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Explorations of Acoustic Trends in Data Logged in K-12 Classrooms

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EXPLORATIONS OF ACOUSTIC TRENDS IN DATA LOGGED IN K-12 CLASSROOMS

by

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EXPLORATIONS OF ACOUSTIC TRENDS IN INDOOR ENVIRONMENT DATA LOGGED IN K-12 CLASSROOMS

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The classroom environment influences the ability of children to learn. To ascertain the effect of indoor environment parameters on student achievement, a large-scale project was launched, collecting time-logged data from 220 k-12 classrooms in the eastern Nebraska region for six days each. Data were collected from a variety of disciplines, including acoustics, lighting, indoor air quality, and thermal comfort. This thesis focuses on the acoustic parameters, looking first at how overall classroom values–including average sound levels and room reverberation time–influence student achievement. Using structural equation modeling, the average sound level during times with speech present was discovered to have a negative effect on math achievement scores while room reverberation time had no statistical effect on either math or reading in the sample. Second, the time–logged data within each measured day were explored, observing specifically how the fluctuations over time correlate to the fluctuations in the data from other disciplines, including indoor air quality, thermal comfort, and illuminance measures. Indoor air quality parameters, including carbon dioxide concentration and particulate matter counts, were found to be most closely correlated with sound level over time. Finally, the effect of ventilation system type was analyzed, observing how it affects both overall values and time logged correlations. Classrooms with unit ventilators were observed to have the highest overall non-speech sound levels and a higher likelihood of finding a strong correlation between sound level and coarse particulate matter.

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I am deeply grateful to those who have helped me on this journey. I could not have done it without the support of my advisor, teachers, and classmates. I would like to thank my friends for keeping me sane, feeding me, and helping me have balance. I would especially like to thank my family and my dear parents for always believing in me and thinking everything I do is incredible, although I'm sure they are particularly proud of this work.

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Chapter 1
Introduction

1.1 Importance of Classroom Acoustics

Students are the future leaders of society, making education a crucial component of a community's infrastructure. A variety of parameters within the building affect the comfort and performance of occupants. Among these are the acoustics of the classroom, including reverberation time and noise levels within the room. Numerous metrics exist that characterize the sound within a room and several are explored within this project. This thesis describes the acoustic results from a project undertaken to measure acoustic and other indoor environment parameters within schools.

1.2 Healthy Schools Project

A grant from the U.S. Environmental Protection Agency (EPA) enabled the long-term collection of data within 220 K-12 classrooms in the eastern Nebraska region of the U.S. (EPA Grant R835633). The project is entitled "Evidence-Based Interactions between Indoor Environmental Factors and Their Effects on K-12 Student Achievement" and uses direct measurements of indoor environment parameters to predict student achievement in classrooms.

220 Schools were measured for this project, with a sampling of rooms from the 3^{rd} grade (74), 5^{th} grade (70), 8^{th} grade (32) and the 11^{th} grade (44). The classrooms were chosen from 5 districts, with samplings ranging from 10 to 80 schools per district. Acoustic, Indoor

Air Quality (IAQ), Thermal Comfort, and Lighting parameters were measured in each of these classrooms for two days during each of Fall, Winter, and Spring seasons. These data are considered here for analysis, with particular attention to the acoustic measured data.

1.3 Summary of remaining chapters

Chapter 2 describes the literature within the field and the research that has been done, looking specifically at classroom acoustics research and studies that have measured sound levels, their effect on student achievement, or their interaction with other indoor environment parameters. This chapter outlines further the importance of acoustics within the classroom.

Chapter 3 provides an overall view of the acoustic component of the Healthy Schools Project, describing the acoustic measurements and metrics and the subsequent statistical analyses that relate these parameters with student achievement. Averaged acoustic parameters were calculated for each classroom, such as the A-weighted equivalent continuous sound level ($L_A eq$) and octave band levels. K-means clustering was used to divide time-logged data into times when speech was present and times when speech was not present. From these divisions, overall sound levels were also calculated for speech and non-speech categories. Various other acoustics metrics, including statistical levels, were calculated from the classroom data.

A description of collected demographic variables follows, including percent gifted, percent special education, and percent free and reduced lunch recipients within each classroom. Subsequently, outcome variables are described, including standardized test scores in the form of average percentile rankings in reading or math.

A structural equation model is presented that relates the acoustic variables to the outcome variables, controlling for demographics. The unit of analysis is the classroom, where the analysis tests for the impact of indoor environment conditions on student achievement. An effect of speech sound level on math achievement is observed, with higher noise contributing to lower math achievement percentile rankings.

Chapter 4 takes a deeper dive into the temporal fluctuations of the data in contrast with the averaged values utilized in Chapter3. Data processing techniques are explained and correlational analyses were undertaken. Variation of acoustic data was correlated with temporal variation within other discipline's metrics, with particular attention to IAQ metrics. In particular, positive correlations were found to be likely between sound level and carbon dioxide and between sound level and coarse particulate matter.

A single classroom case study is presented that measured occupancy count logged over time in conjunction with the usual indoor environment metrics. Occupancy was found to significantly correlate with overall sound level and 10μm particle counts in this case. A-weighted L_Ae1 fluctuations significantly correlated with all measured quantities in the sample. Correlations between specific octave frequency band fluctuations, including 125 Hz and 1 kHz, and slecet parameters are also explored, with 1 kHz noise correlating strongly with all measured parameters, similar to the overall level, and 125 Hz noise correlating with fewer parameters.

Chapter 5 explores the effect of a significant contributor of noise in classrooms: the heating, ventilation, and air conditioning (HVAC) system, looking at HVAC system effects on both the averaged acoustic parameters and temporal interactions between parameters. Classrooms are characterized by secondary system type and grouped by building. Significant differences in non-speech sound level are observed by system type, with unit ventilators producing the highest average noise levels. With the temporal data, little variation was found between system type and likelihood of finding a significant correlation except int he case of fine particulate matter (PM), where classrooms with unit ventilators are more likely to have significant correlations between temporal variation of sound level and fine PM.

Overall, the acoustics measured in classrooms are considered holistically, first looking at averaged values and their effects on student achievement. Next, the fluctuations of acoustic and other parameters throughout the school day are considered. Finally, a characterization of noise level by HVAC system type is undertaken.

Chapter 2
Literature Review

The quality of education is always a key concern in society. In the past few decades, research on how the classroom itself influences education has come to the forefront. This chapter will review relevant literature exploring the impact of the environment on student performance as well as research on some of the nuanced interactions between indoor environmental parameters.

2.1 Acoustics in Classrooms

First, the classroom environment has numerous contributing factors to the ambient conditions, such as the amount of light in the room, air quality, thermal comfort, and sound level. Vischer (2008), in a review of literature about workspace environmental psychology, proposed the category of ambient environmental conditions as one of three critical components in a workspace (the other two being office layout and process issue). The category includes lighting, noise, indoor air quality, and thermal comfort. While a classroom is not a workplace, it bears similarity in the amount of time spent and the need for productivity. In fact, a recent literature review highlights the effects of classroom architecture on academic performance from each of the aforementioned disciplines (Lewinski (2015)) and another cites the classroom's 'structural environment'–comprised of lighting, acoustics, temperature, air quality, and accessibility–as one of the key components contributing to an environment that engenders student achievement (Cheryan et al. (2014)). Since student spend a significant proportion of their time in classrooms (Zomorodian et al. (2016)), studies have been devoted to each of these aspects with regards to their effect on student performance, typically isolating one or two disciplines, although some studies have sought a more holistic approach (Barrett et al. (2015),Astolfi & Pellerey (2008)). While much could be said about each discipline (Lau et al. (2016)), this paper focuses primarily on the acoustics, thus the literature reviewed pertains specifically to sound levels and acoustics factors within classrooms or studies that consider the interaction of acoustic parameters with others.

While the acoustic conditions are important for any grade level, there are significantly different spatial and acoustic needs for grade schools versus the university environment, which often consists of lecture halls and larger class sizes. Studies have been done in several countries looking at the acoustics of either university classrooms (Zannin & Ferreira (2009),Ricciardi & Buratti (2018),Edgett et al. (2006),Hodgson (1999)) or primary and secondary school classrooms (Sato & Bradley (2008)). The latter are the focus of this study, with measurements taken in classrooms ranging from 3^{rd} through 11^{th} grade.

2.1.1 Importance of Speech Intelligibility

First, speech intelligibility in classrooms is a key component when determining how the environment impacts student learning. In fact, Hodgson (2002) used speech intelligibility as the quality factor when ranking classrooms at a university in order to determine which should be renovated. Extensive research has been done in exploring speech intelligibility issues in classrooms. For example, J. Bradley & Yang (2009) looked at how reverberation time, early reflections, and different signal to noise ratios affect the speech intelligibility in classrooms for various ages of children, finding that the signal to noise ratio had the greatest effect on speech intelligibility, followed by reverberation time. It has been said that the two key factors determining speech intelligibility are the background noise and the reverberation time in a space Houtgast (1981), and research has been conducted to understand and even predict these two parameters in classrooms Hodgson et al. (1999),Hodgson (2001).

2.1.2 Background and Ambient Noise

As for background noise, the classroom is made up of a complex soundscape of noises with a variety of characteristics Pakulski et al. (2016). Regardless of the complexity, measuring background or ambient noise level in some respect is crucial when quantifying the acoustics of a classroom and when regarding speech intelligibility. Some studies have considered the contribution of outdoor noise, such as traffic or transportation noise (Shield & Dockrell (2004),Bronzaft (1981)) or noise from the schoolyard Sarantopoulos et al. (2014), many concluding that higher outdoor noise levels affect the sound level within the classroom itself, and even the performance of students within the classroom (Shield et al. (2015)). Other researchers found that higher ambient noise within the classroom, such as from student activity, contributes to raised vocal production levels in teachers Rantala et al. (2015). J. E. Dockrell & Shield (2006) explored the effects of both 'babble' (unintelligible speech) and 'environmental' background noise on student achievement in speed and literacy performance tasks, finding that both had potential negative effects on the students' abilities, varying depending on the task. Recently, Connolly et al. (2019) found that high background noise levels significantly impacted student reading and vocabulary performance for the worse, where students performed less accurately in reading comprehension tasks in the presence of background noise. This effect was significant when looking at the difference between 50 dBA background noise and 70 dBA background noise levels, but more difficult to discern when the second level was lowered to 64 dBA.

While many studies measure noise according to the ANSI S12.60 standard in an unoccupied room, several studies additionally address the importance of considering occupied sound levels within a classroom (Chan et al. (2015)) or measuring and utilizing both occupied and unoccupied levels Hodgson (1994). Studies measuring the signal to noise ratio (SNR) in classrooms take into account both occupied levels and the levels of speech that the teacher uses when instructing and significantly interact with the speech intelligibility within a classroom (J. S. Bradley et al. (1999)). A group of researchers in Canada, early in speech intelligibility research, acknowledged the complexity of speech intelligibility, considering early and late sound ratios, center time, early decay time, background noise level, and reverberation time. They concluded that useful/detrimental ratios of noise can be used as an alternative to using background noise and reverberation time to determine speech intelligibility (J. S. Bradley (1986b),J. S. Bradley (1986a)), but this idea has not been embraced widely.

In subjective surveys, correlations between perceived annoyance from sound and actual measured noise levels were found to have a low correlation in Lundquist et al. (2000). Another group postulated that room acoustic conditions led to modifications in occupant behavior in school buildings, such as moving locations for speech communication issues (Bernardi et al. (2006)). When actual subjective speech intelligibility was measured by Escobar & Morillas (2015), it was found to correlate strongly with Sound Transmission Index (STI), suggesting that the metric does a good job of predicting actual speech intelligibility. Bradley 2008?

The research presented in this thesis considers the noise within the occupied classroom with the reasoning that this is what the children will experience as they go about their daily tasks. This noise is further divided into two categories–speech and non-speech noise–that will be explained in subsequent sections.

2.1.3 Reverberation Time

The other important aspect in determining speech intelligibility is reverberation time, a key component in most studies on classroom acoustics. For example, Astolfi et al. (2008) considered both occupied and unoccupied reverberation time, suggesting the importance of considering both the occupied and unoccupied conditions of a classroom. A majority of studies have concluded that lower reverberation time can contribute to better conditions for communication. Both J. Bradley & Sato (2008) and Hodgson & Nosal (2002) warned, however, that a 0 s reverberation time is never the ideal and that excessively low reverberation times should be avoided. Early reflections can help support intelligibility.

The two critical components impacting speech intelligibility, noise and reverberation time, are not entirely independent of each other. A study of classrooms in England, Shield et al. (2015) measured reverberation time and both occupied and unoccupied sound levels, finding that the unoccupied parameters and occupied noise conditions were related. For example, they found that a higher speech transmission index (STI) was correlated with lower equivalent sound levels during lessons.

2.2 Acoustics and Achievement Scores

Research linking acoustic factors and actual student achievement have had mixed results. The group in England, in 2007, studied the effect of classroom noise on student achievement in young children using standardized test scores. They found that higher noise in the classroom indeed correlates with lower student achievement scores J. Dockrell & Shield (2008). Considering external noise, Bronzaft (1981) found that classrooms experiencing higher noise due to proximity to train tracks had lower reading achievement scores and that the difference between reading scores in those classrooms disappeared after a noise abatement program was undertaken. On the other hand, another study found almost no effect of environmental noise on student achievement (Xie et al. (2011)), but only external environmental noise was considered. Eagan et al. (2004) studied the effect of aircraft noise on student achievement for elementary, middle, and high school students, looking specifically at state-standardized achievement scores and finding that noise reduction helps lower achieving students, making them less likely to fail. They found little difference in results between math and reading scores.

2.3 Interactions Between Disciplines

The focus of this thesis is the acoustic conditions within classrooms. However, some interactions between disciplines are considered. For the past few decades, the literature has addressed indoor environment parameters from a variety of disciplines. While the majority of studies isolate one or two factors, several recent studies have highlighted the importance of the interactions between factors. Zhang et al. (2016) notes the additive effect of physical conditions on young students, suggesting that they are more impacted by environmental factors than adults, looking at temperature, relative humidity, carbon dioxide level, illuminance, and sound level. Recently, a study looking at the effect of lighting on student focus (van Mil et al. (2018)) used student activity noise level as a measure of focus, implicitly suggesting a relationship between the two factors.

Other studies do not explicitly suggest relationships, but when considering results from studies in a single discipline, possible relationships between other discipline can be entertained. For example, a study exploring how CO_2 feedback in classrooms improves air quality found relationships between indoor air quality, thermal comfort, and window opening (Wargocki & Da Silva (2012)), which would certainly impact how outdoor sound levels impact classroom noise. Another study looked at how cognitive development in children was affected by traffic-related air pollution in schools, finding that children in schools with higher air pollution (which had quantifiably louder outdoor sound levels due to proximity to heavy traffic) experienced less growth in cognitive development (Sunyer et al. (2015)).

Several studies have specifically aimed at quantifying the correlations between indoor environment qualities, such as the work done by Wang et al. (2015), which found significant correlations between indoor air quality, illuminance, and thermal comfort measures in classrooms, but did not consider sound level. Others, such as Barrett et al. (2015) have considered the interaction of different environmental variables-—including acoustic variables-—with a holistic approach, noting correlations between indoor environment parameters. They used measurements from 153 classrooms that were collected at one time on a single day and observed correlations between the averaged values of the classrooms. The sound levels from this study did not have significant correlations to any of the other variables. The sound had a low negative correlation with light and air quality, and a low positive correlation with temperature, but none were statistically significant at either the 0.01 or 0.05 level.

In a similar study headed by another member of that research team, Zhang et al. (2016) measured 203 English schools, collecting indoor environment data at a single isolated time and found that noise level had a significant positive correlation (0.203) with CO_2 (p<0.01), but had no significant correlations with illuminance, temperature, or relative humidity. The study also considered the state of occupancy, finding that sound level and occupancy had a correlation of 0.456 for their sample, significant at the .01 level, a finding supported by the work of Shield & Dockrell (2004), which also found a significant positive correlation (p<0.01) between number of students and noise level. Some studies, unrelated to noise, even suggest using CO_2 sensor data as a feedback aid in measuring occupancy Pedersen et al. (2017) using adaptive gray-box (Ebadat et al. (December 2015)) or white-box models (Ebadat et al. (2017)). Another study considered the use of machine learning on measurements from various disciplines (lighting, temperature, humidity, and CO_2) to predict occupancy, but they do not include sound level in the proposed model (Candanedo & Feldheim (2016)). A relationship between occupancy and sound level is clear, but several confounding components complicate the sound-occupancy relationship, such as the reverberation time decreasing as occupancy increases because of the additional absorption of bodies within the room Hodgson & Nosal (2002).

Toftum et al. (2014) measured CO_2 and sound level over logged intervals in six classrooms, using an averaged sound and CO_2 levels for each lesson–segments of the teaching day–as the unit of analysis. They found a similar relationship between noise level and CO_2 concentration, where higher CO_2 concentration throughout the day correlated with higher noise levels. They suggested that high occupant density (more students) combined with poor ventilation may lead to elevated levels of CO_2 and that this may adversely affect student behavior and contribute to higher noise. They also suggested that as the school day progresses, so does pupil tiredness, which may also lead to elevated levels in both categories. Forns et al. (2016) studied traffic-related air pollution and noise and found that they both negatively affected student behavior at school.

2.4 Time Variation of Indoor Environment Parameters

Some of the studies looking at the interactions between the indoor environment parameters considered averaged values within the classrooms and others looked at the variation of parameters over time within a single or multiple classrooms. Chapter 4 considers time-logged data from several disciplines as they fluctuate throughout a school day and relate to each other. Some studies have emphasized the importance of considering the time variation of these data within a classroom. One indoor air quality study (Angelon-Gaetz et al. (2015) conjectured a time-based relationship between relative humidity and noise level in classrooms, suggesting that occupants may turn of the unit ventilators to reduce noise, resulting in increased humidity, although this relationship was never quantified. Vilcekova et al. (2017) explored the relationships over time between temperature, relative humidity, carbon dioxide concentration, and air pollution in a sampling of five classrooms in the Slovak Republic. They logged the data for a week in each classroom at regular time intervals and reported correlations over time. While they mentioned noise level along with the aforementioned parameters and logged it over time, sound level correlations with other parameters were not reported.

There is a suggested grade difference in Barrett et al. (2015), indicating that learning in children is non-linear with respect to grade level and suggesting that student age should be controlled for in analyses.

2.5 Motivations for This Work

Chapter 3 describes work done in deriving the acoustic metrics for a larger study, the EPA Healthy Schools project. While preliminary acoustic results are presented, the focus of this work is to describe the acoustic data collection and processing method. Full statistical analysis including all indoor environment parameters is being performed by the whole team and results will be published as they are formulated. Statistics in this chapter should be considered exploratory and evolving.

Chapter 4 dives into time-logged relationships between various indoor environment parameters. While previous studies have looked at relationships between sound level and other parameters, most have either taken isolated measurements and correlated a classroom average or taken time-logged data but performed averaging and looked at correlations on the classroom leve. Studies that have looked at the time-logged relationships between disciplines have much smaller sample sizes and have not included extensive discussion of sound level. This work takes a large sampling of classrooms (n=220) and for each one, looks at the relationships of the parameters over time, enabling the observation of trends over a large number of classrooms.

Chapter 5 explores the effect of mechanical system type on noise, helping quantify a relationship that is typically assumed to exist–that HVAC system type affects noise. Again, the number of classrooms sampled helps illuminate true trends in a dataset that was collected from systems functioning in situ. Limited research exists quantifying the effect of HVAC system type on sound level and particularly on the interaction between sound level and indoor air quality.

Chapter 3
Acoustic Analyses of Averaged Classroom Data

3.1 Overview of Data

A wealth of data from acoustic, lighting, thermal comfort, and indoor air quality disciplines has been collected from 220 K-12 classrooms. Additionally, demographic information and student achievement scores were collected in average from each classroom. In this chapter, the acoustic variables, demographic variables, and outcome variables (achievement scores) will be described, including a description of collection and calculation methods for each. Within this chapter, the unit of analysis is the classroom, so data will be described in terms of classroom averages. Finally, statistical analyses using the classroom unit will be discussed.

3.1.1 Indoor Environment Data Overview: Unoccupied and Logged

Classroom characteristics, such as room dimensions or room reverberation time–an acoustic characteristic of a room indicating how long it takes for sound to decay 60 dB–were collected in unoccupied classrooms, resulting in one value per classroom.

In addition to unoccupied room characteristics, data were logged during the school day to measure conditions during occupied hours. Logged data include sound levels, air pollution, carbon dioxide (CO_2) concentration, formaldehyde concentration, illuminance, door state (percent open), temperature, and relative humidity. These data were collected over two consecutive days—logged at regular time intervals—in each classroom three times throughout the school year, roughly corresponding to once per season. This collection method produced six total days of logged data for each classroom. Sound levels were logged every 10 seconds while other metrics were logged every 5 minutes. Details about acoustic data collection methods can be found in Section 3.1.2 and about the processing of other variables in Section 4.1.1.

To undertake statistical analyses relating achievement to measured variables in each classroom, a single value was needed for each of the test variables. A value was calculated for each of the six days and those six were then arithmetically averaged to produce a typical or likely value for the classroom. The method of calculation for the value within each day varied based on the metric. For example, temperature was taken as a simple average of the values experienced each day, averaging between meters. Equivalent continuous sound levels ($L_A$eq), however, was averaged logarithmically. Logged data and their variation over time will be considered in Chapter 4. The sound levels and derived acoustic metrics are discussed in further detail in the subsequent section. In Appendix B, a table of all collected variables is presented.

3.1.2 Measured Acoustic Variables

This section describes the acoustic variables that were gathered for each classroom, starting first with unoccupied classroom data then describing the metrics derived from the logged levels within each classroom.

First, impulse responses were taken in each classroom, resulting in reverberation times and clarity values. A omnidirectional dodecahedron loudspeaker was used in conjunction with Type I Larson Davis sound level meter and EASERA software to capture the impulse response of the room. One source location (at the front of the room, where the teacher instructs) and two receiver locations within the student seating in the classroom were utilized and sine sweeps were chosen for the test signal. , separating the low, mid, and high frequency values. Reverberation time (T_{20}) values were collected in the low frequency range ($T_{20,\mathrm{low}}$), mid-frequency range($T_{20,\mathrm{mid}}$), and high-frequency range ($T_{20,\mathrm{high}}$). Additionally, clarity (C_{50}) values were also calculated in each classroom.

Next, 1-minute unoccupied background noise level measurements (BNL_{1min}) were taken in each of the classrooms using ANSI S12.60 guidelines. Values for the BNL_{1min} ranged from 25.2 dBA to 55.1 dBA, with an arithmetic average of 42.9 dBA. 202 of the classrooms with valid BNL_{1min} measurements (n=214), or 94% of measured classrooms exceeded the ANSI recommendation of 35 dBA. This finding is consistent with other literature, such as the study by Zhang et al. (2016) that found indoor ambient noise levels between 40 to 80 dBA–somewhat higher than this sample–and only one classroom of 203 that adhered to the local standards for noise level and the work by Knecht et al. (2002) that found only 4 of 32 classrooms measured had levels below the ANSI recommended 35 dBA.

In addition to the unoccupied variables, acoustic data were logged throughout the school days. Two BSWA Type II sound level meters were deployed in each classroom, one in a measurement kit placed near the teacher's desk in the classroom and the other hanging from the ceiling. These meters logged sound levels, including overall levels and octave band levels from 32 Hz to 16 kHz, every 10 seconds for three 2-day segments in each classroom. An logarithmic energy average of the two meters was calculated for each measurement point in time, representing the average sound level in the room. Known unoccupied hours were removed, resulting in single–day sequences of time–logged acoustic data during the occupied school day, typically from 08:30 to 15:30, but variable depending on the school.

A variety of metrics were obtained using the logged data from the sound level meters. First, the overall $L_A$eq values were extracted from the meters. Additionally, k-means clustering, an unsupervised machine learning technique, was used to classify each measurement point in the time series as either a time where speech sounds were present or a time when non-speech sounds were present based on the frequency and level content of the signal. For each day, the speech levels and the non-speech levels were each grouped together and logarithmically averaged to produce a single value per day. The six school days (two in Fall, two in Spring, two in Winter), were arithmetically averaged to produce a single value for each classroom, resulting in the following two metrics: speech equivalent levels ($L_{Aeq,sp}$) and non-speech equivalent levels ($L_{Aeq,ns}$). These two metrics contain information from all frequency bands, so to understand better the potential contributions of specific frequency bands, octave band information from 32 Hz to 16 kHz was also extracted from the sound level meters.

Similar to the overall levels, the octave band information was taken and divided into speech and non-speech times, logarithmically averaged to produce one value per day, and arithmetically averaged between the six days in each classroom to produce a single value for each room. For example, each classroom has a value for speech levels in the 500 Hz octave band ($L500Hz_{sp}$) and a value for non-speech levels in the 500 Hz octave band ($L500Hz_{ns}$). Figure refHist500 shows a histogram of these 500 Hz octave band values for the 220 measured classrooms. Not all octave bands were of interest in the analysis. The following octave bands were used to calculate speech and non-speech variables and histograms of their distributions can be found in Appendix A.1.1:

- speech: 250 Hz, 500 Hz, 1 kHz, 2 kHz
- non-speech: 125 Hz, 250 Hz, 500 Hz

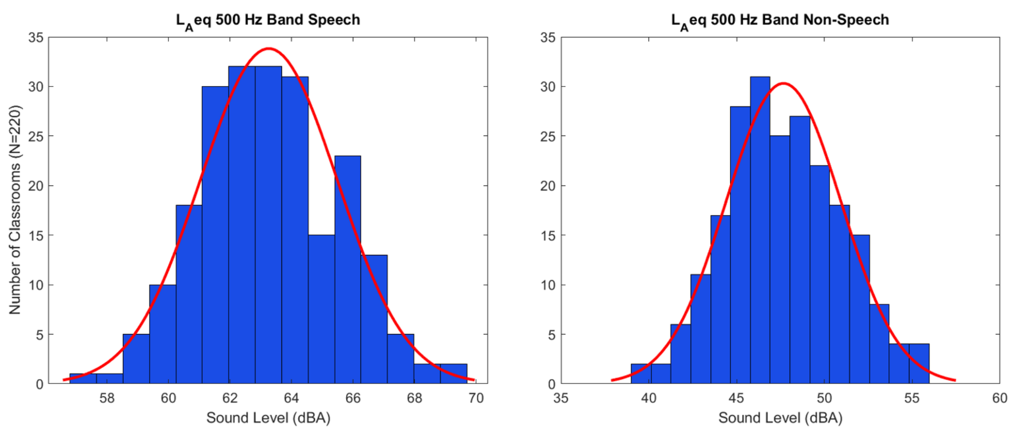


Figure 3.1: Histograms of the daily averaged 500 Hz levels within each classroom for speech (left, N=220) and non-speech (right, N=220) times during the school day

3.1.3 Derived Acoustic Variables

In addition to the equivalent levels in each octave band, the time-logged nature of the data allows for the extraction of other metrics that incorporate behavior over time. A variety of statistical levels and percent exceeded values were calculated for each of the classrooms.

First, statistical levels were calculated for both speech and non-speech data. Statistical levels (L_N) refer to the level exceeded N percent of the time. For example, $L_{90,ns}$ refers to the level that was exceeded 90% of the time when speech was not present for a given day. These metrics are calculated by taking the time-logged levels in either the speech or non-speech category, ordering by magnitude, and identifying the value at which N% of the data falls above said value. For each classroom, the following statistical levels were calculated in the speech and non-speech times: L_{10}, L_{25}, L_{35}, L_{50}, L_{75}, L_{90}. Additionally, the common $L_{10} - L_{90}$ value was calculated for each classroom and noise type; this metric provides some sense of the difference between typical maximum and typical minimum levels.

Second, percent exceeded values were calculated for each of the classroom and noise types. Percent exceeded values refer to the percent of time that a certain value was exceeded during a measurement period. For example, $\%\text{time} > 65\text{dBA}_{sp}$ refers to the percent of time with speech noise present that the level of said sound exceeded 65 dBA. This is calculated by taking the vector of time-logged speech values and dividing the number of time units with values above 65 dBA by the total number of time units with values. For speech times, 60, 65, and 70 dBA were used to calculate percent exceeded values and for non-speech times, 45, 50, and 55 dBA were used, resulting in the following metrics:

- speech: $\%\text{time} > 60\text{dBA}_{sp}$, $\%\text{time} > 65\text{dBA}_{sp}$, $\%\text{time} > 70\text{dBA}_{sp}$
- non-speech: $\%\text{time} > 45\text{dBA}_{ns}$, $\%\text{time} > 50\text{dBA}_{ns}$, $\%\text{time} > 55\text{dBA}_{ns}$

It was discovered that the distributions of percent exceeded levels best approximated a normal distribution at 65 dBA for speech and 50 dBA for non-speech (see Figure 3.2. Accordingly, it is recommended that these levels be used when characterizing speech and non-speech sounds in this manner. Histograms of each of the other statistical levels and percent exceeded variables can be found in Appendix A.1.1.

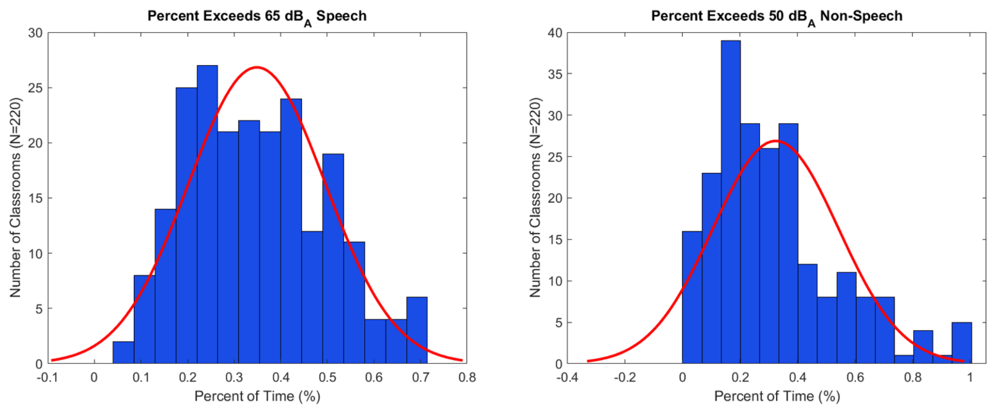


Figure 3.2: Histograms of the percent exceeds values in classrooms for 65 dBA during speech times (left, N=220) and 50 dBA for non-speech times (right, N=220)

3.1.4 Demographic Variables

To better understand how indoor environment variables affect student achievement, it is helpful to collect demographic data so the effects of demographics can be controlled for in the the analyses. For example, classrooms with a high percentage of gifted students would be expected to have higher achievement scores. Measuring these percentages allow for the effect to be removed in the overarching analyses.

The demographic variables that were collected and controlled for in analyses include the percentage of special education (SPED) students in each classroom, the percentage of free and reduced lunch (FRL) recipients, and the percent of gifted students in each classroom. Histograms of the distributions of these variables can be found in Appendix A.1.2.

Table 3.1: Descriptive statistics of demographic variables

Variable	Mean	Stdev	Skew	Kurt
%FRL	37.8	29.9	.304	-1.377
%SPED	14.4	12.0	3.226	19.720
%GIFT	13.5	13.7	1.580	3.714

Table 3.1 shows descriptive statistics of the demographic variables used in the analyses, including the mean, standard deviation, skewness, and kurtosis. The classrooms had widely ranging demographic profiles, as noted by the high standard deviations in comparison with the means. Of possible concern is skew of the percent of special education students in classrooms, which has slightly larger values for skewness and kurtosis than would be desirable, indicating that the distributions of these variables do not perfectly follow the assumption of a typical normal distribution, which can be observed in the histogram (A.35). The skewness and kurtosis were noted and robust sampling was used in later analyses to address any non-normal distributions. The sample size of 220 was chosen such that the effects of interest would become apparent above and beyond other possible confounding variables, such as skill of the teacher or availability of specific resources. Grade levels was also used in some of the analyses, with 3^{rd} grade used as a reference for the other three grades.

3.1.5 Outcome Variables

Ultimately, the overarching goal of the project is to link measured environment variables to student achievement, with the outcome variable for the statistical analyses being student test scores. Standardized state-wide test scores in the form of percentile rankings were obtained as an average for each classroom in the study. Student percentile ranking scores on standardized tests were obtained from the schools for each of the classrooms in the sample and scores were combined into a classroom average. For elementary school classrooms, both reading and math achievement scores were obtained, as students learn both subjects

Table 3.2: Descriptive statistics of demographic variables student percentile scores on standardized achievement tests

Value	PR_{Read}	PR_{Math}
Valid N	181	178
Mean	55.6%	56.7%
Min	5.0%	18.3%
Max	87.3%	96.0%
Stdev	14.1%	14.6%
Skew	-.506	.073
Kurt	.311	-.258

in the same classroom. For high school and middle school classrooms, math and reading achievement scores were obtained in conjunction with the type of instruction performed in each classroom. For example, some high school classrooms are used only for math instruction, so only math achievement scores for students in those classrooms were obtained for the analysis. The number of classrooms with each type of achievement data can be found in Table 3.2. Math and reading scores are considered in separate and distinct analyses. In other words, the models are run twice, once on math achievement and once on reading achievement in order to consider the effects of room environment variables on math and reading achievement separately.

In addition to the number of classrooms included for each measure of achievement, descriptive statistics of the outcome variables can be found in Table 3.2. The mean scores for both reading an math in this sample were just above the 50th percentiles, at 55.6% and 56.7%, respectively. Both ranged widely from below the 20th percentile to above the 85th percentile with standard deviations of around 14-15% each. Both measures are normally distributed with both skewness and kurtosis values below 1. The achievement data for both reading and math were deemed appropriate for use in statistical analysis.

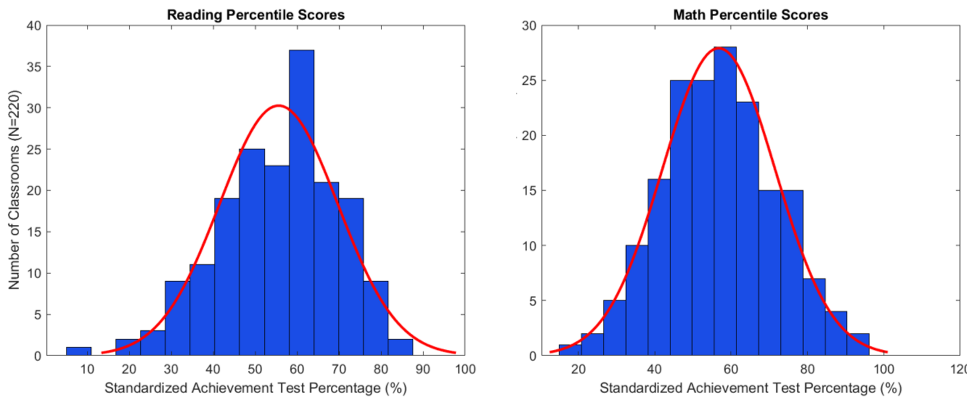


Figure 3.3: Histograms of the distributions of achievement scores for reading (left, N=181) and math (right, N=178) in the classrooms

3.2 Statistical Analysis

The statistical analyses conducted on the dataset will be presented. Preliminary investigation of correlations between raw variables will be presented, followed by a discussion of a measurement model grouping acoustic variables that was used to formulate a structural equation model linking acoustics to student achievement.

3.2.1 Exploration of Correlations

Before embarking on a detailed discussion of the statistical analyses, it is informative to better understand the acoustic, demographic, and outcome data by observing the raw Pearson correlations between select variables. Pearson correlations describe the raw relationship between two variables, or the likelihood that the two variables are related.

First, within the acoustics metrics, as would be expected, correlations were typically high between individual variables. It should be noted that investigating a large number of correlations you examine can introduce experimentwise error. In this case, the assumption is that the variables will typically be correlated (as opposed to looking for a significant correlation among many), but caution should still be taken when interpreting these results beyond an exploratory scope.

All speech metrics of interest (including speech octave band levels listed in Section 3.1.2, derived speech metrics, and background noise level) were highly correlated with each other, with all having correlations significant at the .01 level. The strength of the correlations ranged from .497 ($L4kHz_{sp}$ with $L500Hz_{sp}$) to .976 ($L10_{sp}$ with $L_{A}eq_{sp}$) and averaged .816.

Similarly, non-speech metrics of interest (including non-speech octave band levels listed in Section 3.1.2, derived non-speech metrics, and background noise level) were also highly correlated with each other with two-tailed significances at the .001 level. Correlations fell between .438 ($L1kHz_{ns}$ with $L125Hz_{ns}$) and .956 ($L_{50,ns}$ with $L_{A}eq_{ns}$) and averaged .755 per correlation.

When looking at the correlations between variables in the non-speech category with variables in the speech category, correlations were typically significant, but not always. All speech and non-speech variables were considered, including overall levels, octave band levels, statistical levels, and percent exceeded values for both speech and non-speech categories. For example, speech and non-speech overall levels were significantly correlated at the .01 level, with a correlation coefficient of .347. The average correlation coefficient (for both significant and non-significant correlations) between speech and non-speech variables was .308 and 79 of 90 correlations were significant at either the .05 or .01 level. Figure 3.4 shows a few select correlations between speech an non–speech metrics, with the Pearson correlation coefficient shown in each box and red text indicating that the values are statistically significant ($p<0.05$). For example, this figure shows that the correlation between $L_{90,sp}$ and $L_{90,ns}$ is 0.59 and is significant at the 0.05 level. The ubiquity of statistically significant correlations between speech and non-speech metrics indicates that the two quantities are related and that sound levels during speech times are not independent of sound levels during non-speech times.

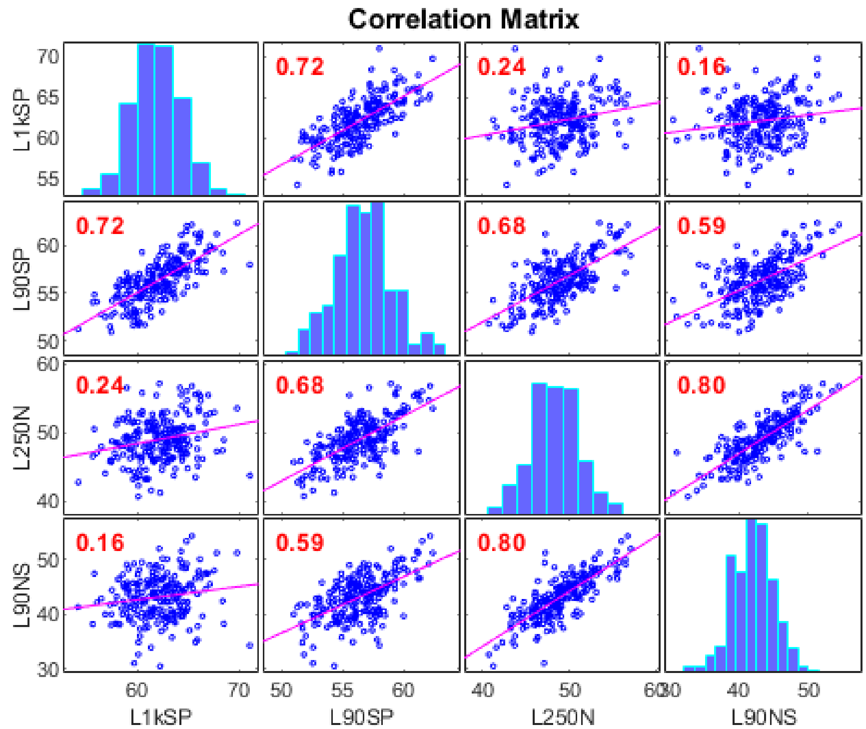


Figure 3.4: Correlations between select speech and non–speech metrics for the whole datset of 220 classrooms

Reverberation time ($T20_{mid}$) had significant correlations with other acoustics metrics for 8 of the 19 correlations. For example, $T20_{mid}$ correlated significantly (p<.05, r = .145) with the non-speech average levels but not with the speech average levels.

Next, correlations between demographic and outcome variables will be discussed. It is postulated that demographic variables will highly correlate to outcome variables, leading to reasoning that they should be controlled for in statistical analyses. Table 3.3 shows the correlations between demographic and outcome variables of interest.

From this table, it is apparent that there is a clear correlation between all three measured demographic variables and the outcome variables. For example, the percent of free and reduced lunch recipients in each classroom has a -.430 correlation with reading achievement scores and a -.572 correlation with math achievement scores. Each of these correlations had a two-tailed significance at the .01 level, indicating that an increase in the percentage

Table 3.3: Raw Pearson correlations between demographic and outcome variables

	FRL	SPED	Gifted	PR_{Read}	PR_{Math}
FRL	1				
SPED	.209**	1			
Gifted	-0.073	-.253**	1		
PR_{Read}	-.430**	-.395**	.513**	1	
PR_{Math}	-.572**	-.334**	.519**	.763**	1

$^{**}p < 0.01$, $^{*}p < 0.05$

of free and reduced lunch recipients in a classroom significantly corresponds to a decrease in achievement scores. Knowing the raw relationships between variables can engender an understanding of the raw data and give meaning to relationships and patterns that emerge in analysis. Demographics are controlled for in subsequent analyses to better understand the true effect of acoustic conditions on student outcomes. Multivariate analysis takes that concern into consideration and uses several variables in conjunction with one another to describe more complex relationships. For models where multiple measures can be logically grouped, however, an alternative approach called structural equation modeling can prove useful when dealing with several variables that can be lumped into categories.

3.2.2 Structural Equation Modeling Exploration

To understand the contribution of a predictor variable on an outcome variable, a simple raw correlation is helpful but cannot illuminate more complex groupings or interactions. Controlling for other variable, such as in a multivariate regression, is helpful in isolating a relationship but again, is difficult to group related variables and can get complicated with a large quantity of related variables. To address these limitations, structural equation modeling (SEM) was considered on a local (considering acoustics variables only) and a global (considering variables from each discipline) scale within the Healthy Schools project. In this thesis, the acoustic analysis will be considered exploratorily, as the model is evolving and will undergo revision as it develops and combines with other disciplines. Other work by researchers on the project will describe the full structural equation model. SEM allows for grouped effects to be tested and uses the concept of latent variable constructs to group related measured variables into meaningful partitions. These latent variable constructs are typically concepts that are not directly measurable, but have measurable indicators. For example, in the global model, if one wants to know the effect of acoustics on student achievement, the concept of 'acoustics' is not directly quantifiable, but indicators such as reverberation time can be measured and are an indicator of one facet of acoustics. Combined with other indicators of acoustics, this measure helps describe the overall factor.

Within the acoustics discipline, several variables were measured and calculated, leading to a wealth of potential variables in the model. A full list of variables considered in this chapter is found in Section 3.1.2. Not all acoustics variables were used in the structural equation model. Logically, an expectation of three groupings of acoustic variables exist, based on the exploration in Chapter 2, which explored how level of speech, background noise, and room characteristics all factor in to how acoustics affect the human experience and specifically the student experience in a classroom. While the model was formed through logical and theoretical groupings, exploratory Factor Analysis (EFA) on all variables of interest revealed clear divisions between speech, non-speech, and reverb variables. Principal axis factoring was used in SPSS, with direct oblimin rotation and 3 factors were fixed for extraction. The pattern matrix can be found in Appendix E (Table E.1). Alternative EFAs with 2 factors fixed resulted in a multiplicity of problematic secondary loadings and with 4 factors resulted in not only many problematic secondary loadings but also a factor loading greater than 1. While the groupings make sense, several of the variables are considered redundant and only some were chosen to proceed with the analysis.

Starting with the speech category, metrics were chosen that represented distinct components of speech noise. First, octave band levels were sampled from the speech frequency range, one from the low-mid part of the speech range (500 Hz) and one from the mid-high portion of the speech range (2 kHz) Everest & Pohlmann (2009). One statistical level was chosen, L50, representing the level exceeded 50% of the time during speech, corresponding with an average or likely value for the speech noise. Finally, one metric representing variations in time, $\%\text{time} > 65\text{dBA}_{\text{sp}}$ was selected, this one due to its distribution most closely approximating a normal distribution, as opposed to the left and right skew of the percent exceeded values when considering surrounding decibel levels (see Figures A.12, A.13, and A.14).

A similar process was followed with the non-speech category, with a frequency band selected (125 Hz) that represents what is considered some of the most annoying and ubiquitous noise within buildings Leventhall (2004). For the statistical levels, L_{90} was selected as the best representation of background noise (Rogers et al. (2006)). Finally, the percent exceeded variable was selected to be %time $> 50\text{dBA}_{\text{ns}}$ for the same reasoning as above (see Figures A.25, A.26, and A.27).

Finally, $T_{20,\text{mid}}$ was selected because of its representation of mid-range frequencies and precedence in other studies (Ellison & Germain (2013)).

After exploring the data and hypothesizing likely divisions, the variables that were kept for the model include the following, grouped into three factors called speech, non-speech, and reverberation:

- speech: $\text{L500Hz}_{\text{sp}}$, L2kHz_{sp}, $L_{50,\text{sp}}$,%time $> 65\text{dBA}_{\text{sp}}$
- non-speech: $\text{L125Hz}_{\text{ns}}$, $L_{90,\text{ns}}$, %time $> 50\text{dBA}_{\text{ns}}$
- reverberance: $T_{20_{\text{mid}}}$.

An EFA using just the above variables does not converge within 100 iterations, which can be considered a limitation of this study.

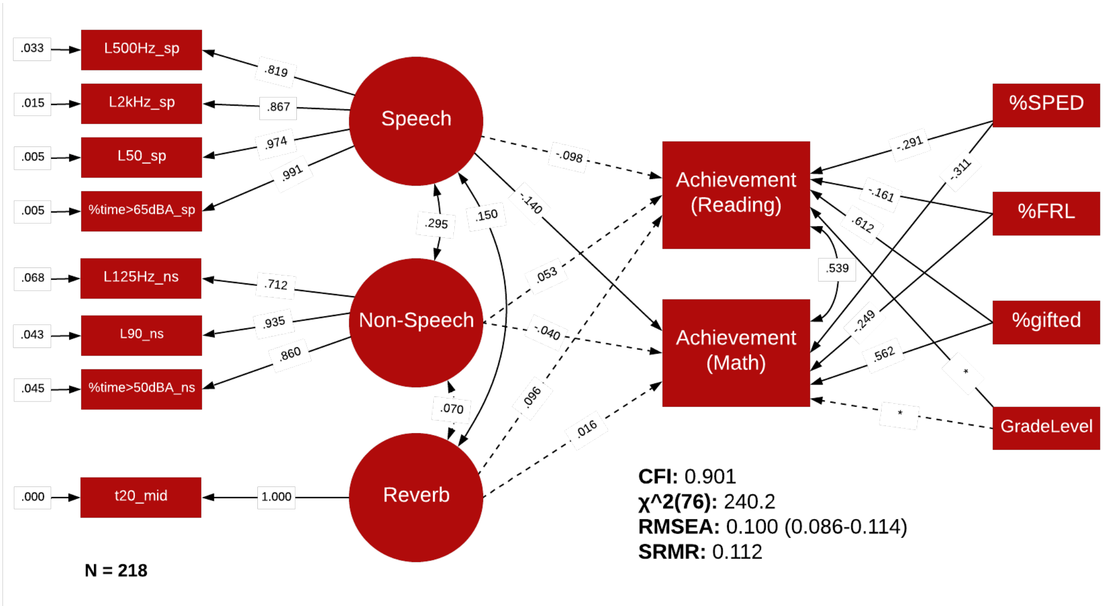
Members of the statistical team within the Healthy Schools project, in conjunction with members of the acoustics team, utilized the acoustic variables to form and test measurement models and structural equation models. Mplus was utilized to run confirmatory factor analysis (CFA) on the measurement model and run the the structural equation model. Robust standard error settings were used (Estimator=MLR) with Huber-White standard errors to deal with any potential non-normality, as stated before. Multilevel modeling was used and the data were clustered by school because of strong relationships within the schools themselves (type=complex was used in Mplus), A number of different hypothesized measurement models and see if the relationships between variables fit before looking at any effects on the student achievement. The final measurement model with the most logical grouping of variables was linked with the demographic and outcome variables discussed previously to form a complete structural equation model and observe grouped effects (Figure 3.5). Latent variable constructs are represented by circles and measured indicators are represented by rectangles. The arrows from the latent variables to the indicators show the strength of the factors loadings. The covariances between the latent variables are indicated by the double-headed arrows between the factors. The measurement errors are indicated by the single numbers pointing to the boxed variables (note: the $T20_{mid}$ measurement error was fixed at 0). The reverberation factor has only a single indicator, so it should be noted that the indicator could replace the superfluous latent variable and yield the same results. Significant results ($p < 0.05$) are indicated with solid arrows and dotted lines indicate results that were not statistically significant.

The fit of the model is not ideal but this model was selected over better fitting models due to better theoretical and logical grouping of measures. While not within the scope of this thesis, many models were tested, comparing fit parameters and logical groupings, and future publications will further explore comparisons in models. For the selected model, the χ^2 value of 240.239 is for 76 degrees of freedom (df) within an N = 219 model (the sample size is 219 due to a missing reverberation time value in one of the 220 classrooms). The Comparative Fit Index (CFI) is a measure of model fit that falls between 0 and 1–with higher values being better fit–and is calculated using the ratio of the difference of $\chi^2 - \text{df}$ of the null model and $\chi^2 - \text{df}$ of the proposed model to the null model alone. In the past, CFI values of 0.90 or above have indicated acceptable fit, but more recently the accepted value is 0.95 and above to avoid accepting misspecified models (Hooper et al. (2008)). The CFI of 0.901 for this model is below the suggested value of 0.95. Both the root mean square error of approximation (RMSEA) and the standardized root mean square residual (SRMR) indicate better fit the closer the value is to 0. While both are low, around 0.1, even lower values are needed for a good fit.

Modification indices for this model indicate ways to correlate portions of the model to improve fit. A modification index of 11.7 for correlating the measurement error for $L_{90,ns}$ and $L125_{n2}$ was tested, but resulted in a problematic negative variance and was thus rejected. The residuals of the covariances were also considered to see which portions of the model might be problematic. Using the standardized residuals, it was discovered that the grade levels had high residuals for the covariances with most of the variables. Removing grade completely as a covariate resulted in an excellent fit for the model (see Figure D.1). While the fit was much better, eliminating grade level in an acoustics model suggests that there grade level is not important in determining the effects of acoustics on achievement, but various studies suggests that noise affects people of different ages differently, such as the study by Wroblewski et al. (2012) that found that children require a higher signal to noise ratio to have the same speech intelligibility as older colleagues. Thus the measurement model including grade level was chosen despite poor fit. Future work should explore the most effective way to incorporate grade level, as it is of clear importance but is not being incorporated effectively in the current proposed model.

There was no evidence for nonlinear relationships between the latent variables and the outcome variables (see Figure E.1). For both the reading and math SEM, demographic variables, including percent free and reduced lunch recipients, percent gifted, and percent special education learners, were all significant at the .001 level (see Table 3.4). The standardized beta coefficients indicate that percent free and reduced lunch recipients had a similar strength effect on math achievement as percent gifted students in a classroom, although percent FRL had an inverse effect. In other words, higher %FRL in a classroom are associated with lower achievement scores while higher % gifted are associated with higher achievement scores. Percent SPED in a classroom had a lower standardized effect absolute value, indicating a somewhat lower strength effect but still highly statistically significant. The negative direction of the effect indicates that a higher percentage of special education students in a classrooms are associated with lower percentile scores in math. The effects of grade level are also shown in Table 3.4, with various results.

Figure 3.5: Structural Equation Model with Acoustics Variables



Similar effects are observed between the demographic variables and the reading achievement percentile scores, with relationships with all three main demographic variables being significant at the 0.01 level and the direction of the effects remaining the same. However, in this case, the %gifted exhibited the strongest relationship, followed by %FRL and finally %SPED (Table 3.4). The clear effect of demographics on the outcome variables demonstrates how crucial it is that they be controlled in the analysis (see Figure 3.5).

Table 3.4: SEM results from Acoustics models for both math and reading achievement including coefficients (B) and standardized coefficients (β)

	Math		Reading	
	B	β	B	β
Speech	-2.20**	-0.14**	-1.43	-0.10
Non-Speech	-0.62	-0.04	0.78	0.05
Reverb	0.25	0.02	1.41	0.10
% Free Reduced Lunch	-0.25**	-0.47**	-0.16**	-0.33**
% SPED	-0.31**	-0.24**	-0.29**	-0.24**
% Gifted	0.56**	0.49**	0.61**	0.57**
% Grade 5	-3.027	-0.090	-3.428	-0.109
% Grade 8	1.074	0.024	-2.516	-0.061
% Grade 11	-2.786	-0.070	-13.584**	-0.366**

$^{**}p < 0.01$, $^{*}p < 0.05$

Preliminary observations about effects of acoustics on achievement are considered in the following sections. Care should be taken, however, in drawing absolute conclusions from these results, as the model is still evolving and variables will ultimately be combined into a much larger, more complex model that will be discussed in future work. After making these controls for demographics, when considering reading achievement scores and acoustics, it was found that none of the three latent variable constructs had a significant ($p < 0.05$) effect on reading achievement scores within the SEM. This could be in part due to the limited range of noise and reverberation time values included in the sample. For example, the work by Connolly et al. (2019) found that detrimental effects on reading comprehension became clear at 70 dBA background noise levels, but our sample only included values up to 57.7 dBA for non-speech $L_A$eq.

The finding that reverberation time was not found to have a significant effect on reading achievement in this model does not correspond with literature regarding reverberation time and student performance, such as the study done by Klatte et al. (2010) indicating a significant effect of reverberation time on word comprehension in young children. However, the reverberation times used in their study had a much wider range, from 0.49 to 1.11 seconds, perhaps allowing an effect to be discovered whereas the present sample had a much lower range of reverberation times with none approaching or exceeding 1 second and most within or near acceptable ranges for classrooms (see Figure A.29). Bistafa & Bradley (2000) suggest that reverberation times between 0.4 and 0.5 seconds are ideal and can result in possible 100% speech intelligibility. J. Bradley & Yang (2009) suggests a range of 0.3 to 0.9 s as acceptable reverberation times. The sample used in this research falls within that range and is confined to a much smaller range of measured reverberations times than other studies, from 0.3 to 0.8 s for mid-frequency reverberation time, as opposed to the aforementioned study or another by Knecht et al. (2002) that measured reverberation times ranging from 0.2 to 1.27 s. The idea that both extremely low and extremely high reverberation times may be detrimental to student performance suggests some sort of nonlinear effect. However, the sample collected from these classrooms does not provide the range necessary to test that kind of effect, as the reverberation times fall within a normal, desirable range and none approach extreme values for a classroom.

Another reason why other studies may have found an effect of reverberation on reading comprehension may be that the effects noted by other studies (like Knecht et al. (2002)) are often immediate effects of performance on a task in a controlled amount of time. In contrast, our study takes the aggregate of an entire year's worth of study in the classroom environment. While reverberation may have a clear negative effect on student reading ability during a single reading session, over the course of a year, other experiences like independent study, out-of-classroom activities, and general ability to aggregate knowledge may compensate for the detrimental effects of room reverberation on reading. Additionally, J. Bradley & Yang (2009) found that the ideal reverberation time for speech intelligibility was typically right around a half second, a value typical in the classroom sample discussed in this paper.

For math, the standardized coefficient for the effect of the 'speech' latent construct on math achievement percentiles was found to be significant ($p < 0.001$) with a value of -2.20 and a standardized value of -0.14, indicating that higher sound levels (at times when speech are present) decrease math scores. The non-speech and reverb latent variables did not have a significant impact on math achievement percentile scores.

Overall, structural equation modeling was used to make a preliminary exploration of the effect of acoustics on student achievement, controlling for demographics. First, the model was tested with reading achievement percentiles and second, the model was tested with math achievement scores. No statistically significant effect of acoustics was discovered for reading achievement in this sample. On math achievement, a statistically significant effect of noise levels during speech times was found, with higher noise levels associating with lower math scores. No statistically significant effect was found for the effects of reverberance or non–speech noise. However, there is a relationship between speech and non–speech noise and potential links have been explored in literature, suggesting that speaking in noise causes vocal levels to be raised (Pisoni et al. (1985)). It is possible that the effect of non-speech noise on achievement is being obscured by the effect of speech noise or even that an indirect effect of non–speech noise on achievement through speech noise could be present. These hypotheses were not tested in the proposed model here, but further work could pursue an exploration of if non-speech noise has an effect on student performance. It is important to note that these results are still exploratory and are part of an evolving model incorporating components from various disciplines. While preliminary results show an effect of acoustic variables, more work is needed before forming conclusions. Ultimately, a structural equation model incorporating acoustics, lighting, thermal comfort, and indoor air quality will be formed and tested by the EPA Healthy Schools Project team and results will be published.

Chapter 4
Temporal Variation in Logged Classroom Data

This chapter considers data logged at regular time intervals not only from the acoustic discipline but also from several other disciplines participating in the Healthy Schools project. Correlations between the temporal data between disciplines are considered on the classroom level.

4.1 Methods and Data

The analysis in the previous section described averaged measured parameters for each classroom and correlations with achievement factors. The numbers used in the previous analysis were reliable because they were based on data averaged over a long period of time, as opposed to data collected at a single random time during the day. A wealth of time-logged data were measured within each room; for example, in acoustics, a single sound level can describe the average value experienced during a school day, but large level fluctuations occur between silent times and times when there is a lot of student activity or teacher instruction. Two classrooms could have the same average level but one could experience generally stable levels while the other could experience lower steady-state levels but more frequent interruptions of higher-level noise. To capture these fluctuations and the potential impacts and interactions they have with other parameters, an analysis of the data over time was conducted.

For this analysis, the data were considered in vectors separated by school day, omitting the periods of time where data were logged overnight. Just as single values were calculated for each of six days in the previous chapter, vectors of data logged at regular intervals were created during the hours school was in session for each of the six days in this chapter.

4.1.1 Description of Time-Logged Metrics

For the acoustic data, sound levels were logged every 10 seconds for the duration of the measurement period. These levels include $L_A$eq values as well as individual octave band levels. For example, for two sample classrooms during a school day, the fluctuations in overall $L_A$eq and in the $L_A$eq in the 125 Hz and 1 kHz octave bands are visually represented in Figure 4.1.

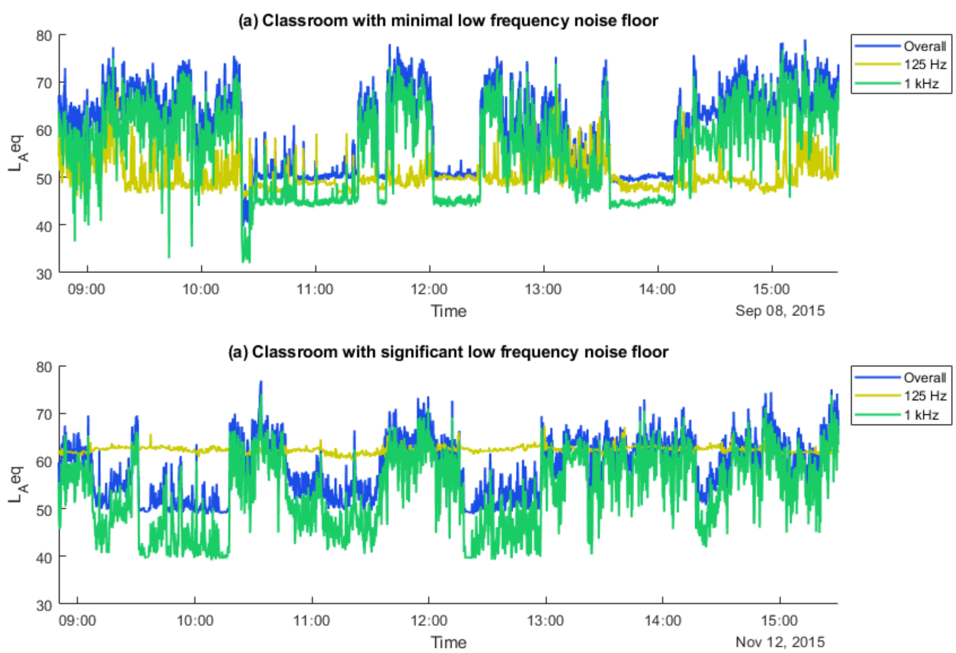


Figure 4.1: Variation of sound level over time for a single day in two representative classrooms, (a) one with a moderate low-frequency noise floor and (b) one with a significantly higher low-frequency noise floor

It is interesting to note the fluctuations in the sound levels within the different octave bands. The sound level in the 1 kHz octave band closely follows the overall level fluctuations. This mirroring could be related in part to the 1 kHz band containing much of the speech noise, with speech being one of the main contributors to sound level within the classrooms. Contrastingly, the 125 Hz octave band frequency levels in Figure 4.1a remain steadily below the overall level, with some mild fluctuations while in Figure 4.1b they remain fairly constant, with values much higher than the average and the 1 kHz levels. This could perhaps be due in part to a noisy HVAC system with semi-constant levels over time.

In this chapter, time-logged data from other disciplines are considered in conjunction with acoustic data. Most of the other time-logged data were measured in 5-minute increments, including carbon dioxide (CO_2) concentration, particulate matter (PM), temperature, relative humidity, and illuminance. The relationship between these parameters and the sound levels will be considered in this section.

The CO_2 concentration in parts per million (ppm) in the classroom was logged by three different meters throughout the measurement period: one in the measurement kit near the teacher's desk, one in or near the supply vent, and another in or near the return duct. For this analysis, an average of the three indoor meters will be considered.

The air pollution takes the form of particulate matter (PM) of difference sizes that floats in the air and is measured by meters that detect the particles. A sample of the presence of all measured sizes of particulate matter over a two-day period is shown in Figure 4.2, excluding the smallest size for graphical scaling purposes. For this analysis, two categories of particulate matter are considered: fine and coarse. Fine particulate matter consists of a geometric average of all particles less than 2.5 microns in diameter and coarse consists of a geometric average of particles between 2.5 and 10 microns in diameters.

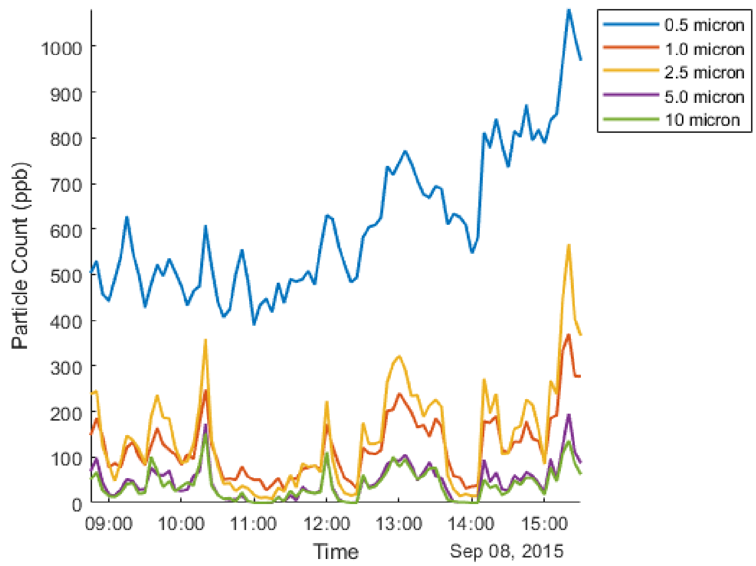


Figure 4.2: Variation of particulate matter count over time for the span of one school day in a representative classroom

Finally, illuminance values are divided into two categories based on which meter logged the values. The average of two 'natural light' meters—one in the window and one hanging from the ceiling near the window—comprise the 'natural illuminance' values in the room, an approximation of daylighting. The average of two other meters—one in the light fixture and one in the kit by the teacher's desk—constitute the 'artificial illuminance' in the room. These two illuminance categories and their relationship with acoustic parameters are considered distinctly.

The temperature is an average of several different meters that were placed throughout the room and as part of other measurement devices. For example, each CO_2 logger has a built-in thermometer and readouts from each were included in the temperature average. Similarly, each of the four illuminance meters measured temperature, and the particulate matter counter had a temperature sensor, making the temperature readings and average of those eight meters. Similarly, the average of eight meters–three within the CO_2 meters, four within the illuminance meters, and 1 within the particle counter–comprise the time-logged values for relative humidity.

It is important to note that the sampling frequency with which the data were collected varies between the acoustics and the other parameters (10-second increments for sound levels and 5-minute increments for most other parameters), so the sound level series' were modified to match the rest of the data. Logarithmic averaging was used to condense each of thirty 10-second sound levels values into one 5-minute increment, allowing the acoustic data to correspond to the other data. Putting all of the parameters on the same time scale enables the use of statistical analysis procedures to understand how the data correlate over time.

Before running correlational analysis on data that were taken over time, it is important to make the data stationary over time, eliminating possible spurious trend effects due to natural patterns over time. This is done by fitting a linear trend to the model and then subtracting the deviation of the data from the trend line, effectively removing any positive or negative trend over time and preserving only the fluctuations of the data about that trend. Figure 4.3 shows a sample of fine particulate matter, taken from a representative day, made stationary. In blue, the original data (translated downward to fit on the same graph as the stationary data) has a clear upward trend over time, which could be due to any number of factors related to the natural duration of the school day. Below, in green, represents the data made stationary in time by plotting the deviations from the linear fit. It is important to note that this rise in level over time was not necessarily indicative of every day in the sample, it was chosen because it clearly demonstrated the processing. It is evident in this process that the fluctuations over time are preserved while the overarching trend is removed. This enables accurate evaluation of the correlation of the various disciplines over time because if two variables experience an upward trend due to any number of unrelated reasons, they would be strongly correlated no matter regardless of the pattern of the smaller fluctuations. This stabilization process enables the comparison of the smaller-scale fluctuations in the data, comparing the 5-minute incremental changes to each other instead of linear trend that could overpower those small effects. This processing was done to all disciplines for all days before proceeding with the analysis.

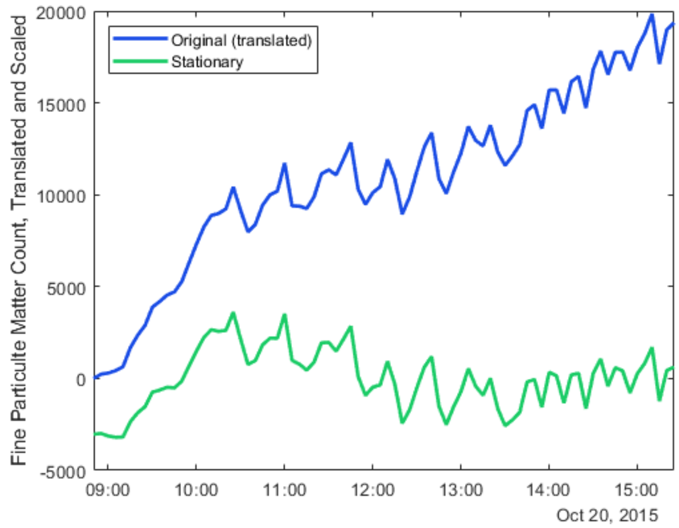


Figure 4.3: Example comparison of original time series data and the stationary version, after removing the linear fit

After the data were made stationary over time, correlations were drawn between them. Figure 4.4 shows the variation in the logged measurements (processed to be made stationary) over the course of a day in a representative classroom. The data were also normalized in this figure, enabling the juxtaposition of all disciplines with vastly different scales and ranges. This process makes the y-axis in units of standard deviations from the mean. For example, a point that has a value of 1 would be one standard deviation above the mean of that discipline's time series data. From this figure alone, some general patterns visually emerge, where certain parameters rise and fall together. These relationships will be quantified in the subsequent sections.

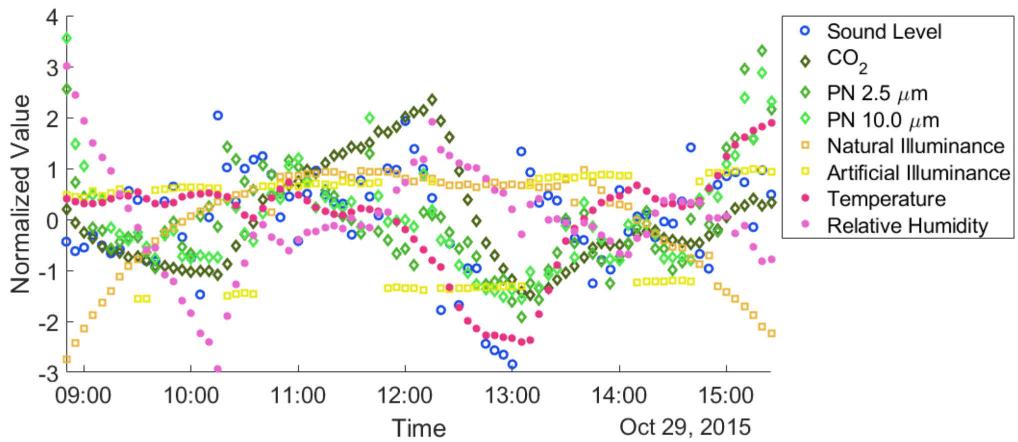


Figure 4.4: Variation in logged data over the course of a single school day in a sample classroom. All parameters are normalized using z-scoring

A similar figure could be generated for each of the six days of measurement that took place within each of the 220 classroom, although occasionally one or two disciplines experienced an equipment malfunction, leading to some missing data within the complete set.

4.1.2 Statistical Procedures

Raw Pearson correlations were calculated between the time logged acoustic and other disciplines' data for each 1-day vector for each season in each classroom. This results in each classroom having a correlation coefficient (r) and statistical significance (p) between acoustics parameters and each of the other discipline parameters for each of the two days in Fall, Winter, and Spring. For example, Classroom 1 has an R and p value for the relationship between overall $L_A$eq and the CO_2 concentration during day one of measurement in the Fall season, another set of values for day two in Fall, and so forth. For a more generalized analysis, correlational values for each classroom were calculated by concatenating the daily vectors to create one large vector of time-matched data for which R and p values were calculated. In other words, each daily vector consists of paired data, like a vector of sound level where each component has a corresponding carbon dioxide value. Six of these vector pairs exist per classroom and they were placed end to end to create a giant pair of vectors that represents matched data over the course of six days. It would not make sense to graph this data over time, as the days were not continuous, but the one-to-one correspondence between the data allow for correlational comparisons to be drawn.

4.2 Results and Analysis

Results are presented, first considering the whole dataset and patterns in the correlations and second considering a case study that measured the occupancy in a classrooom in conjunction with the other measured parameters.

4.2.1 Trends in Complete Dataset

In this section, the data are considered by day in each classroom, with each correlation representing the relationship between two parameters in a classroom where the parameter vectors are comprised of all six days in all three seasons concatenated into a single vector. Correlation coefficients and significances were then calculated for each classroom. There is significant variation between the results within each classroom, so compiling the correlation results for the whole dataset sheds light on what is typical and what is not. While simply averaging the Pearson correlation coefficients for all correlations between certain disciplines cannot determine a meaningful generalized average for the relationship between two parameters in the dataset, it is helpful to look at the general trends in how strong and significant the correlations are between different parameters by viewing the results in aggregate. Figure 4.5 shows the significant correlations between disciplines for all classrooms as histograms of statistically significant correlation coefficients. Each subplot represents the correlations between sound level and the discipline listed.

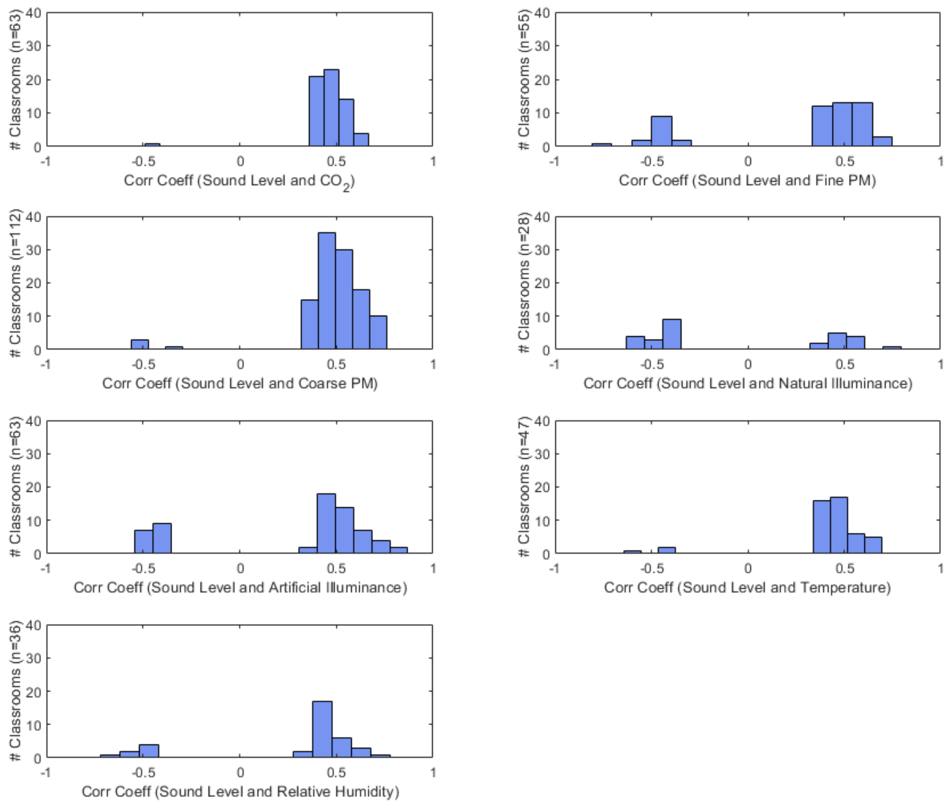


Figure 4.5: Histograms of the significant correlation coefficients within each classroom between sound level and other parameters using six days of time-logged data

This figure sheds light on the strength and frequency of correlation between parameters. For none of the disciplines were all of the correlations statistically significant. However, for the indoor air quality parameters, including CO_2, fine particulate matter, and coarse particulate matter, over half of the correlations were significant, with coarse particulate matter showing the greatest number of significant correlations at 158 out of 218 possible correlations (not 220 due to missing data in two classrooms), or 72.4% of valid correlations being significant. For each of the other parameters, at least 68 of the measured classrooms saw significant correlations with sound level. However, for some of the measures, like illuminance or relative humidity, the frequency of negative correlations was comparable to positive correlations, shown by a balance in the histogram, with a cluster of negative correlations on the left side and a cluster of positive correlations on the right side. The absence of correlations near zero is likely due to the fact that only significant correlations are included in the figure and many of the correlational values closer to 0 were not significant.

This same analysis was conducted in the 125 Hz and 1 kHz octave band noise as opposed to A weighted equivalent continuous levels (representing a frequency average). The 1 kHz correlations bore similarity in quantity and value to the overall $L_A$eq correlations. The 125 Hz correlations were typically less likely to be significant and took overall lower values. No particularly standout results occurred from this analysis.

Overall, the IAQ metrics together showed the strongest clustering effects with positive correlations. Table 4.1 shows descriptive statistics of the positive, statistically significant correlations between sound level and IAQ metrics.

Table 4.1: Descriptive statistics of significant positive correlation values between sound level and IAQ metrics of interest

	CO_2	Fine PM	Coarse PM
n	62	41	108
mean	0.472	0.503	0.515
sd	0.073	0.098	0.100
min	0.360	0.369	0.361
max	0.661	0.738	0.746

The mean correlational value was not incredibly strong for any of the relationships between sound level and IAQ parameters, with the average significant positive correlation being around 0.4 for both the relationship between sound level and CO_2 and between sound level and fine PM. The average significant positive correlation between sound level and Coarse PM was somewhat higher, approaching 0.5. The standard deviations for each of these collections of correlations were just above 0.1 each and the ranges were fairly similar, from around 0.2 to around 0.7, with coarse PM having the highest maximum correlation coefficient case of 0.746.

Overall, the ubiquity of significant correlations between sound level and IAQ parameters suggests an important connection. All of these metrics have logical ties to occupancy. More people in a room typically means higher sound levels. Similarly, more people in a room should increase the carbon dioxide concentration through natural human exhalation. More activity in a room results in the stirring up of particulate matter, particularly in sizes greater than 2.5µm, or coarse particulate matter.

4.2.2 Case Study Controlling for Occupancy

We postulate that a large part of the reason some of the metrics are correlated is due to the room occupancy. To test this assumption, in one of the classrooms, a pilot study collecting room occupancy information was conducted simultaneously with the usual measurements. Using thermal imaging, the number of people in the classroom was logged at regular time intervals. Studies have looked at automating the use of infrared sensors to extract occupancy Raykov et al. (2016), but for this study, the number of occupants per time-lapse image was extracted manually. The correlations between acoustic and other variables are considered while controlling for occupancy. Figure 4.6 shows the 5–minute variations of the data over time during the course of a school day. Each of the parameters were normalized using z-scoring in order to enable comparison within the same figure. The y–axis then represents the standard deviations of each data point with respect to the mean.

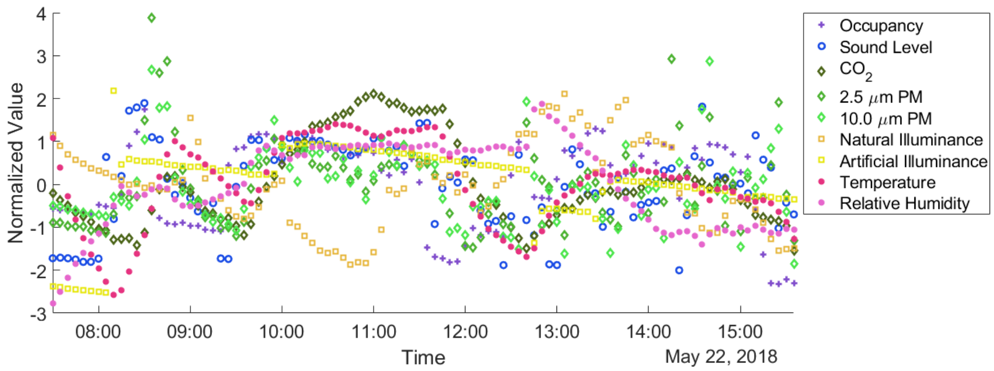


Figure 4.6: Normalized data values, including occupancy, are plotted over time from various disciplines over the span of one school day

This figure of the variability of parameters over time begins to show apparent trends. Some of the parameters seem to 'follow' one another throughout the course of the school day, similar to the data shown in Figure 4.4. The additional component here is the occupancy data, shown with a purple '+' marker. The variability and fluctuation of occupancy somewhat follows the overall trends that are roughly apparent in this figure.

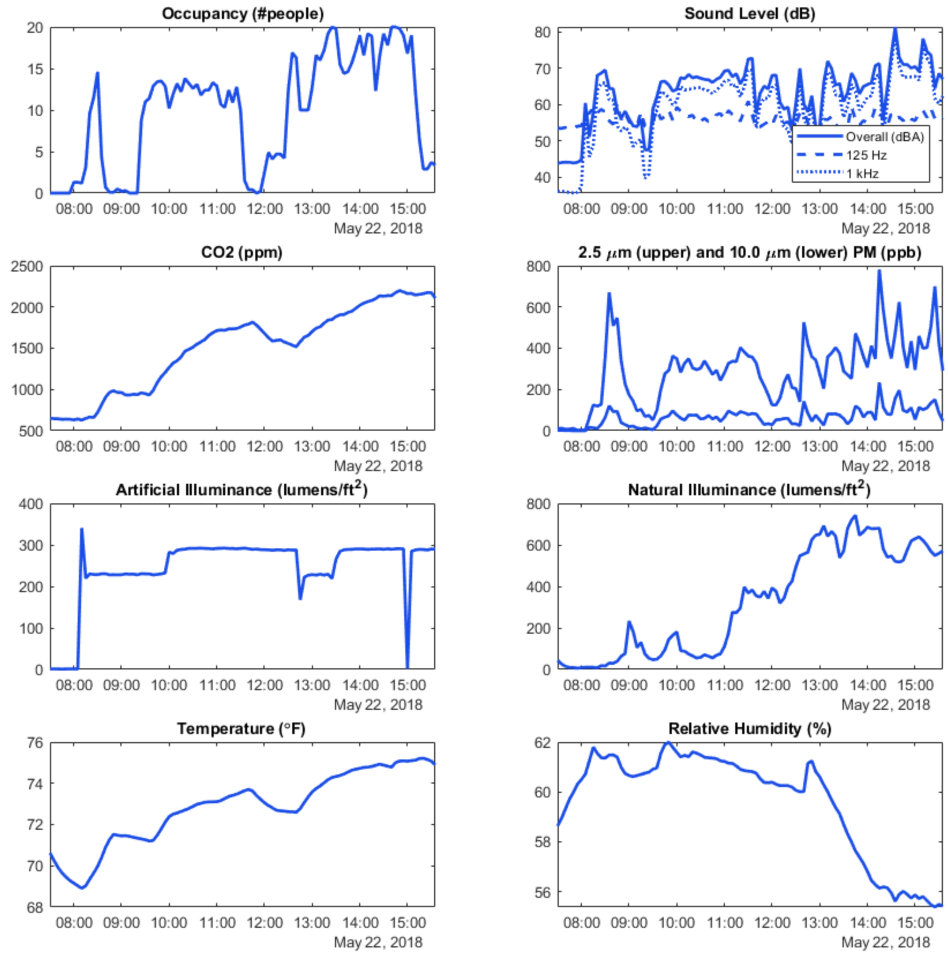


Figure 4.7: Variation of of logged data over time from various disciplines for the span of one school day in separate plots for each discipline

For further clarity on the trends over time and more illumination on scaling, figure 4.7 shows each of the metrics of interest juxtaposed and within their own metric scale. The range of each y–axis can illuminate information about how much these values actually fluctuate over time. For example, the temperature measurements have a relatively small range, from around 69° to 75°, while the particle matter, by nature of its metric, spanned from 0 to around 800 ppb and experienced more up and down fluctuations throughout the day.

While several metrics appear related over time, correlations can be statistically analyzed to verify this assumption, as was done with the full data set. Again, these data were taken sequentially in time, so as a time series, they were pre-processed to be made stationary over time in order to illuminate pure trends. A correlation matrix including occupancy, sound level, and select IAQ parameters shows each parameter plotted against each of the others (Figure 4.8). The numbers in each box indicate the correlation coefficient, or the strength of the relationship, and the color indicates significance, where red numbers are significant at the p=0.00089 level (chosen by using the Bonferroni correction for the comparisons between each of 8 variables).

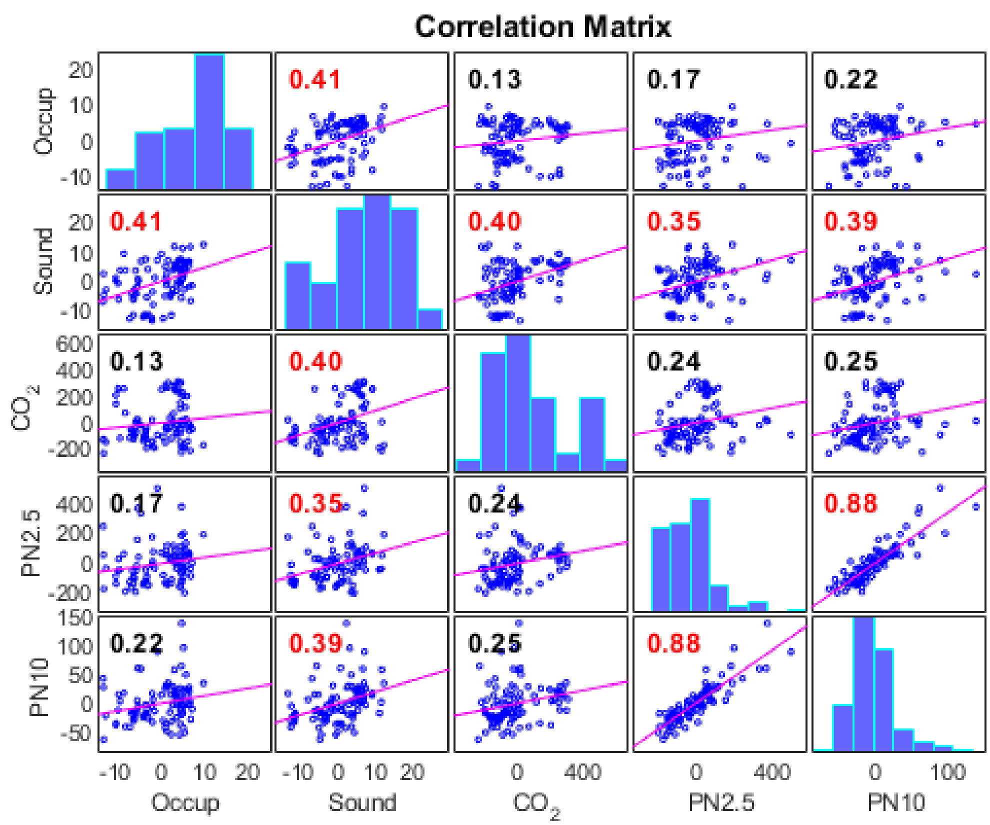


Figure 4.8: Matrix showing the Pearson correlations of select variables with each other. Red text indicates that the correlation is significant at the p=0.05 level

Occupancy correlations are found in the first column and significant relationships are observed between occupancy and sound level and occupancy and 10µm particle counts. The correlations between occupancy and CO_2 and between occupancy and 2.5µm particle counts were significant before processing the data and making them stationary in time, but after this transformation, the correlations were not significant, as shown in Figure 4.8.

Some of the correlations are not plotted here, such as with thermal comfort and lighting parameters, so all raw Pearson correlations are shown in Table 4.2.

Table 4.2: Correlations between all measured variables for one-day case study.

	Occup	$L_A$eq	CO_2	PN2.5	PN10	ILN	ILA	Temp
Occup	1							
$L_A$eq	0.41***	1						
CO2	0.13	0.40***	1					
PN2.5	0.17	0.35***	0.24*	1				
PN10	0.22*	0.39***	0.35*	0.88***	1			
ILN	0.00	-0.38***	-0.35***	-0.15	-0.21*	1		
ILA	0.13	0.48***	0.41***	0.31**	0.27**	-0.31**	1	
Temp	0.16	0.30**	0.84***	0.29**	0.25*	-0.23*	0.35***	1
RH	0.19	0.30**	0.37***	0.11	0.02	0.03	0.52***	0.22*

$^{***}p < 0.00089, ^{**}p < 0.01, ^{*}p < 0.05$

When considering all the measured data, occupancy is not highly related to most of the parameters. Sound level, on the other hand, shows highly significant, although not necessarily very strong, relationships with all measured parameters in this sample. While not necessarily within the scope of this paper, it is still interesting to observe the various significant correlations (or lack thereof) between thermal, IAQ, and lighting parameters. Future work could explore these correlations further using the entire dataset.

Acoustically, the relationships between the parameters can vary by which octave band is considered. The correlations in Table 4.2 considered the overall level in the form of equivalent continuous A-weighted sound level, including all measured octave bands. Relationships, however, change when only the 125 Hz band or the 1 kHz band, for example, are considered. Table 4.3 shows the correlation coefficients between the time fluctuations in both the 125 Hz and 1 kHz octave bands with other disciplines in this single day case study.

Table 4.3: Correlations between select octave band frequency levels and other parameters.

	125 Hz	1 kHz
125Hz	1	0.60***
1kHz	0.60***	1
Occup	0.21*	0.41***
$L_A eq$	0.62***	0.99***
CO_2	0.11	0.42***
PN2.5	0.27**	0.36***
PN10	0.30**	0.39***
ILN	-0.22*	-0.35***
ILA	0.36***	0.50***
Temp	0.04	0.32**
RH	0.04	0.35**

$^{***}p < 0.00056$, $^{**}p < 0.01$, $^{*}p < 0.05$

Here, some strong correlations are evident. Similar to the overall level, the 1 kHz noise is highly correlated with all parameters. Figure 4.1, shown earlier in the chapter, illustrates how closely 1 kHz noise typically follows the overall level, making this observation not surprising. For the 125 Hz band, however, some interesting results become evident. There is no significant correlation with CO_2 in this sample, as might be expected. Carbon dioxide emissions from people's mouths as they breathe and speak are correlated with the amount of speech they produce, which would be reflected in the 1 kHz noise and not the 125 Hz noise, especially for a group of young children whose vocal production frequencies lie generally above that range. Temperature and relative humidity also lose their significance in correlation with the 125 Hz levels, perhaps due in part to the lack of fluctuation in the 125 Hz levels. Overall, the 1 kHz correlations follow the overall correlations but the 125 Hz noise is much less likely to be correlated with other parameters. Note, however, that 125 Hz noise is still correlated with various indoor air quality and lighting variables.

Besides looking at simple correlations, it is hypothesized that both sound level and indoor air quality parameters are significantly affected by occupancy. This would mean that the relationships between these variables would be affected or driven by the occupancy. In order to test this theory, a measurement model was created using the test data from this sample classroom. Three models were tested, each checking to see if the relationship between sound level and an indoor air quality parameter (including CO_2, PN2.5 and PN10.0) was affected by occupancy. The measurement model is shown in Figure 4.9.

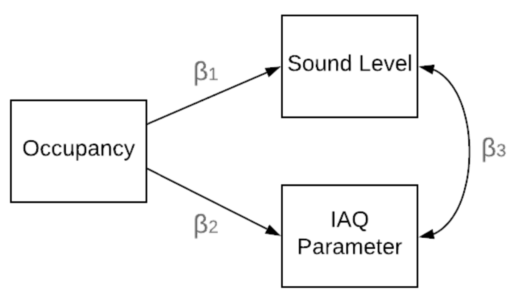


Figure 4.9: Measurement model with occupancy leading to sound level and an indoor air quality parameter

To do this kind of modeling, it must be determined that the measures are reliable. The CO_2 scale (an average of supply, return, and kit meters) had a cronbach's alpha of

0.994, indicating that there was no significant measurement error associated with the scale, indicating that the average can serve as a measure rather than needing to represent the three as a latent variable construct. The particulate matter variables are single measures and are highly reliable measurements. The sound level is a logarithmic average between two meters, representing the average sound level in the room. Figure 4.9 shows the model that was used for testing sound level with each of the three indoor air quality parameters of interest as separate tests.

For this particular classroom on this day, the direct relationship between occupancy and each of the IAQ parameters (β_2) was not significant, nullifying the results of the measurement model. β_1 was significant in each of the models as was β_3. While not much can be concluded from this particular set of data, the lack of results here cannot be generalized because it is an isolated sample. In light of the variability seen in the simple correlational analyses mentioned earlier in this chapter, generalizations cannot be drawn from this single classroom example with occupancy. This case was the only instance that occupancy was measured, but future work is suggested to explore this relationship on a larger scale with more examples.

4.3 Conclusions and Discussion

The classroom measurements in the Healthy Schools project resulted in a wealth of time-varying data gathered in classrooms over the course of six days each. To better understand these data and their interactions, various analyses were undertaken. First, a correlational analysis looked at how related each of the measured parameters were over time, specifically looking at the sound level with other parameters. Care was taken to pre-process the time series data and make it stationary over time to avoid false correlations. The entire dataset was analyzed to see how likely it was to get correlations between certain parameters. Often, sound level was found to significantly correlate with indoor air quality parameters, especially CO_2 and coarse particulate matter.

To explore the possible effect of occupancy on the variation of the aforementioned parameters, a study was undertaken, supplementing the typical indoor comfort measurements with occupancy count logged over time. Occupancy correlated strongly with sound level, but was not found to have a clear effect on IAQ parameters in this example. Further work, however, should explore how common this is within a larger classroom sample. That being said, metrics that are affected by human occupancy and behavior, like IAQ and sound level, are more likely to be correlated with each other. Some relationships that showed potential significance, such as sound level and temperature (see Figure 4.5) were not explored in detail and could be the subject of further study.

Chapter 5
Ventilation System Effects on Acoustic Parameters

This chapter explores the interactions between ventilation system type and acoustical parameters. It is generally understood that the heating, ventilation, and air conditioning (HVAC) systems in a building contribute to the background noise levels, which can then deteriorate speech intelligibility in classrooms Hodgson (2002). Manufacturers provide noise data from extensive tests and acoustical consultants use various softwares and calculation methods to predict the noise level in a complete system based on the components used. However, assumptions are often made that may not produce reliable results Liu et al. (2017). Predicting noise from HVAC sources, which travels through ducts and enters rooms along with the airflow requires extensive measurement or knowledge specific system parameters Kårekull et al. (2014). In this sample, since actual noise data was collected in classrooms and the HVAC system types in the classrooms are known, an empirical exploration of their interaction was undertaken. First, a description of the ventilation systems incorporated in the sample of schools provides a framework for the analysis. The interactions between ventilation system type and overall classroom parameters is then addressed. Finally, the effect of ventilation system type on the time logged interaction between acoustic and other variables (described in Chapter 4) is explored.

5.1 Ventilation Systems in Schools

The heating, ventilation, and air conditioning (HVAC) systems within schools consist of primary and secondary systems, which provide a widely varied collection of options. For this sampling, the system types were divided categories based on their secondary system. For example, a single–zone system can consist of buildings with centralized systems, typically utilizing variable air volume (VAV) boxes or air handling units (AHUs). Other systems include multi–zone systems and can include schools that have unit ventilators or heat pumps in their ventilation systems, where the HVAC components are not centralized. The three categories chosen to group the classrooms in this study are:

- Centralized Systems with VAV or AHU (n = 41)
- Heat Pumps (n = 104)
- Unit Ventilators (n = 59)

Classrooms with unknown or ambiguous system types were omitted from the analysis. For example, some of the classrooms were in temporary, portable structures outside the regular building and were not included in the analysis. The overall speech and non-speech levels in classrooms are considered first, then other select acoustic metrics are considered, namely those used in the creation of the SEM in Chapter 3. Finally, the effect of HVAC system type on the interactions over time between sound level and select indoor air quality parameters are considered.

For the first portion of the HVAC analysis, the speech and non-speech average levels ($L_A$eq) are considered. Figure 5.1 shows histograms of the distributions of speech sound levels within the classrooms, divided by HVAC system type. Likewise, Figure 5.2 shows the histograms of the distributions of non-speech sound levels within the classrooms, divided by HVAC system type. While it is apparent that there are more classrooms with heat pumps than the other two system types in consideration, there are also differences in the means and the distributions, especially with the non-speech levels. The differences in the means will be explored numerically in subsequent analyses.

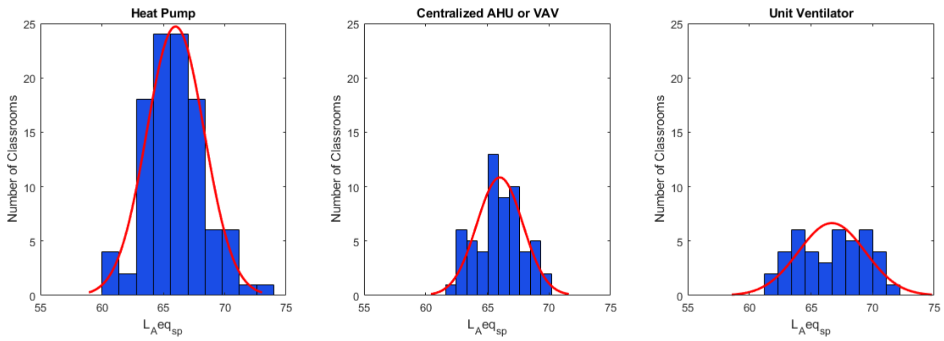


Figure 5.1: Histogram of distributions of speech sound levels within classrooms, divided by HVAC system type

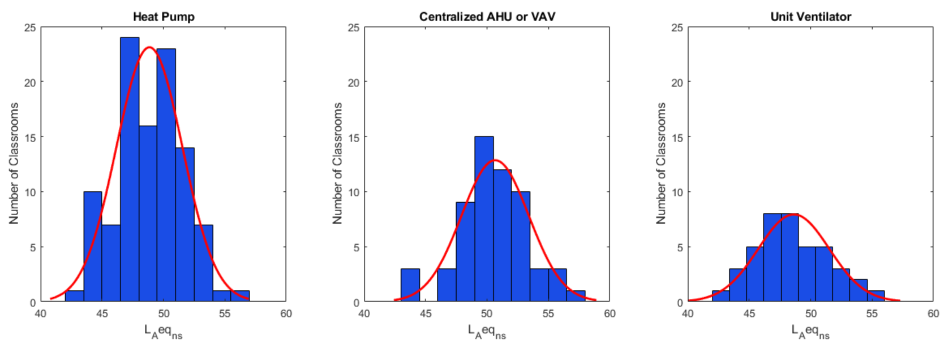


Figure 5.2: Histogram of distributions of non-speech sound levels within classrooms, divided by HVAC system type

5.2 Ventilation Systems and Overall Classroom Acoustic Parameters

An analysis of variance (ANOVA) has been conducted to determine if there are any significant differences between sound level in classrooms with these different types of mechanical heating, ventilation, and air conditioning systems. It is postulated that unit ventilators will contribute the highest levels of sound, due to their location inside the classrooms. Heat pumps are proposed to contribute less noise, followed by systems using VAV boxes or AHUs.

First, using effect coding, the three divisions within the secondary system types were dummy coded in two ways in order to see differences between groups.

In both cases, the classrooms with heat pumps were used as a reference and coded with a -1. The first case codes unit ventilators as 0 and centralized systems as 1. The second case reverses the effect coding to enable comparison, representing the centrailzed systems with 0 and unit ventilators with 1. Using a multivariate regression method, one-way ANOVA results were obtained for the linear model including the two effect-coded variables. For each analysis, Equation (5.1) below was tested for overall significance and each beta coefficient was tested individually for significance.

$$\mathrm{SoundLevel} = \beta_1 X_1 + \beta_2 X_2 \tag{5.1}$$

here β_1 and β_2 are the standardized regression coefficients and X_1 and X_2 are the contrast codes as described above. This equation was used for several analyses, with the the left hand side of the equation, sound level, being replaced each time by a different sound metric. As described in Chapter 3, various metrics were measured and calculated that help represent the sound level within the room, such as overall level when speech was present and overall non-speech level.

Since classrooms in the same building typically have the same HVAC system type, the analysis uses grouping by building. This is particularly important because some of the classrooms are actually connected to the same equipment, such as in the case of the centralized systems. With the classrooms grouped by building, the sample size decreases. The number of buildings employing unit ventilators is 12, with 7 buildings using centralized systems and 19 employing heat pumps.

For this analysis, the building average level for speech times and the average level non-speech times averaged across all classrooms within a building are considered. These two metrics were analyzed to see if there was any difference in level by system type. The means of the speech and non-speech average sound levels are shown for each category in Table 5.1.

Table 5.1: Group means by system type for speech and non-speech average levels

Average Sound Level (dBA)		
	$L_A eq_{sp}$	$L_A eq_{ns}$
Unit Ventilators	65.9	50.6
Centralized	66.5	48.4
Heat Pumps	66.1	48.7

Conducting the ANOVA illuminates whether or not the differences in the means have statistical significance. For the speech levels, the omnibus test failed to be significant, suggesting that the null hypothesis that the means for each of the three groups are not different from each other cannot be rejected (see Table 5.2). In other words, there is no significant difference between the sound levels experienced during speech times with regards to what HVAC system type is employed in the classrooms. The effect size (η^2) for this ANOVA is 0.018 indicating that only 1.8% of the total variance is accounted for by the HVAC type, so even if it were significant, the test would not indicate that HVAC type significantly affects speech noise.

Table 5.2: ANOVA table for speech noise divided into HVAC categories

Model	SS	df	MS	F	p
Regression	1.506	2	.753	.324	.725
Residual	81.262	35	2.322		
Total	82.769	37			

On the other hand, the omnibus ANOVA results for the non-speech average level was significant, indicating quantifiable differences between the means of the non-speech level when categorized into secondary HVAC system type (see Table 5.3). The effect size for this analysis is also much larger than the previous ($\eta^2 = 0.202$), where 20% of the variance in non-speech noise is accounted for by HVAC system type. With a significant omnibus test, looking into each beta coefficient can reveal differences between the specific divisions, including the direction of the trends.

Table 5.3: ANOVA table for non-speech noise divided into HVAC categories

Model	SS	df	MS	F	p
Regression	30.558	2	15.279	4.424	.019
Residual	120.885	35	3.454		
Total	151.443	37			

For the non-speech noise, the β_1 coefficient was not significant, indicating that classrooms with VAV boxes or AHUs experienced no difference in non-speech sound levels on average than classrooms with heat pumps (see Table 5.4). The second beta coefficient (β_2) was, however, significant ($p<0.01$), and has a value of 0.59, indicating that those classrooms that include unit ventilators in this sample experienced higher non-speech levels than classrooms with heat pumps (see Table 5.4). While no statistical conclusion can be drawn regarding the difference between the non-speech levels in centralized system classrooms vs. unit ventilator classrooms from the analysis with the analysis as designed, it is likely that there would be, since the average level in the classrooms with centralized systems is even lower than those with heat pumps. Overall, this analysis provides quantifiable evidence that unit ventilators contribute to higher noise levels in classrooms. Concern could arise from noting that the difference between the means of the groups is small. For example, the difference between the unit ventilator non—speech noise mean and the heat pump non—speech noise mean is only about 2 dB. Taking into account the meters used—BSWA Type II meters—ANSI S1.4 gives $\pm$dB for maximum allowable errors for exponential time averaging for this type of meter. However, this difference does not translate directly to the margin of error within which a true difference can be observed because of the aggregate nature of the overall values per system type. To find the true margin of error, a detailed error propagation analysis would have to be pursued, taking into account the averaging at different levels, the sample size, and so forth.

Table 5.4: Beta coefficients for both speech and non-speech noise divided into HVAC categories

	X_1		X_2	
	B_1	β_1	B_2	β_2
$L_A eq_{sp}$	.33	.17	-.25	-.15
$L_A eq_{ns}$	-.85	-.33	1.33**	.59**

$^{**}p < 0.01$

Overall, a difference between non-speech sound levels is observed between grouping of HVAC system types, while speech levels do not experience a comparable difference. Classrooms with heat pumps and centralized systems experience similar average sound levels, while classrooms with unit ventilators experience higher average non-speech levels overall.

5.2.1 Additional ANOVAS using metrics from the SEM

The above section considered the measured speech and non-speech building average levels, which should not be confused with the 'speech' and 'non-speech' latent variables discussed in Chapter 3. The latent variables are not directly measured, but are concepts that have multiple measured indicators. These seven indicators–four for the speech latent variable construct and three for the non-speech latent variable construct–were tested with the same method as the speech and non-speech noise, with the hypothesis that the speech metrics would not yield significant results and the non-speech metrics would. The ANOVA results for the four speech metrics (including $L500Hz_{sp}$, $L2kHz_{sp}$, $L_{50,sp}$, and %time > $65dBA_{sp}$) were not significant, indicating that for those specific measures, there is no categorical difference when grouping the school buildings by system type.

For the non-speech metrics, results varied. The ANOVA for the non-speech noise in the 125 Hz band was not significant (p=0.072), indicating that the difference between means of 125 Hz octave band noise in each HVAC category were not statistically significant at the 0.05 level. The next metric considered was the percentage of time non-speech noise exceeds 50 dBA. The ANOVA comparing the means of this metric between the three HVAC divisions was significant (p<0.05), indicating a statistically significant difference. Using equation (5.1), the first beta coefficient was not significant (p=0.055), indicating no significant difference in the percent of time 55 dBA is exceeded during non-speech times between centralized systems and heat pumps. The second beta coefficient, however, was significant (p<0.01), indicating a difference between the average %time > $50dBA_{ns}$ for heat pumps and unit ventilators, with unit ventilators exceeding 55 dBA more frequently than heat pump systems.

The third and final non–speech metric considered was the level exceeded 90% of the time (L_{90}) for non-speech noise. This metric also had a statistically significant ANOVA (p<0.05) when considering HVAC categorizations. As before, the first beta coefficient was not significant (p=0.168), indicating no significant difference in L_{90} between centralized systems and heat pumps for non-speech L_{90}. The second beta coefficient, however, was significant (p<0.01), indicating a difference between the average L_{90} for heat pumps and unit ventilators, with unit ventilators having higher values overall, lending further evidence to the hypothesis that unit ventilators contribute to higher background noise in rooms.

Reverberation time was also considered for the sake of being thorough, although theoretically no difference is expected with the reverberation times between different system types. The results of the ANOVA were not statistically significant (p=0.898) confirming no substantial difference in $T_{20,mid}$ between the system types.

Overall, the metrics used in the SEM were analyzed by HVAC category to see if different values resulted from the different HVAC groupings. Significant differences were found in two of the three non-speech metrics–non-speech L_{90} and %time > 50dBA$_{ns}$, indicating that in this category, unit ventilators correlate to higher levels in the classroom overall. As expected, the reverberation time and speech noise metrics saw no difference between HVAC types.

5.3 Ventilation Systems and Time-logged Interactions

The above analyses considered overall values, averaged between all measured data in the classroom, as was done in the analyses in Chapter 3. Next, the effect of HVAC system type was considered on the time-logged interactions between the data (see Chapter 4). Specifically, the question of interest is whether the relationship over time between sound level and indoor air quality parameters was affected by the type of HVAC system employed in the building.

ANOVAS were conducted with the correlations as the variable of interest and the schools as the unit of analysis, grouped in the same way as the previous section. Only significant correlations were considered, so some schools were represented by an average of fewer correlations than the number possible due to some classrooms in the group not having significant correlations. The results of the ANOVAS are not presented as none were significant, indicating that the differences in the r values were not affected by system type, considering only the significant correlations.

While interesting, the above result does not reflect results from the entire dataset. For some of the HVAC types, less than half of the classrooms had significant correlations between sound level and certain IAQ parameters. While the HVAC system type did not have a quantifiable effect on the values of significant correlations, it is interesting to observe the percentage of significant correlations between sound level and IAQ parameters for the various categories. Table 5.5 shows these correlations, divided by system type.

Table 5.5: Percentage of significant correlations between each HVAC category

		% Significant
CO2	Heat Pump	29%
x	VAV	34%
$L_A$eq	Unit Ventilator	29%
Fine PM	Heat Pump	23%
x	VAV	39%
$L_A$eq	Unit Ventilator	58%
Coarse PM	Heat Pump	51%
x	VAV	49%
$L_A$eq	Unit Ventilator	53%

For the correlations between CO_2 and overall $L_A$eq, each of the three categories saw about a third of the correlations significant (p<0.00089), so little difference was observed between the HVAC categories. Similarly, the correlations between coarse particulate matter and sound level do not seem to depend on HVAC system type, with each of them falling around half significant. While no difference was observed between system types, it is notable that a higher ratio of correlations was significant overall, with around half of the correlation being significant (at the Bonferroni corrected level of $p < 0.00089$), suggesting once again a strong relationship between sound level fluctuation and coarse particulate matter in the classroom.

While both CO_2 and coarse particulate matter correlations with sound level did not seem to change between system types, for fine particulate matter, a difference was observed. For systems with heat pumps, only 23% of the correlations were significant. For centralized systems with VAV boxes or AHUs, 39% of the correlations between sound level and fine particulate matter were significant. However, when considering classrooms with unit ventilators, 58% of the correlations were significant, suggesting a stronger relationship between fine particulate matter and sound level in rooms with unit ventilators. Perhaps this could be due to the way the unit ventilator brings in outdoor air, so when the system kicks on, leading to more sound, particulate matter from outside is also brought in. Further exploration should explore if there is any veracity to this conjecture.

For time-based interactions between sound level and indoor air quality parameters, HVAC system types do not seem to make a difference except in the special case of the correlation between sound level and fine particulate matter, with classrooms with unit ventilators experiencing a much higher number of significant correlations. The actual value of these correlations, however, does not significantly vary between schools.

5.4 Conclusion

Building occupants often complain about noisy HVAC systems. To explore the effect of HVAC system type on sound level in actual classrooms, an analysis of how sound levels are different with system type was undertaken. First, various sound metrics were tested using ANOVA to see if there was a difference in level between the groups of classrooms with different HVAC system types. The average sound level in the classroom during times when speech was present was no different between types of HVAC system. However, the average sound level in the classrooms during times when no speech was present was different depending on the system type, with unit ventilator classrooms experiencing the highest levels overall and classrooms with centralized systems and heat pumps experiencing lower overall levels. While it is clear that HVAC system type does contribute to noise and noise does affect student achievement, the actual link between HVAC type and student achievement still needs more quantification. Jaramillo (2013) found subjectively that teachers typically do not notice HVAC noise or believe that it affects learning in the classroom, although Ronsse & Wang (2010) found that higher levels of mechanical system noise do negatively impact student achievement, although no distinction was made between system types. Future work can explore relationships between system type and achievement more in depth.

HVAC system type not only impacts sound level but also affects indoor air quality parameters. To look at how the time-logged relationship between sound level and select IAQ parameters was affected by HVAC system type, an ANOVA was conducted with the significant correlations between the various parameters. The ANOVA produced no significant results, indicating no quantifiable difference in the strength of the significant correlations in different categories. However, classrooms with unit ventilators were much more likely to see a significant correlation between average sound level and fine particulate matter than those with other HVAC system types.

Chapter 6
Concluding Remarks

6.1 Discussion and Future Work

6.1.1 Averaged Parameters and Student Achievement

A statistical analysis was conducted, relating measured acoustic parameters in classrooms with student achievement in reading and math. Three categories were considered, including sound during speech times in classrooms, noise when speech wasn't present, and reverberance. Structural equation modeling was used to link these parameters in the form of latent variable constructs to student achievement, controlling for demographics. The analysis revealed no effect of the acoustic parameters on reading achievement. For math, a statistically significant negative effect of speech noise was found on math achievement.

The lack of statistically significant effects on reading achievement is hypothesized to be due in part to the limited range of values in this sample, with reverberation times generally falling between 0.29 and 0.84 and averaging 0.47. Detrimental effect on reading, for example, would not likely occur until values reach at least 1 second or more.

The higher speech levels and their effect on math achievement suggest that when teachers need to raise their voice to instruct, the students do not benefit. While no statistically significant effect of non-speech noise on match achievement was observed, non-speech noise and speech noise are related in complex ways and are not entirely independent. Further exploration is needed to understand the complex relationships between occupied speech and non-speech noise in classrooms and if there is a causal relationship. This sample found a clear relationship between the two but cannot establish causal order between the two measured parameters. For example, it could be said that higher speech noise is correlated with higher non-speech noise in this sample, but it cannot be concluded that higher non-speech noise causes higher speech noise.

A sample of classrooms with 'worse' acoustics may yield different results from this analysis that includes classrooms that generally contain reasonable values for reverberation time and background noise. While the background noise levels were typically not below the ANSI S12.60 maximum value of 35 dBA in this sample, the maximum level observed was 55.1 and the minimum was 25.2, with an average of 42.91. None of these levels are extraordinarily high and may not be quantifiably detrimental to student performance.

6.1.2 Temporal Variation in Indoor Environment Parameters

Building off the averaged values considered in the analysis in Chapter 3, the time variation in logged parameters values were considered in Chapter 4. In particular, the question addressed was: do the various measured parameters relate in how they rise and fall throughout the school day? For sound level and indoor air quality parameters, the answer is typically yes, with more than half of classrooms experiencing significant correlations both between $L_A eq$ and CO_2 over time and between $L_A eq$ and fine particulate matter over time. Nearly three quarters of classrooms (73%) experienced statistically significant correlations between sound level and coarse particulate matter.

These relationships result in part from natural human tendencies within occupied spaces. For example, more people in a room means louder sound levels due to talking and activity. Correspondingly, people also stir up particle matter by their activity and emit carbon dioxide simply by breathing. Thus, the correlations over time between these parameters confirm a logical assumption that conditions in a room vary with occupancy, perhaps with occupancy driving the values of these parameters. Statistically, however, this assumption was unable to be verified. A measurement model was created for each of these interactions with occupancy as the predictor variable for both sound level and the select indoor air quality parameter, but the path between occupancy and the IAQ parameter was not significant, regardless of which was used in the analysis. Sound level, however, did correlate significantly with occupancy.

Occupancy is critical when considering the time variation of indoor environment parameters within classrooms, especially sound level and indoor air quality. Since this occupancy analysis was only performed on one classroom, further measurement and exploration is needed to form conclusive results. It is suggested that similar measurements to those discussed in this paper be taken with the addition of occupancy counts over time in a greater number of cases in order to observe correlational patterns over a greater sample size. Additionally, further exploration of thermal parameters with consideration of occupancy could also yield interesting results, as those were not explored in depth in this paper.

In light of the importance of occupancy, design standards should consider occupied conditions more frequently, especially in acoustics. There is a clear relationship between occupied conditions and student achievement, so taking into consideration the occupied condition can yield a better environment overall.

6.1.3 HVAC Analysis

A significantly higher non-speech sound level was observed for classrooms containing unit ventilators, a discovery that is not unexpected to one familiar with HVAC system types. For systems with unit ventilators, the average value of non-speech noise experienced was 50.6 dBA while for centralized systems and heat pumps, the average values were lower, at 48.4 and 48.7 respectively. While the difference between these average values is not above the just noticeable difference, it is still statistically significant and could have imperceptible overall effects.

Average speech values were, however, not found to be any different between classrooms of different system types. If average values for speech levels are the same but for non-speech levels are much higher for unit ventilators, the signal to noise ratio within these classrooms would likely be lower, causing lower speech intelligibility within this subsection of classrooms, a factor shown repeatedly to affect occupants' ability to listen and perform.

No clear effect of HVAC system type on the strength of time-based interactions between acoustics and IAQ was discovered. Overall, further work can explore the relationships of HVAC system type on indoor environment parameters and their relationships. Perhaps different or more detailed divisions can be explored to isolate more nuanced effects.

Appendix A
Additional Figures

A.1 Distributions of Classroom Averaged Parameters

A.1.1 Acoustics

Figure A.1: Histogram of Average Speech Sound Levels in Classrooms

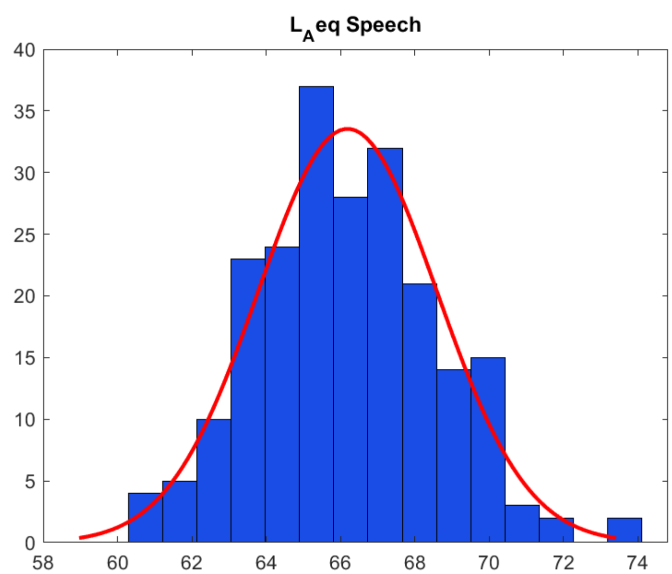


Figure A.2: Histogram of Average Speech Levels in Classrooms for 250 Hz Octave Band

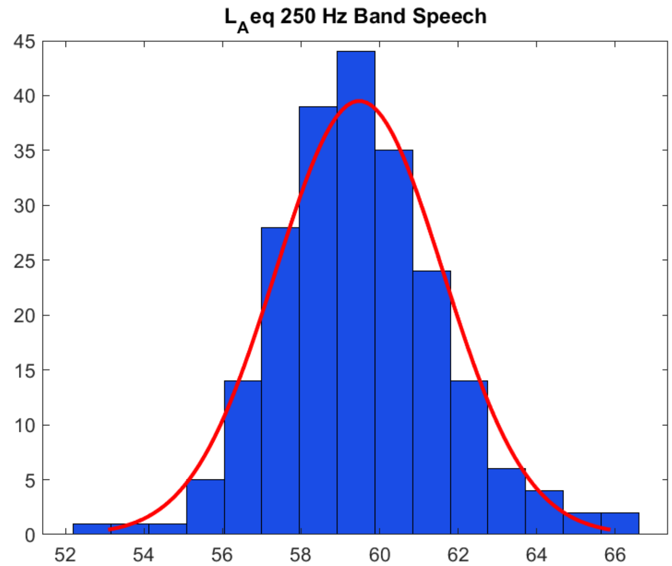


Figure A.3: Histogram of Average Speech Levels in Classrooms for 500 Hz Octave Band

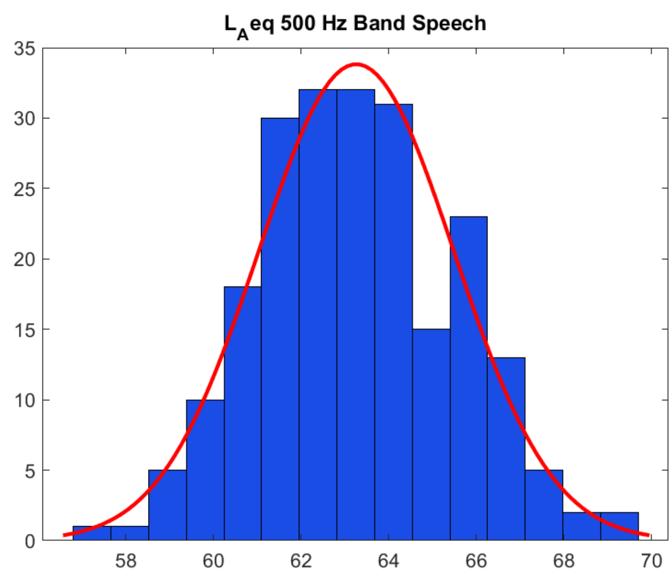


Figure A.4: Histogram of Average Speech Levels in Classrooms for 1 kHz Octave Band

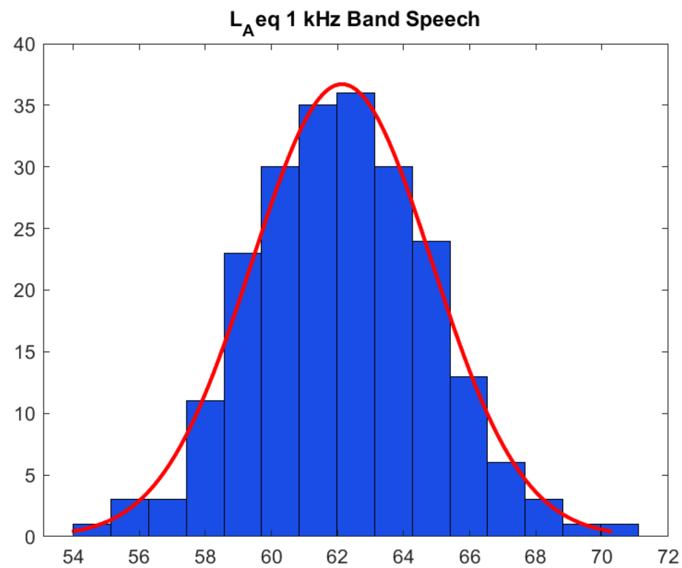


Figure A.5: Histogram of Average Speech Levels in Classrooms for 2 kHz Octave Band

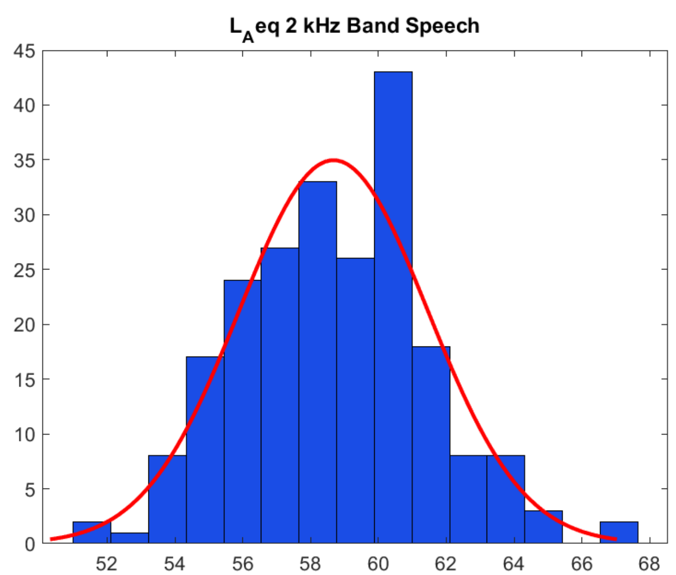


Figure A.6: Histogram of L_{10} Values for Speech Levels in Classrooms

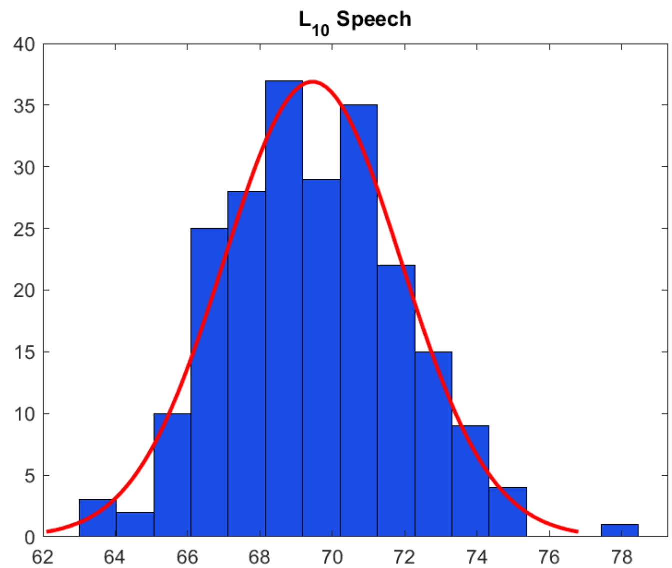


Figure A.7: Histogram of L_{25} Values for Speech Levels in Classrooms

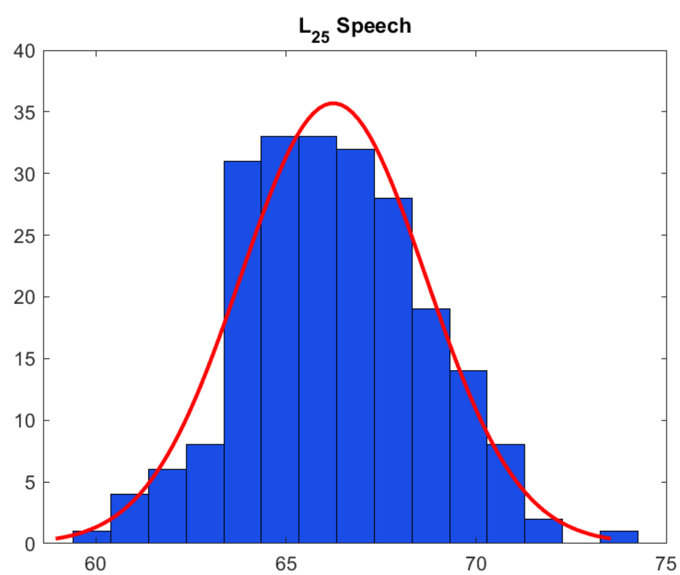


Figure A.8: Histogram of L_{35} Values for Speech Levels in Classrooms

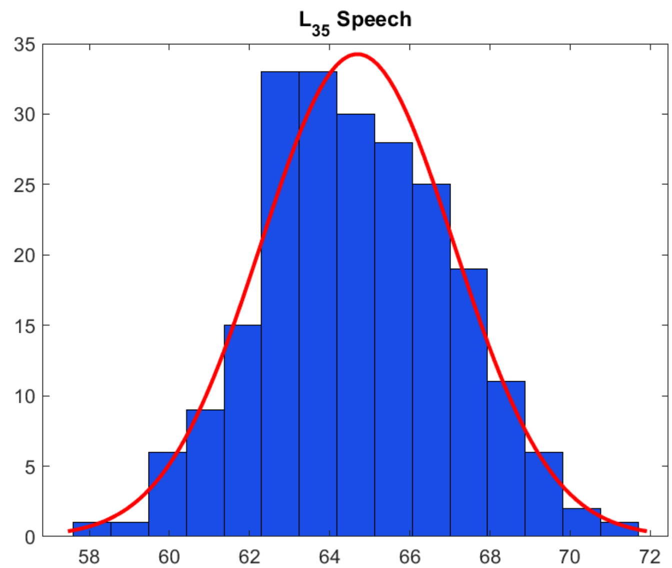


Figure A.9: Histogram of L_{50} Values for Speech Levels in Classrooms

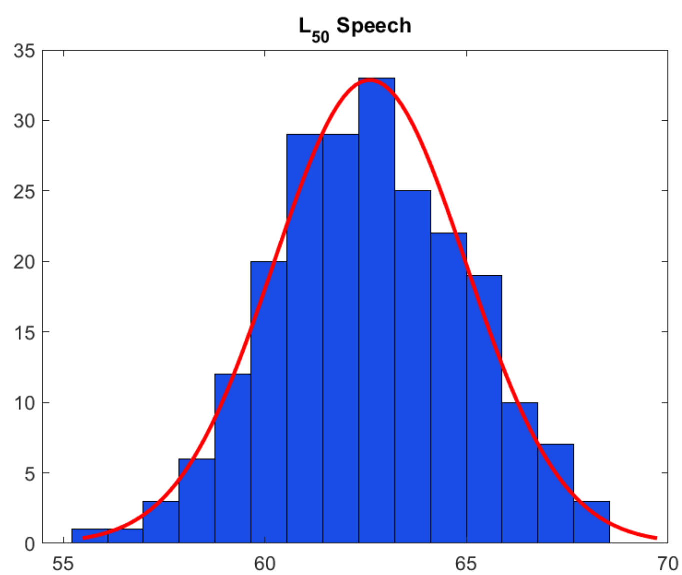


Figure A.10: Histogram of L_{75} Values for Speech Levels in Classrooms

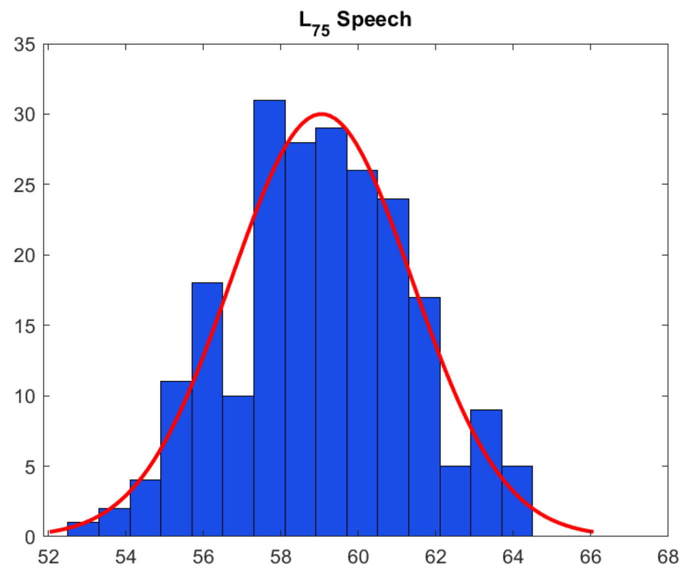


Figure A.11: Histogram of L_{90} Values for Speech Levels in Classrooms

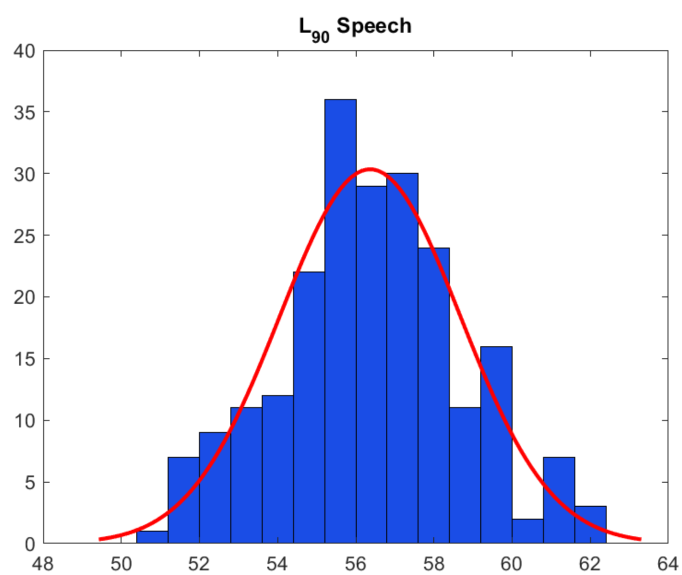


Figure A.12: Histogram of Percent of Time Speech Noise Exceeds 60 dB_A

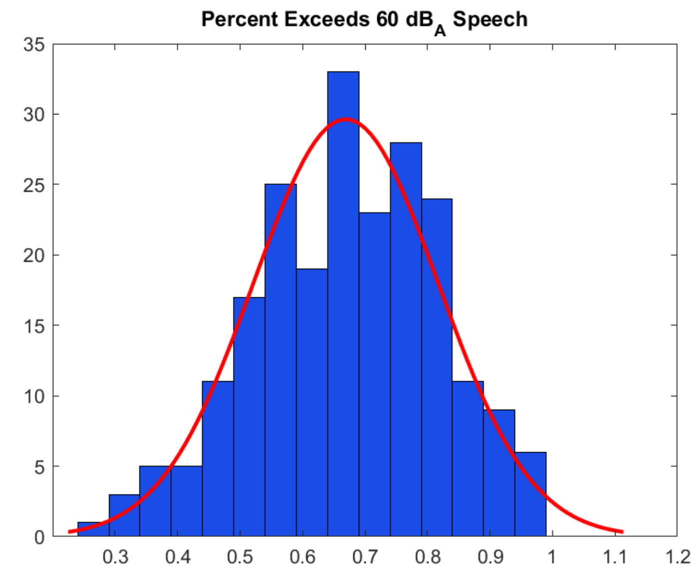


Figure A.13: Histogram of Percent of Time Speech Noise Exceeds 65 dB_A

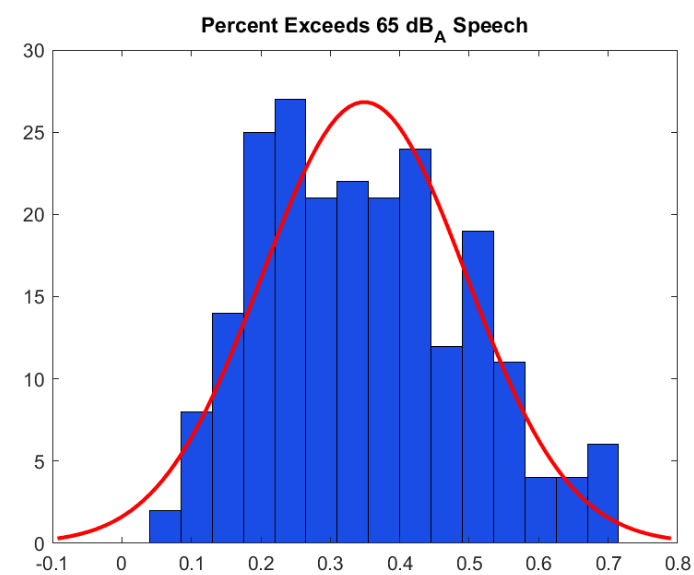


Figure A.14: Histogram of Percent of Time Speech Noise Exceeds 70 dB_A

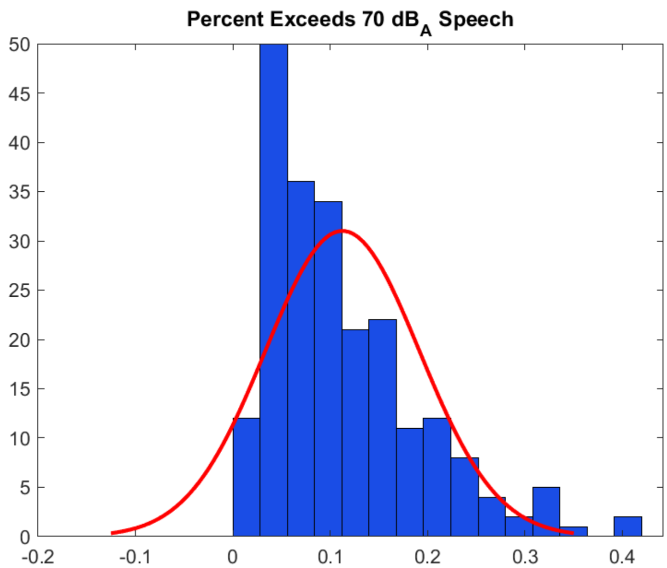


Figure A.15: Histogram of Average Non-Speech Sound Levels in Classrooms

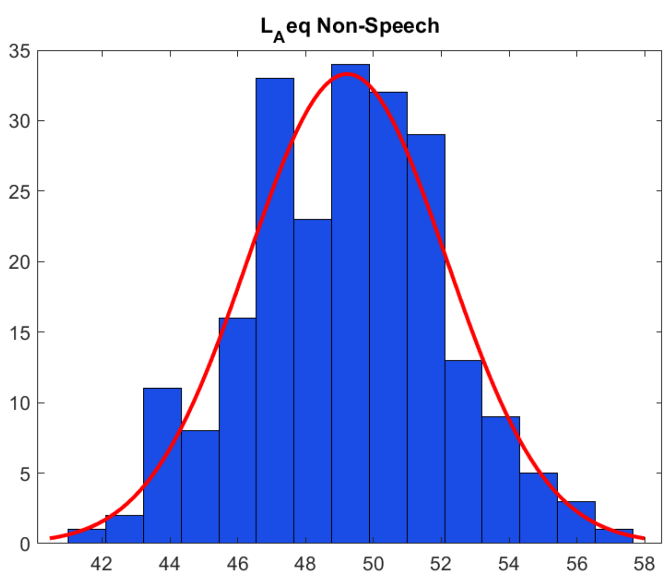


Figure A.16: Histogram of Average Non-Speech Levels in Classrooms for 125 Hz Octave Band

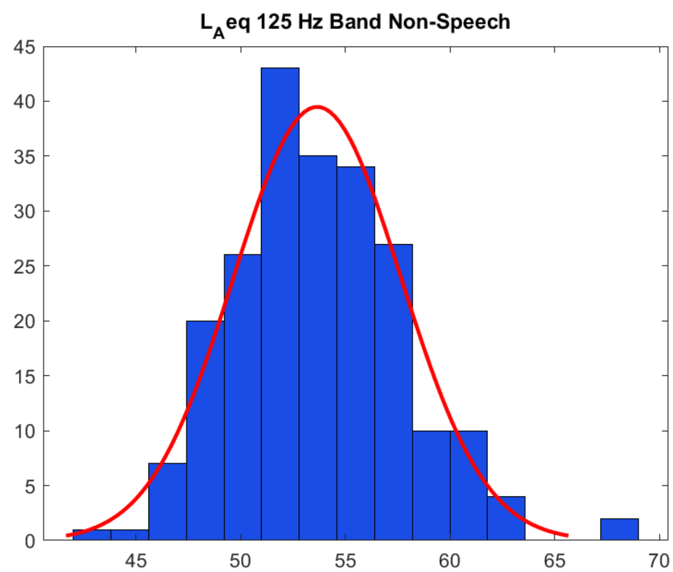


Figure A.17: Histogram of Average Non-Speech Levels in Classrooms for 250 Hz Octave Band

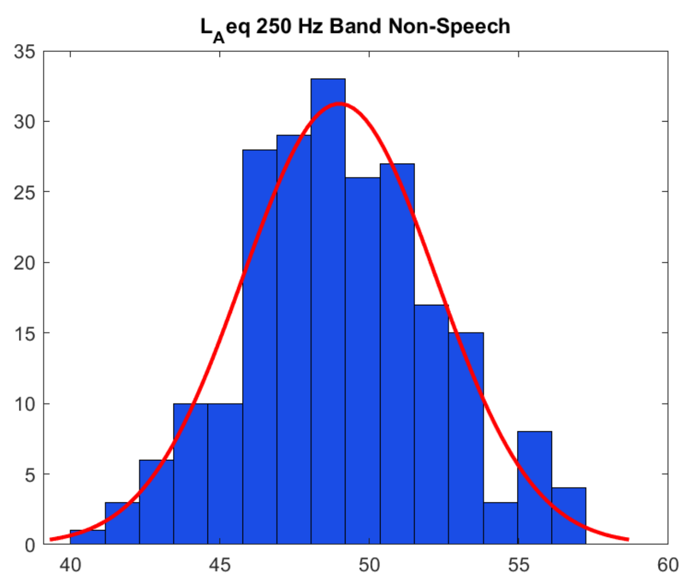


Figure A.18: Histogram of Average Non-Speech Levels in Classrooms for 500 Hz Octave Band

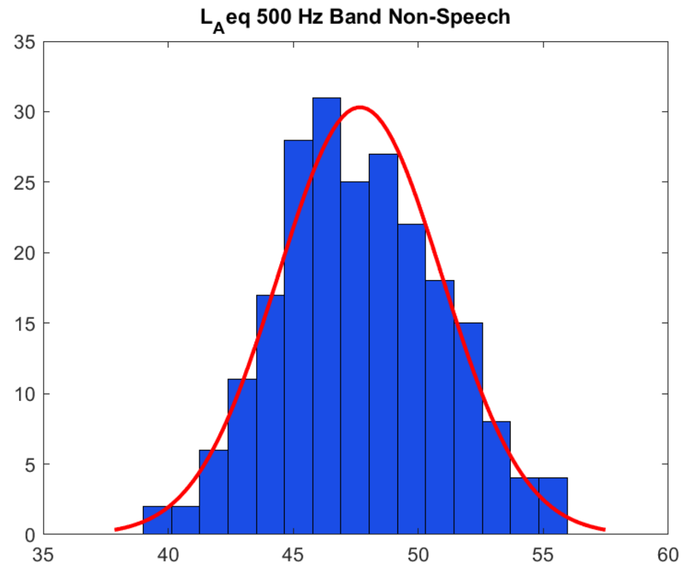


Figure A.19: Histogram of L_{10} Values for Non-Speech Levels in Classrooms

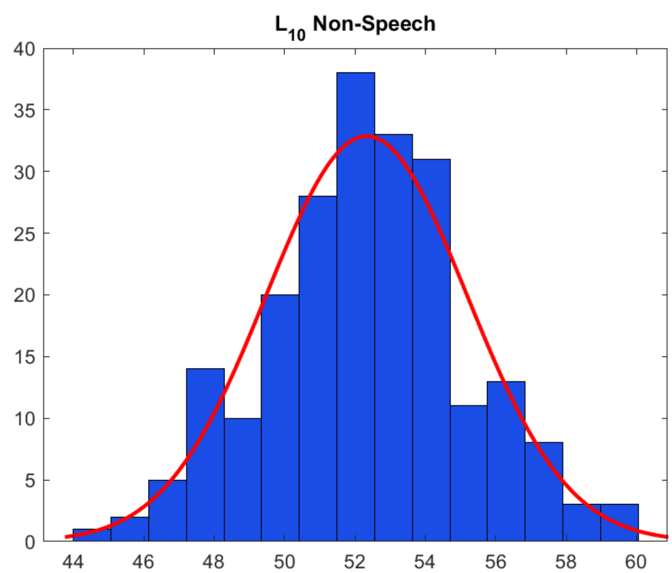


Figure A.20: Histogram of L_{25} Values for Non-Speech Levels in Classrooms

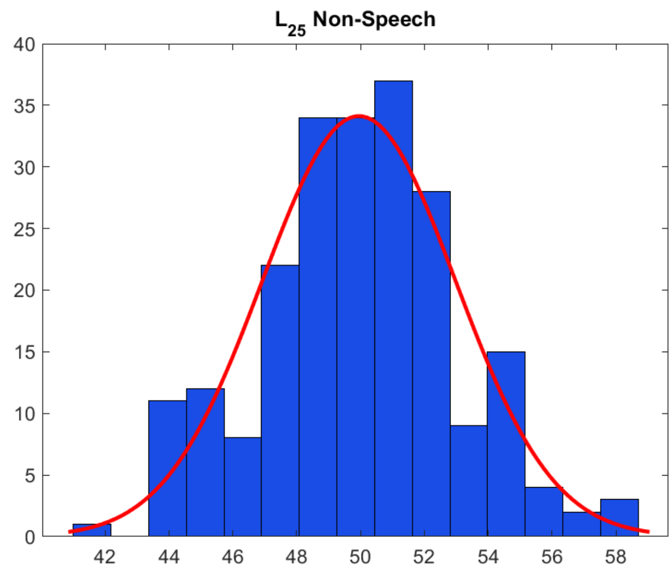


Figure A.21: Histogram of L_{35} Values for Non-Speech Levels in Classrooms

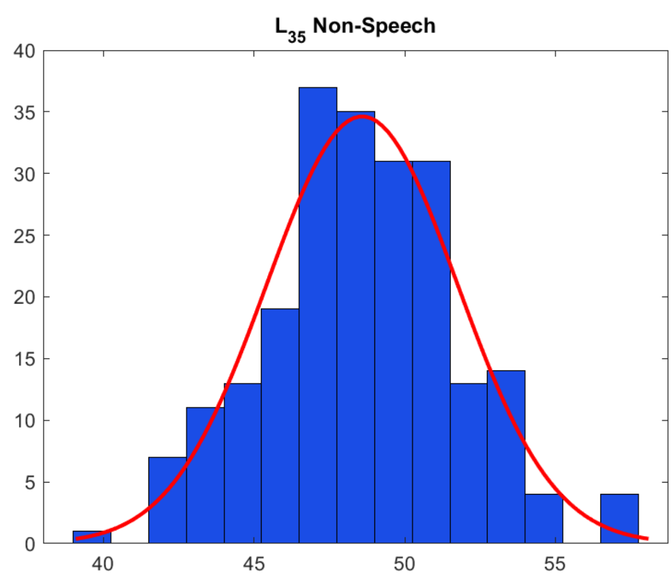


Figure A.22: Histogram of L_{50} Values for Non-Speech Levels in Classrooms

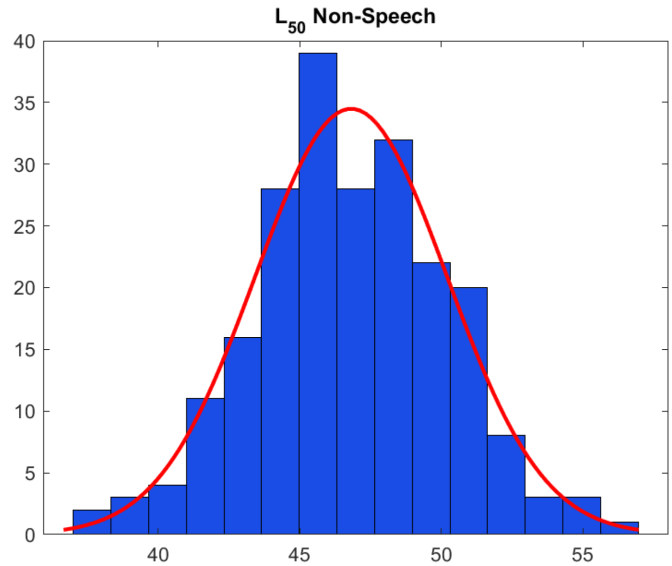


Figure A.23: Histogram of L_{75} Values for Non-Speech Levels in Classrooms

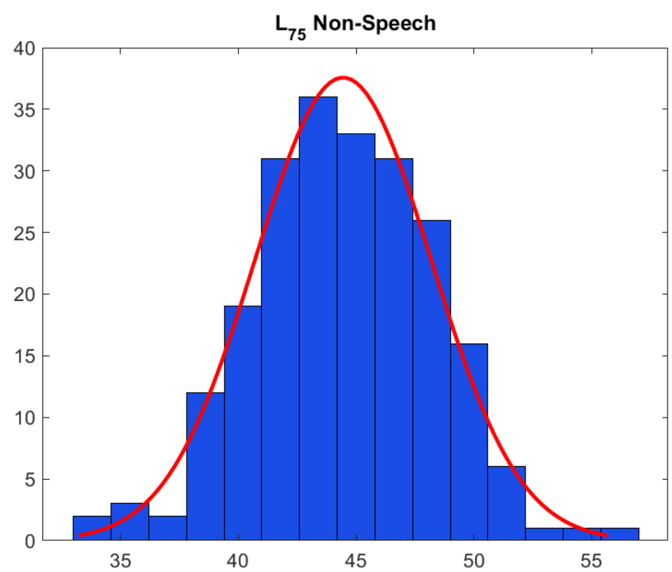


Figure A.24: Histogram of L_{90} Values for Non-Speech Levels in Classrooms

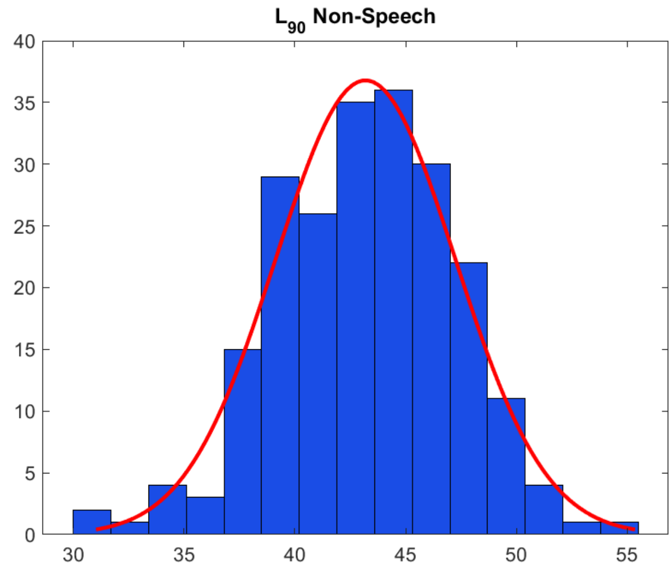


Figure A.25: Histogram of Percent of Time Non-Speech Noise Exceeds 45 dB_A

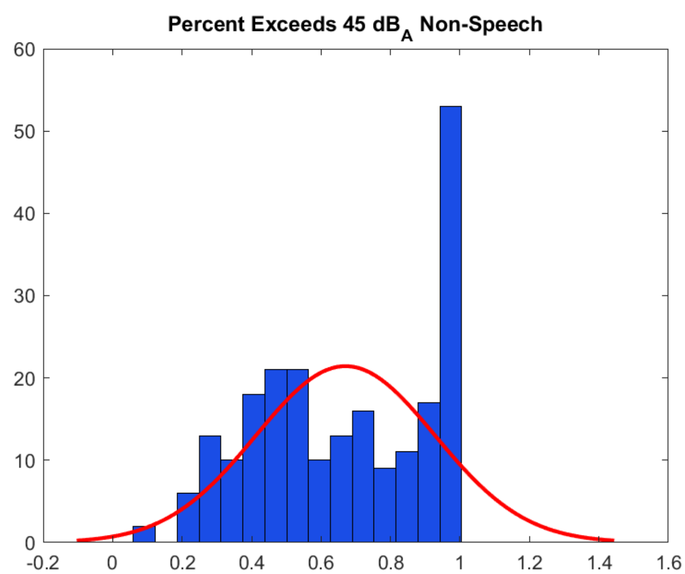


Figure A.26: Histogram of Percent of Time Non-Speech Noise Exceeds 50 dB_A

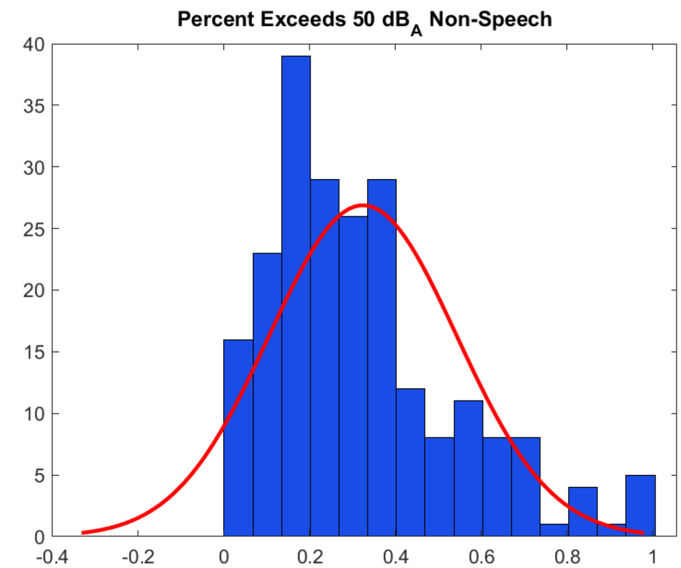


Figure A.27: Histogram of Percent of Time Non-Speech Noise Exceeds 55 dB_A

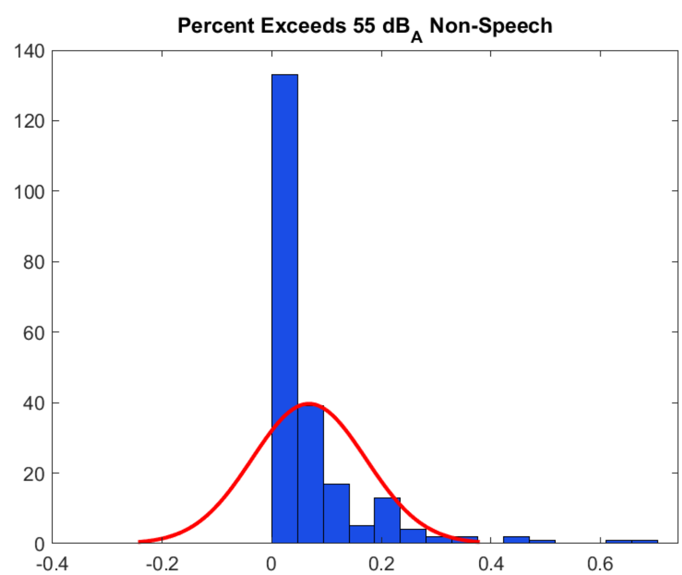


Figure A.28: Histogram of $T20_{low}$ values in classrooms

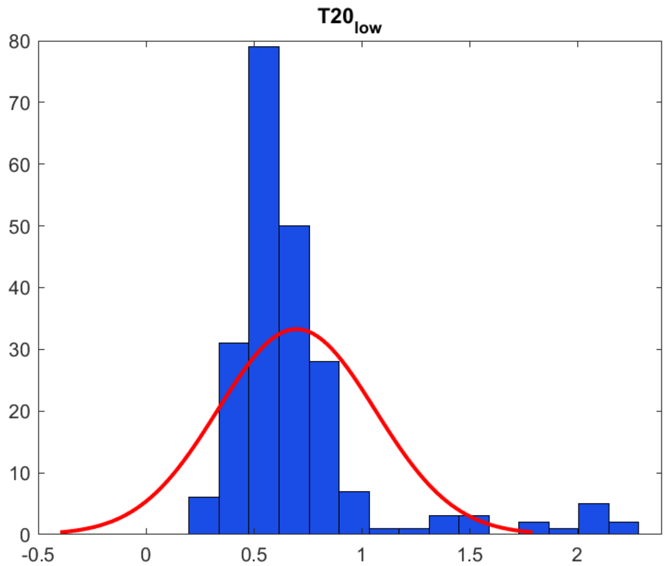


Figure A.29: Histogram of $T20_{mid}$ values in classrooms

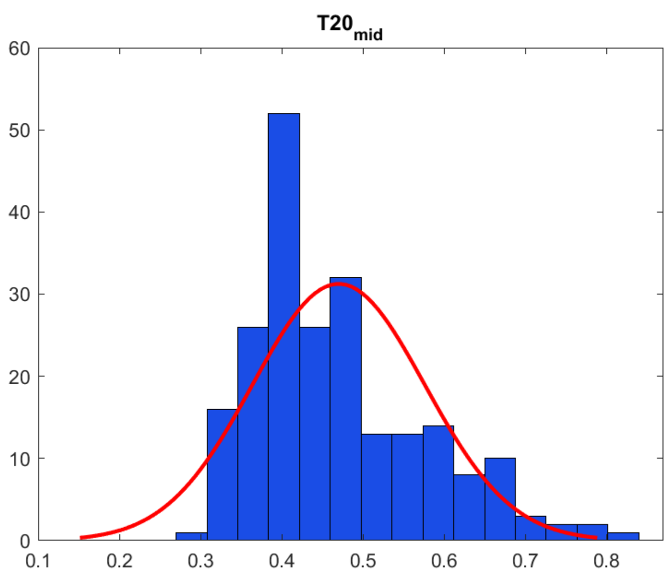


Figure A.30: Histogram of $T20_{mid}$ values.

Figure A.31: Histogram of $T20_{high}$ values in classrooms

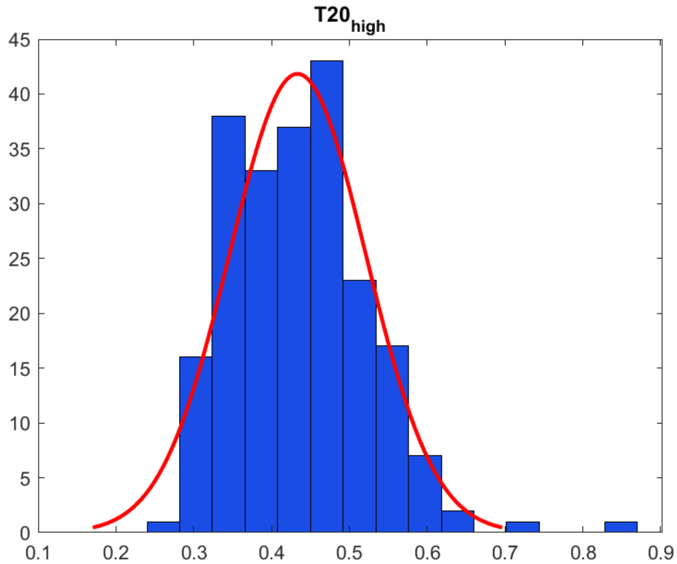
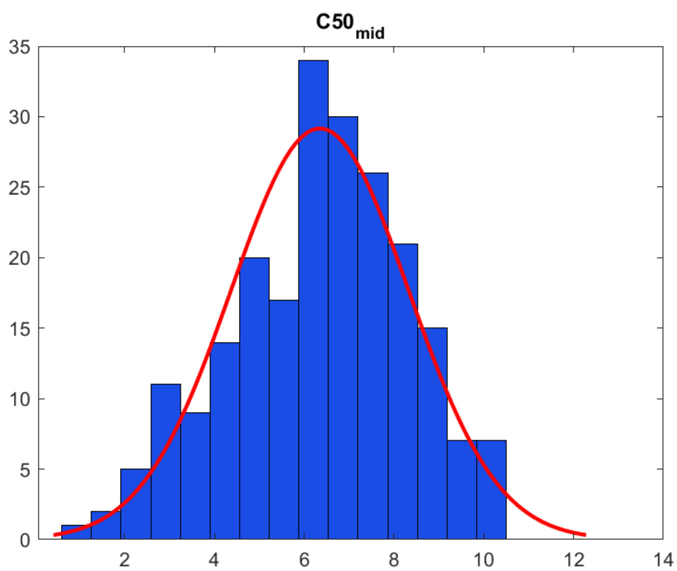


Figure A.32: Histogram of C_{50} values in classrooms



A.1.2 Demographics

Figure A.33: Histogram of percent of gifted students in classrooms

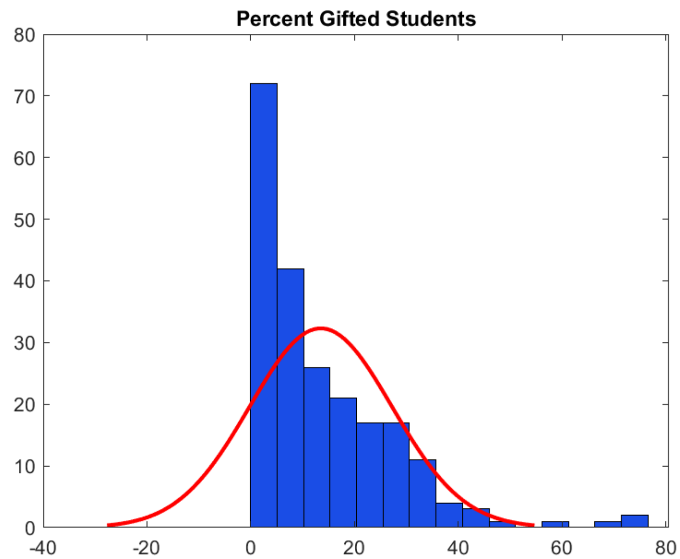


Figure A.34: Histogram of percent of free and reduced lunch recipients in classrooms

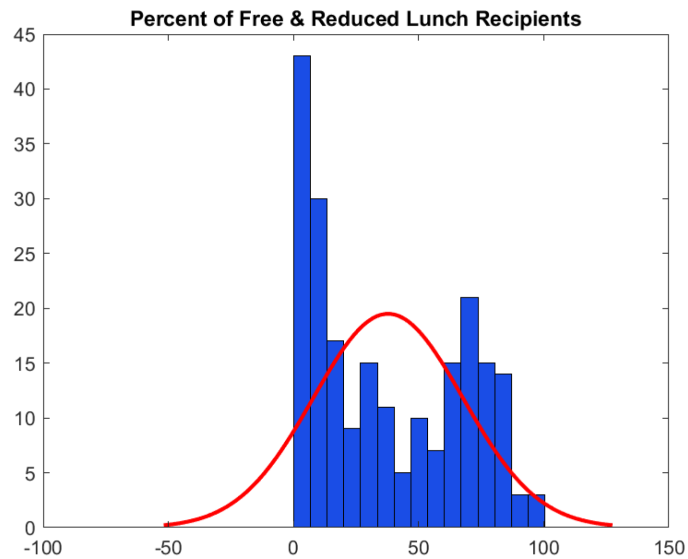
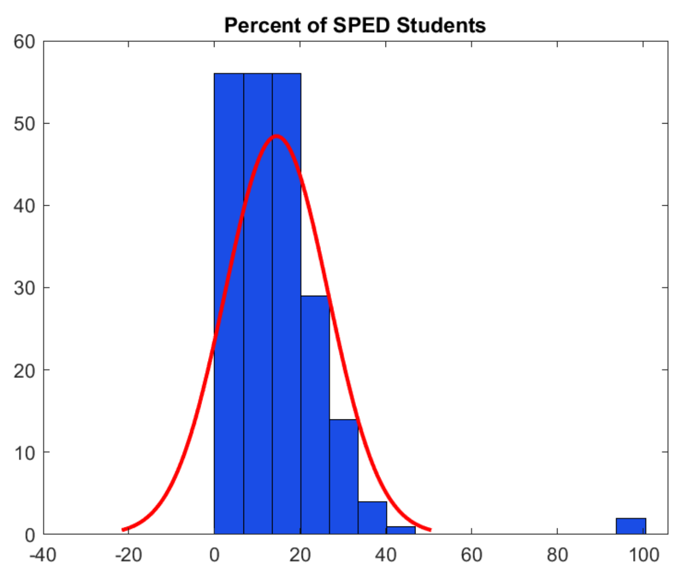


Figure A.35: Histogram of percent of special education students in classrooms



Appendix B
Averaged Data Variable Summary Table

Table B.1: Variable names and definitions for averaged classroom acoustic, achievement, and demographic data

Variable	**Description**
Achievement	
PR_{Read}	Classroom percentile average of state achievement scores in reading
PR_{Math}	Classroom percentile average of state achievement scores in math
Demographics	
%FRL	Percentage of free and reduced lunch recipients in each classroom
%SPED	Percentage of special education students in each classroom
%Gifted	Percentage of gifted students per classroom
Acoustics: K-means Clustered 'Speech' Metrics	

Continued on next page

Table B.1 – *Continued from previous page*

Variable	**Description**
$L_{Aeq,sp}$	A-weighted continuous equivalent sound pressure level during times when speech was present in the classroom
$L250Hz_{sp}$	250 Hz octave band noise level during times when speech was present
$L500Hz_{sp}$	500 Hz octave band noise level during times when speech was present
$L1kHz_{sp}$	1000 Hz octave band noise level during times when speech was present
$L2kHz_{sp}$	2000 Hz octave band noise level during times when speech was present
$L4kHz_{sp}$	4000 Hz octave band noise level during times when speech was present
$L8kHz_{sp}$	8000 Hz octave band noise level during times when speech was present
$L_{10,sp}$	Sound level (dBA) exceeded 10% of the time during times when speech was present
$L_{25,sp}$	Sound level (dBA) exceeded 25% of the time during times when speech was present
$L_{35,sp}$	Sound level (dBA) exceeded 35% of the time during times when speech was present

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Table B.1 – *Continued from previous page*

Variable	**Description**
$L_{50,sp}$	Sound level (dBA) exceeded 50% of the time during times when speech was present
$L_{75,sp}$	Sound level (dBA) exceeded 75% of the time during times when speech was present
$L_{90,sp}$	Sound level (dBA) exceeded 90% of the time during times when speech was present
$\%time>60dBA_{sp}$	Percent of time noise when speech is present exceeds 60 dBA
$\%time>65dBA_{sp}$	Percent of time noise when speech is present exceeds 65 dBA
$\%time>70dBA_{sp}$	Percent of time noise when speech is present exceeds 70 dBA
$L_{10,sp} - L_{90,sp}$	$L_{10} - L_{90}$ during times when speech was present
Acoustics: K-means Clustered 'Non-Speech' Metrics	
$L_{Aeq,ns}$	A-weighted continuous equivalent sound pressure level during times when no speech was present in the classroom
$L125Hz_{ns}$	Non-Speech 125 Hz octave band noise level during times when no speech was present

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Table B.1 – *Continued from previous page*

Variable	**Description**
$L250Hz_{ns}$	Non-Speech 250 Hz octave band noise level during times when no speech was present
$L500Hz_{ns}$	Non-Speech 500 Hz octave band noise level during times when no speech was present
$L1kHz_{ns}$	Non-Speech 1000 Hz octave band noise level during times when no speech was present
$L_{10,ns}$	Sound level (dBA) exceeded 10% of the time during times when no speech was present
$L_{25,ns}$	Sound level (dBA) exceeded 25% of the time during times when no speech was present
$L_{35,ns}$	Sound level (dBA) exceeded 35% of the time during times when no speech was present
$L_{50,ns}$	Sound level (dBA) exceeded 50% of the time during times when no speech was present
$L_{75,ns}$	Sound level (dBA) exceeded 75% of the time during times when no speech was present

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Table B.1 – *Continued from previous page*

Variable	Description
$L_{90,ns}$	Sound level (dBA) exceeded 90% of the time during times when no speech was present
%time>45dBA$_{ns}$	Percent of time noise when no speech is present exceeds 45 dBA
%time>50dBA$_{ns}$	Percent of time noise when no speech is present exceeds 50 dBA
%time>55dBA$_{ns}$	Percent of time noise when no speech is present exceeds 55 dBA
$L_{10,ns} - L_{90,ns}$	L_{10}–L_{90} during times when no speech was present
Acoustics: Unoccupied Room Measurements	
BNL_{1min}	Background noise level collected over 1 minutes (ANSI S12.60)
T_{20}	Reverberation (time it takes for sound to decay 60 dB) extrapolated from 20dB decay starting from 5 dB down point
$T_{20,low}$	T_{20} (see above for definition) for low frequency range
$T_{20,mid}$	T_{20} (see above for definition) for mid frequency range
$T_{20,high}$	T_{20} (see above for definition) for high frequency range
$C50_{mid}$	Clarity index for speech intelligibility using 50ms as the critical time limit

Appendix C
Time-Logged Data Variable Summary Table

Table C.1: Variable Names and Definitions for Time-Logged Classroom Indoor Environment Data

Variable	**Description**
CO_2	The concentration of carbon dioxide in parts per million (ppm)
Coarse PM	Geometric concentration of coarse (2.5µm < x < 10µm) particulate matter in counts/0.05ft^3(air)
Fine PM	Geometric concentration of fine (< 2.5µm) particulate matter in counts/0.05ft^3(air)
Formaldehyde	Formaldehyde concentration in the room in parts per billion (ppb)—not used in statistical analyses
ILA	Artificial illuminance, an indication of the lighting within the room in lumens/ft^3
ILN	Natural illuminance, an approximation of daylighting in lumens/ft^3
L_{Aeq}	Equivalent continuous sound pressure level in dBA—often referred to as 'Sound Level' in the text
L125Hz	Sound Level (dB) in the 125 Hz octave band

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Table C.1 – *Continued from previous page*

Variable	**Description**
L1kHz	Sound Level (dB) in the 1000 Hz octave band
PN2.5	Count of 2.5 µm particles in parts per billion (ppb)
PN10	Count of 10.0 µm particles in parts per billion (ppb)
RH	Relative Humidity (%) within the classroom
State	Door state in percent open (%)—not utilized in statistical analyses
Temp	Temperature in degrees Fahrenheit (°F)

Appendix D
Alternative Acoustics Model

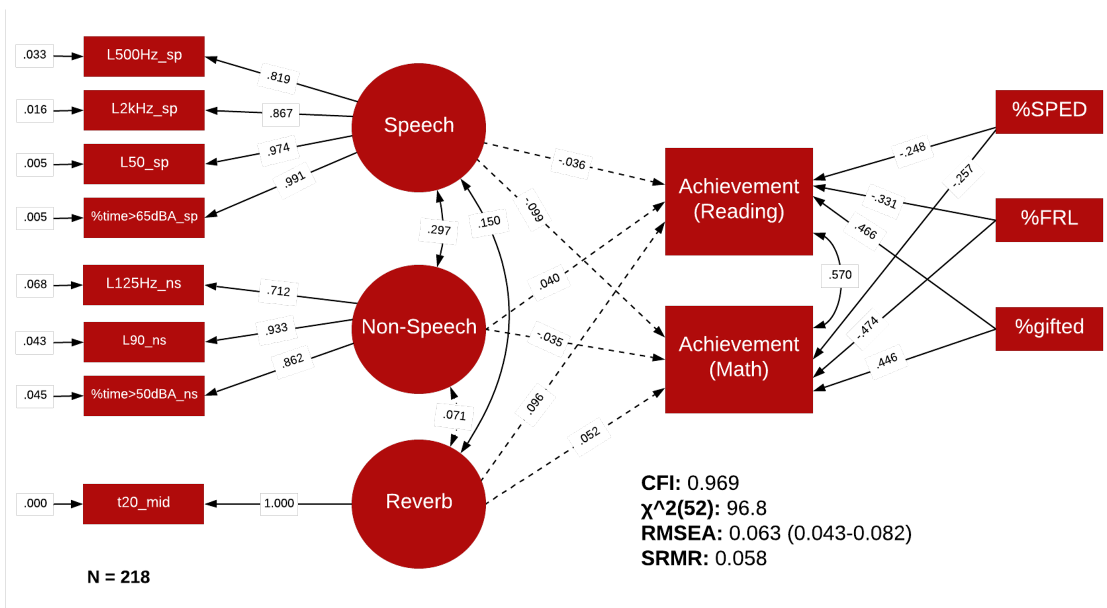

Figure D.1: Alternative model not including grade level as a control

Appendix E
Supporting Statistics

Table E.1: Exploratory factor analysis pattern matrix for speech, non-speech, and room acoustic variables

Variable	Factor 1	Factor 2	Factor 3
$L_{10,sp}$	0.991	0.058	-0.020
$L_{25,sp}$	0.987	-0.016	-0.013
$L_{Aeq,sp}$	0.984	0.021	-0.008
$L_{35,sp}$	0.968	-0.062	0.001
$L2kHz_{sp}$	0.945	0.071	-0.023
$\%time>65dBA_{sp}$	0.945	-0.077	0.008
$\%time>70dBA_{sp}$	0.938	0.048	-0.024
$L1kHz_{sp}$	0.928	-0.007	-0.033
$L_{50,sp}$	0.919	-0.145	0.022
$L4kHz_{sp}$	0.830	0.089	-0.065
$\%time>60dBA_{sp}$	0.827	-0.284	0.046
$L_{75,sp}$	0.809	-0.334	0.034
$L500Hz_{sp}$	0.804	-0.067	0.092
$L250Hz_{sp}$	0.682	-0.114	0.073
$L_{90,sp}$	0.672	-0.548	0.026

Continued on next page

Table E.1 – *Continued from previous page*

Variable	**Factor 1**	**Factor 2**	**Factor 3**
$L8kHz_{sp}$	0.634	0.050	-0.045
$L_{75,ns}$	-0.051	-0.991	-0.025
$L_{50,ns}$	0.026	-0.976	0.000
$L_{90,ns}$	-0.074	-0.958	-0.068
$L_{35,ns}$	0.092	-0.941	-0.009
$L_{Aeq,ns}$	0.168	-0.923	0.022
$\%time{>}45dBA_{ns}$	-0.024	-0.916	0.009
$L_{25,ns}$	0.159	-0.909	-0.019
$\%time{>}50dBA_{ns}$	0.124	-0.886	0.002
$L250Hz_{ns}$	0.117	-0.838	0.018
$L_{10,ns}$	0.285	-0.835	-0.005
$L1kHz_{ns}$	0.212	-0.825	0.021
$L500Hz_{ns}$	0.147	-0.819	0.023
$L_{10,sp} - L_{90,sp}$	0.461	0.760	-0.056
BNL_{1min}	-0.066	-0.701	0.074
$\%time{>}55dBA_{ns}$	0.256	-0.672	0.064
$L125Hz_{ns}$	-0.001	-0.668	0.023
$L_{10,ns} - L_{90,ns}$	0.400	0.550	0.085
$T_{20,mid}$	0.081	0.010	0.965
$C50_{mid}$	-0.064	-0.004	-0.905
$T_{20,high}$	-0.001	0.020	0.764
$T_{20,low}$	-0.110	-0.005	0.458

Rotation converged in 8 iterations

Note: Octave band levels of 1 kHz for non-speech and 4 kHz and 8 kHz for speech times were included in the EFA but not discussed in the text.

Table E.2: Factor correlation matrix for the latent variable constructs

Factor	1	2	3
1	1	-0.222	0.059
2	-0.222	1	-0.11
3	0.059	-0.11	1

Extraction Method: Principal Axis Factoring. Rotation Method: Oblimin with Kaiser Normalization.

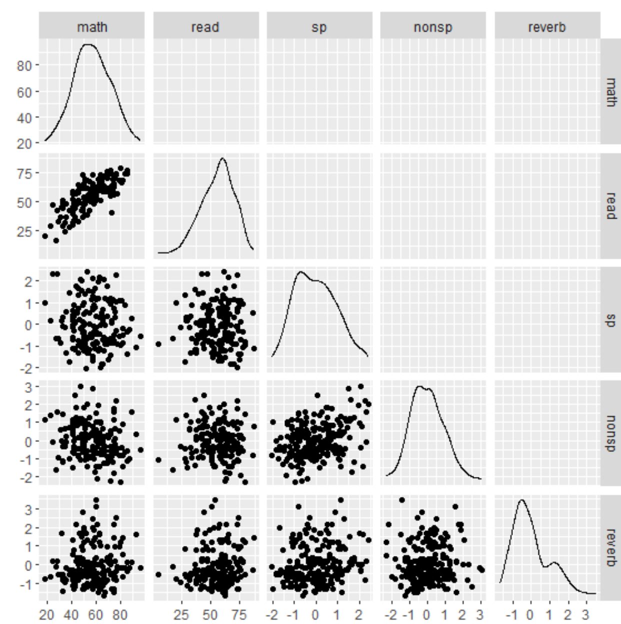

Figure E.1: Scatterplot of latent variable factor scores and outcome variables, showing scattered trends and no clear evidences of nonlinearity

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