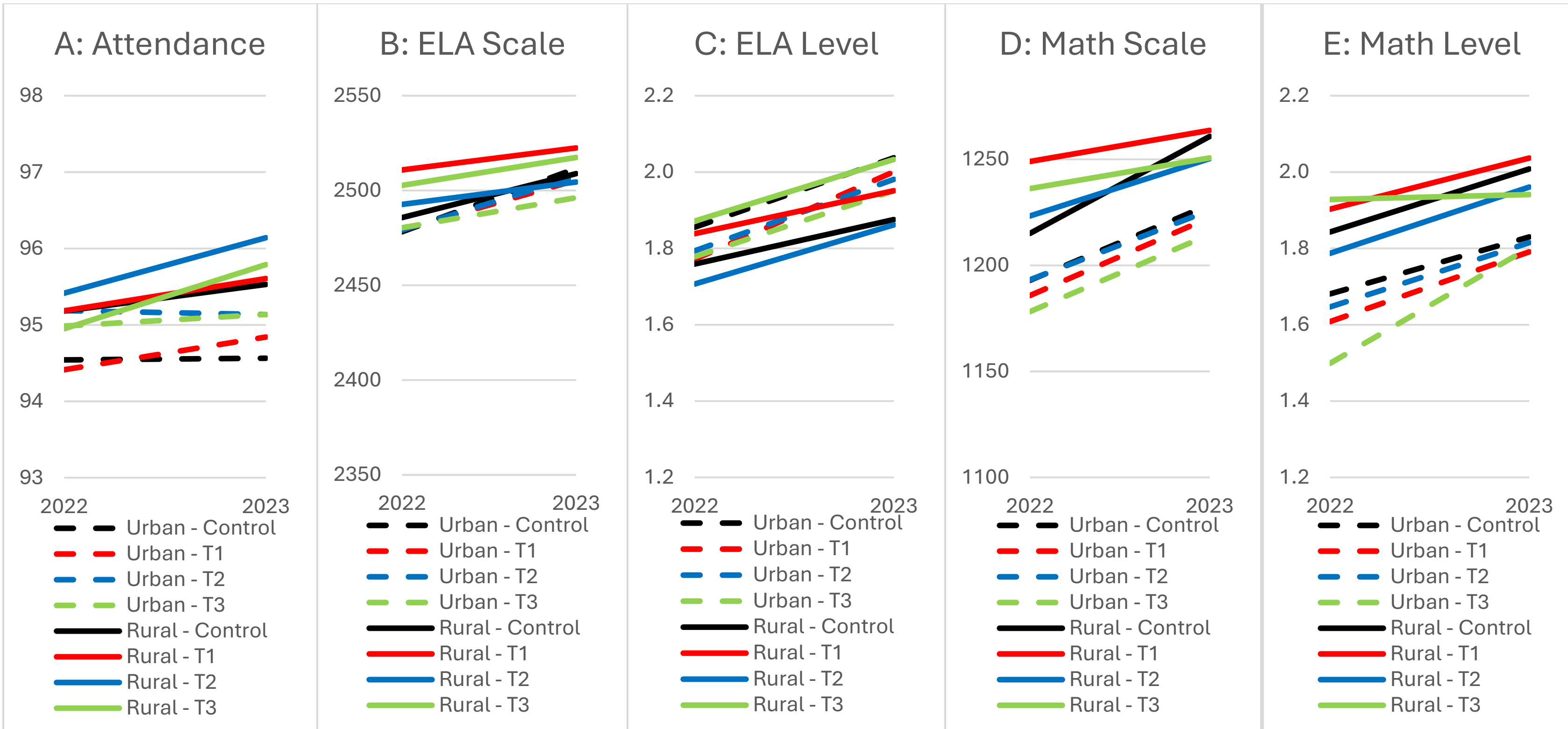

Figure 3.11. Outcomes by Rurality as a school-level moderator

Discussion

This study reports the results of a randomized controlled trial evaluating the effect of portable air purifiers (PAPs) in elementary school classrooms. It focuses on three domains: indoor air quality, illness-related absenteeism, and student academic outcomes. The study draws data from over 4,000 students in 317 classrooms in 51 schools. It addresses both the potential and the limitations of in-classroom air filtration as an educational and public health intervention.

Study 1 essentially serves as a "proof of concept" study to demonstrate that the PAPs perform the function they are intended to – improving classroom air quality. Consequently, and as they should, the strongest and most consistent findings emerged from Study 1. Across multiple model specifications and particle size ranges, portable air purifiers significantly reduced both fine (PM2.5) and coarse (PNcoarse) concentrations relative to the control condition. These reductions were observed across three treatment configurations, all of which included HEPA filtration. The most consistent PAP performance occurred in the HEPA (T1) and the HEPA + Activated carbon (T2) conditions. Results suggest that the experimental manipulation of the PAP filter improved air filtration by meaningfully reducing particulate matter in classrooms.

As expected, PAP effectiveness was moderated by classroom occupancy. Particle concentrations increased during occupied periods. The magnitude of filtration benefits was lower when students were present. This pattern matches known mechanisms of particle generation and resuspension caused by human activity. These findings show that filtration alone cannot fully offset occupancy-driven particle loads. Real-world effectiveness is therefore conditional in a complex context.

While theoretically important for indoor air quality, ventilation was shown to have limited direct effects on fine particles and only modest, context-dependent effects on coarse particles. Notably, ventilation rates varied widely across classrooms, with approximately 68% of classrooms operating below ASHRAE-recommended levels. This widespread under-ventilation is indicative of critical structural issues in school environments that filtration alone may not fully address.

In contrast to the clear improvements in particulate matter, portable air purifiers did not demonstrate meaningful reductions in total volatile organic compounds (TVOC) or ozone concentrations. This null finding is likely attributable to relatively low baseline levels of these pollutants in the sampled classrooms and may indicate a floor effect. It may also indicate that HEPA-based filtration, even when supplemented with activated carbon, can have a limited impact on gaseous pollutants under normal school conditions.

Study 2 examined illness-related absenteeism (IRA), a key outcome linking environmental conditions to student health and effective student learning. Across both full-year and seasonal models, there was no consistent or statistically significant evidence that portable air purifiers reduced absenteeism. Neither the main effects of filtration nor the interactions with ventilation were robust across model specifications.

The absenteeism findings were complex and, at times, counterintuitive. In several models, higher daily ventilation rates were associated with increased absenteeism, while higher classroom- or school-level average ventilation rates were associated with decreased absenteeism. These mixed results likely reflect the challenges of separating environmental effects from broader epidemiological dynamics, including seasonal patterns of respiratory illness, incubation periods, and external exposures. Seasonal analyses demonstrated that relationships between ventilation, filtration, and absenteeism vary across fall, winter, and spring, consistent with known seasonal variation in infectious diseases.

Study 3 extended the evaluation to student academic outcomes as measured by the Nebraska Student-Centered Assessment System (NSCAS), providing a direct test of whether improved indoor air quality may contribute to enhanced student learning. Across multiple outcome measures - including English language arts and mathematics scale scores and performance levels – third through sixth-grade elementary students demonstrated expected year-to-year improvements. However, these gains were not attributable to the portable air purifier intervention. None of the treatment conditions produced statistically significant improvements relative to the control condition. In some cases, treatment classrooms exhibited slightly smaller gains, though these differences were small and not meaningful.

Study 3 also examined whether PAPs indirectly influence academic outcomes by improving classroom attendance. Although attendance was positively associated with academic performance at both the student and classroom levels, the intervention did not significantly improve attendance. As a result, the hypothesized mediation pathway was not supported, and portable air purifiers did not affect academic outcomes either directly or indirectly through attendance.

Moderation analyses indicated that while baseline disparities in academic outcomes existed across demographic groups—including differences by socioeconomic status, race/ethnicity, and English learner status—there was little consistent evidence that the intervention differentially benefited or disadvantaged specific groups. A small number of isolated interactions were observed, but these were inconsistent and did not suggest a systematic pattern of moderation.

Furthermore, variance decomposition results indicated that most variability in academic outcomes occurred at the student level, with smaller contributions from school-level differences and minimal additional variation at the classroom level. This pattern illustrates the dominant role of the individual and broader contextual factors involved in determining academic performance relative to classroom-level environmental interventions.

Taken together, these findings highlight an important disconnect between environmental improvements and downstream educational outcomes. Portable air purifiers clearly improve indoor air quality, particularly by reducing particulate matter. Yet, these improvements did not translate into measurable reductions in absenteeism or gains in academic achievement within the timeframe of this study. Several explanations are plausible. First, the magnitude of air quality improvement, while statistically significant, may not have been large enough to produce detectable changes in health or learning outcomes. Second, the pathways linking air quality to student academic performance are likely indirect and mediated by multiple factors, including health, cognition, and instructional quality, which may require longer exposure periods to manifest. Third, dominant influences on both absenteeism and academic outcomes - such as community disease transmission, student background characteristics, and instructional factors - may overshadow any marginal gains attributable to environmental interventions.

From a policy and practice perspective, this study suggests that portable air purifiers represent a valuable but limited tool. PAPs are effective at improving classroom air quality and may help mitigate exposure to airborne particles, particularly in under-ventilated environments. However, they should not be expected to produce immediate or profound improvements in overall student attendance or academic performance when implemented in isolation. Instead, portable air purifiers may be better understood as one component of a broader strategy to improve school environments, which should also include investments in ventilation infrastructure, infection control practices, and broader public health initiatives.

Future research should focus on longer-term exposure effects, integration of classroom filtration with building ventilation improvements, and more precise measurement of the connection between indoor air quality and student health and learning. In particular, studies incorporating direct measures of bioaerosols and respiratory-related infection transmission, as well as longer follow-up periods, may provide greater insight into the conditions under which environmental interventions can meaningfully influence academic outcomes.

In conclusion, this randomized trial provides strong evidence that portable air purifiers improve classroom indoor air quality but limited evidence that these improvements can be translated into meaningful gains in student attendance or academic achievement. This study contributes important experimental evidence to a growing literature on school environmental quality and reinforces the need for comprehensive, multi-faceted approaches to improving student outcomes.

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