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Applying unsupervised machine learning clustering techniques to early childcare soundscapes

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Early childhood is a critical time period for language, brain, cognitive, and social/emotional development. Out-of-home childcare is a normative, typical experience for millions of young children. Although Indoor Environmental Quality (IEQ) in K-12 settings has received recent, significant attention, the links between IEQ and children's learning and development in early childcare settings is a less understood topic. This work focuses specifically on the sound aspect of IEQ in early childcare settings to better understand typical noise levels and occupant experience. Standard approaches to analyzing background noise will be presented alongside more detailed statistical analyses utilizing unsupervised machine learning clustering techniques. Noise data collected in three daycares will be presented using typical acoustic metrics and clustering techniques to better understand room activity conditions and support new metrics. Overall, this study can lead to a better understanding of daycare soundscapes and pave the way towards a better childcare for young children.

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1. INTRODUCTION

In general, children's early life experiences are strongly linked to lifelong outcomes in health, academic, and social well-being[1]. Out-of-home childcare is a normative, typical experience for millions of young children. In 2019, 59% of U.S. children from birth to age five participated in some form of nonparental care[2]. The form of nonparental care varies, with 62% of those in center-based care located in buildings of their own, places of worship, and public schools. A scarcity of research and measurements exist regarding the Indoor Environmental Quality (IEQ) of these early childcare centers.

This work looks to analyze typical noise levels and understand occupant experience through a soundscape approach, which involves understanding occupant perception, the acoustic environment, and context[3]. Early childcare soundscapes present many challenges to children and teachers. For example, teachers have few opportunities to rest their voice while they need to be speaking in spaces with high background noise levels. One study comparing voice disorders of childcare teachers against hospital nurses found significantly more voice disorders for childcare teachers[4]. Advanced statistical analyses can be utilized to better understand the challenges of early childcare soundscapes. For example, unsupervised machine learning techniques have shown promise in the domains of hospitals, offices, and schools to help better understand patterns of noise in complex soundscapes[5-8]. The application in these other types of environments show utility in being able to separate data into meaningful groups as well as allow for unique metric development and calculation. In this study, both typical analyses and machine learning approaches have been used to measure and help improve understanding of daycare soundscapes and potential implications for occupants.

2. METHODOLOGY

A. SITE AND DATA COLLECTION

Five rooms in three daycares were selected for measurements. Each room had a typical age range associated with it ranging from infant to school-aged. The acoustic environment was measured for 48-hours using dosimeters capturing A-weighted equivalent sound pressure level (LAeq), A-weighted maximum sound pressure level (LAmax), and C-weighted peak sound pressure level (LCpeak) for each minute of the measurement period. A soundscape follow-up survey was administered to capture staff perception with eleven participants responding.

B. CLUSTERING TECHNIQUE

Clustering is applied to group similar instances together utilizing a proximity matrix. Four methods of clustering were selected to compare which model would work best for this acoustic data. These models were selected because they are considered hard techniques, meaning that each data point is assigned to only one cluster. Diana and Agnes are two hierarchical methods that utilize either divisive or agglomerative approaches, respectively[9]. K-means and Pam are two non-hierarchical methods that group data through multiple iterations of assigning data to the closest cluster center, with the center being defined by either the mean or median, respectively[9,10]. The language R was used to implement the machine learning models.

The first step in clustering is to determine how many clusters the data inherently has. For this work, the silhouette method was used, which measures both cohesion and separation[11]. Figure 1 shows an example of the silhouette method using k-means for one of the daycare rooms. Similar results can be seen for the majority of the fifteen rooms and the additional models. The highest average silhouette width, which indicates the optimal number of clusters, was found to be two.

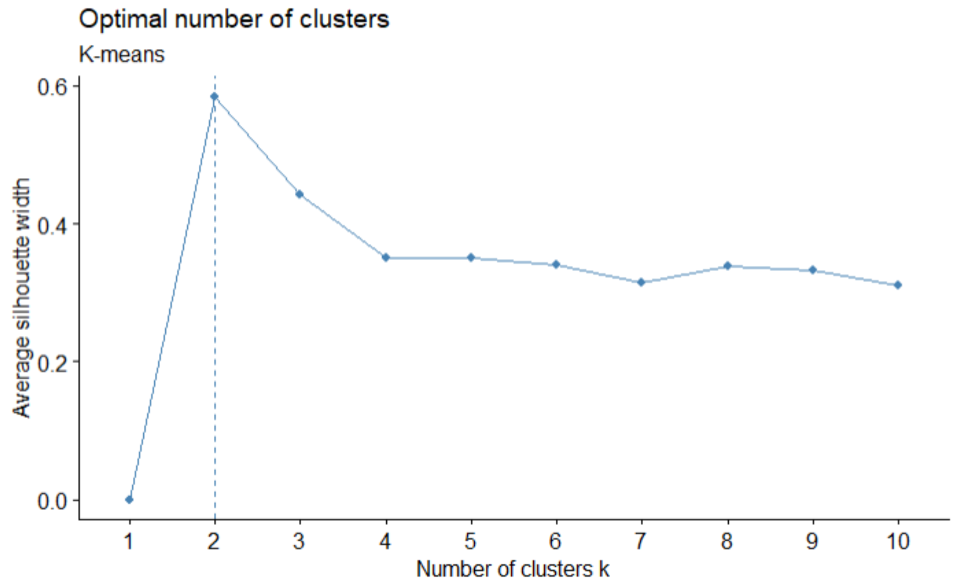

Figure 1: Determination of the optimal number of clusters for one daycare room using the silhouette method

3. RESULTS AND DISCUSSION

A. ACOUSTIC ANALYSES

Figure 2 shows 1-minute LAeq across a 48-hour measurement period for one of the rooms. A clear difference can be seen between the open and closed hours of this measurement as expected. During the open hours the level is highly fluctuating while the closed hours show the steady, unoccupied background noise.

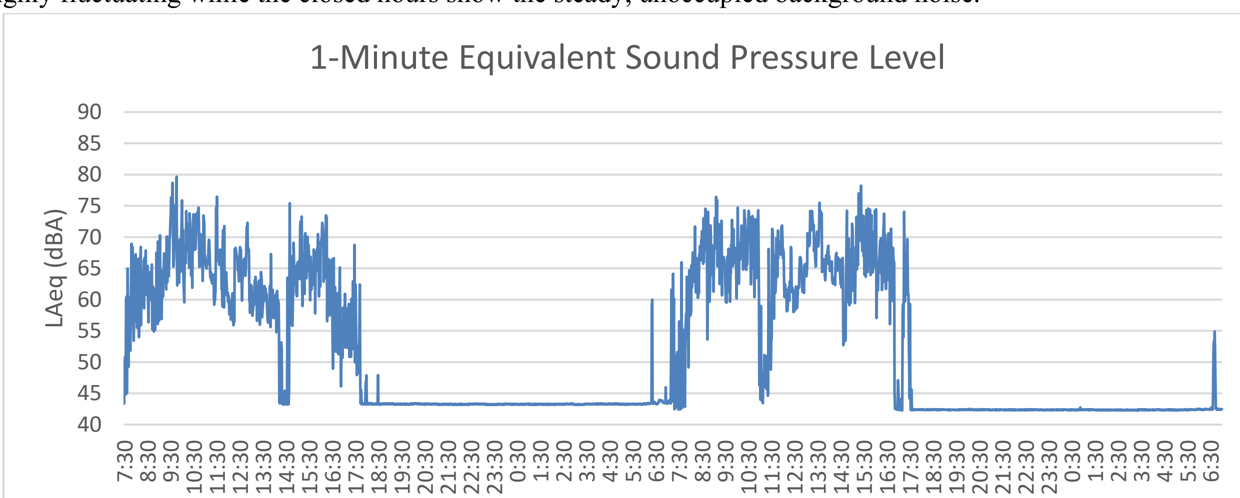

Figure 2: 48-hour time history of LAeq for one daycare room

Each room can be grouped by the typical age range to better understand the sound environment. Figure 3 shows LAeq grouped by typical age range with each grouping separated by open and closed hours. There are no error bar for the school-aged classroom because only one room measured had that age range. The open hours LAeq show a sound environment that is potentially higher than desired. The closed hours give us an insight into the unoccupied background noise level. These levels exceed the World Health Organization recommendations of 35 dBA for preschools and other similar environments[12].

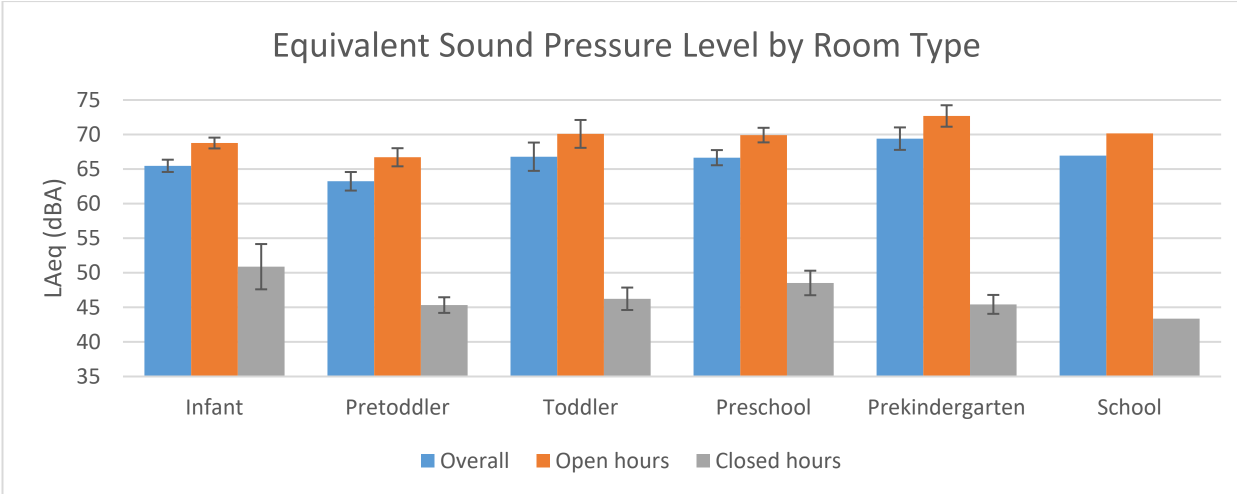

Figure 3: LAeq grouped by typical age range

One method to help understand how often peak sounds occur is through the use of Occurrence Rate. This metric captures how often peak sounds exceed certain thresholds. Figure 4 shows the Occurrence Rate of LCpeak by room type for the open hours. Looking at the range of the plot, a peak value of 80 dBC was exceeded for each minute measurement, while 115 dBC was never exceeded. Breaking down one point on Figure 4, LCpeak exceeded 100 dBC for the prekindergarten rooms for approximately 26% of the time.

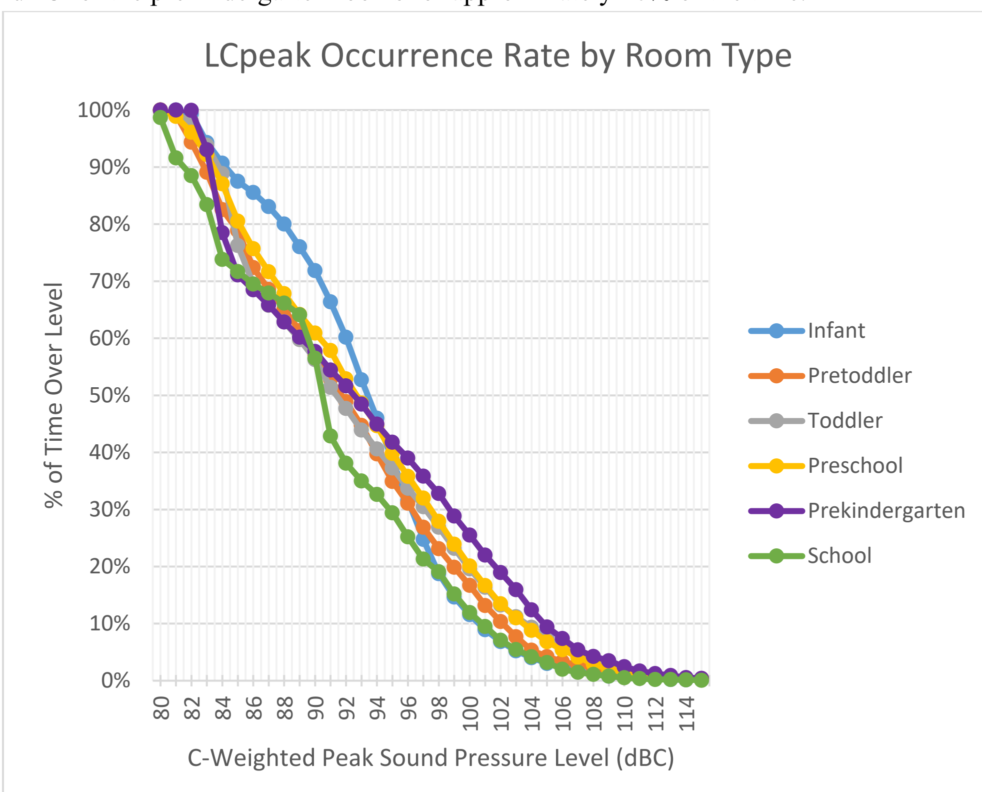

Figure 4: Occurrence Rate of LCpeak by room type

B. OCCUPANT PERCEPTION

A staff follow-up survey was administered to better understand occupant perception. The 11 respondents answered how often they experience seven different items in their main classroom, from never to most of the time. Figure 5 shows the survey results with responses grouped in two categories. Approximately 70% responded that they sometimes to most of the time wish it was quieter. 70% also responded that sound makes it difficult to talk to children or other teachers sometimes to most of the time. Sound also felt overwhelming to 80% of the respondents sometimes to most of the time.

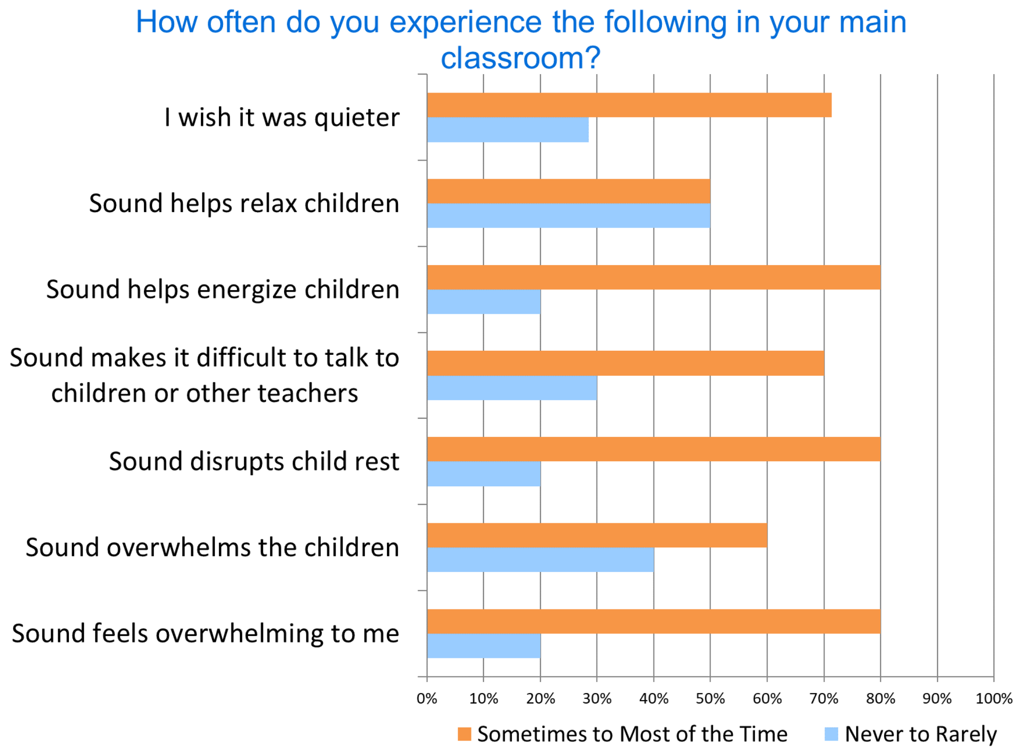

Figure 5: Staff follow-up survey

C. CLUSTERING

Each of the fifteen rooms were clustered into two groups using four different models. The input for each model was 3-dimensional 1-minute acoustic data of LAeq, LAmax, and LCpeak. Figure 6 shows the 3-dimensional acoustic metric space clustered by k-means for one room, with each data point representing a 1-minute measurement of the open hours only. The black data points are shown to have lower values for all three metrics and can be considered to be a nonactive time period, while the red data points indicate an active time period.

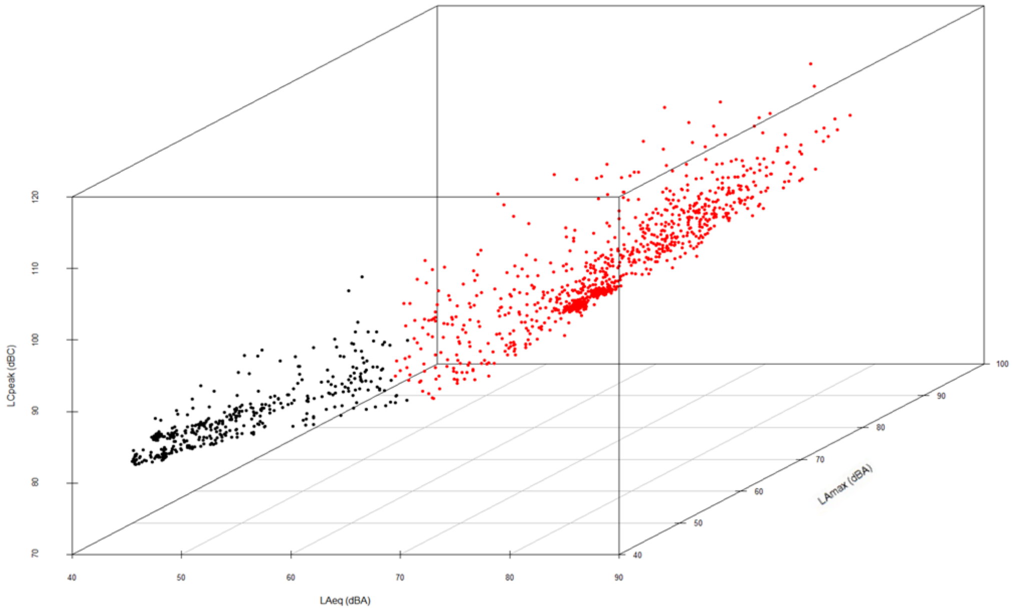

Figure 6: K-means clustering of one room in a 3-dimensional acoustic space

Once each data point has been labelled as either active or nonactive, it is possible to then look back at a time history plot to understand the results in a different way. Figure 7 shows one room during one day's open hours with each minute measurement colored as either active or non-active.

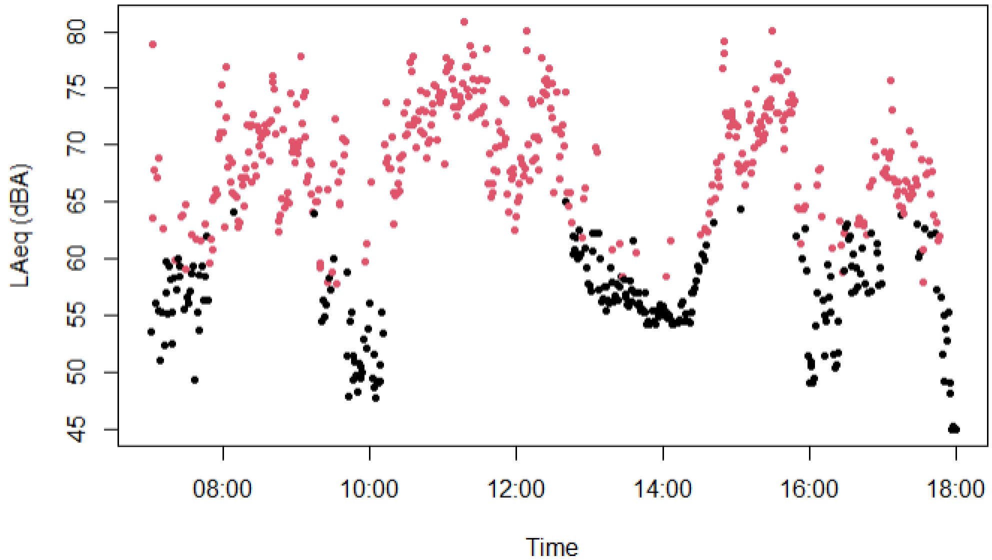

Figure 7: K-means clustered time history plot of one room with red showing active and black showing nonactive

A multitude of metrics can be calculated once the data has been classified as either an active or nonactive time period by each of the models. One such metric is the difference in cluster centers, which shows the difference between active and nonactive cluster centers. Figure 8 shows this metric grouped by age range with the output of each model used. Agnes demonstrated different results than the others.

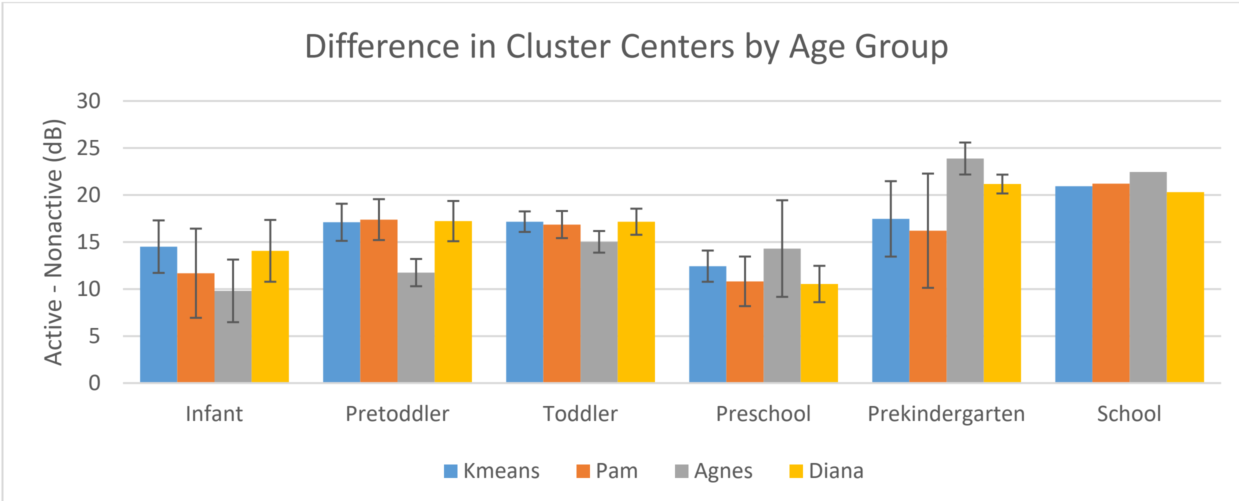

Figure 8: Difference in cluster centers by age group for each clustering model

Additionally, the percent active can be calculated by dividing the number of 1-minute measurements classified as active by the total number of minute measurements for each room. Figure 9 shows the percent active by age group for each clustering model. Agnes again is highlighted as demonstrating different results than the others and has large error bars. While being different than the other models does not indicate that it is incorrectly clustering, its value for the pretoddler rooms highlights its inaccuracies. Knowing that the pretoddler rooms on average were active for more than 10% of the time shows that Agnes is potentially not the best model for this acoustic data set.

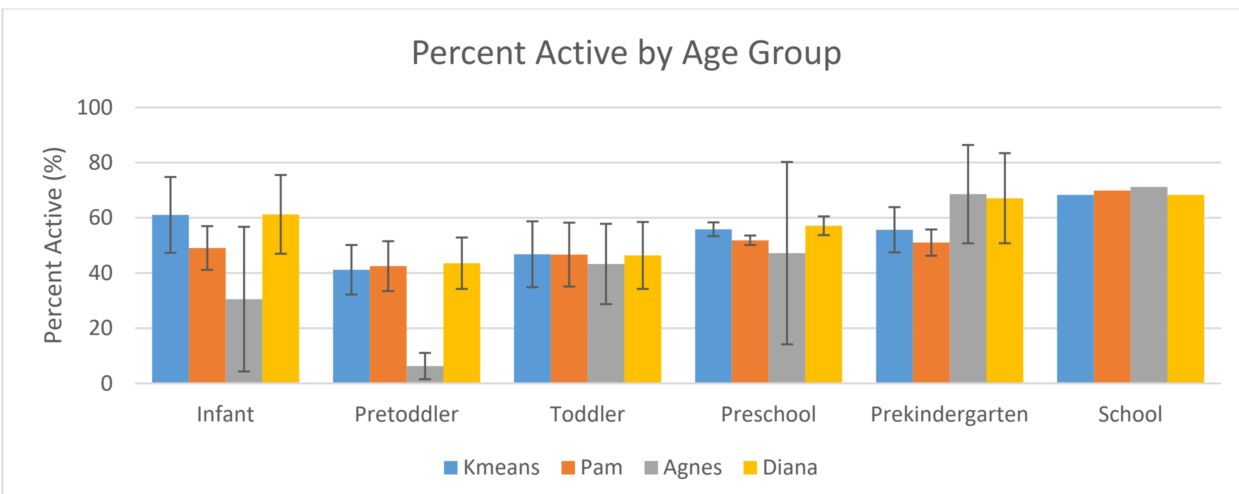

Figure 9: Percent active by age group for each clustering model

Since Agnes was shown multiple times to demonstrate different results from the others, Table 1 shows how often on average each method agrees. On average for each room, 73% of the time all four methods agreed with each other, meaning that each data point was classified as the same across all four methods. Removing one model and keeping the other three shows that Agnes is the outlier. 94% of the time K-means, Pam, and Diana were classifying the same.

Table 1: How often the clustering methods agree on average per room

	All Methods	Without K-means	Without Pam	Without Agnes	Without Diana
Percent Agreement (%)	73	73	76	94	73

4. CONCLUSION

Children's early life experiences are strongly linked to lifelong outcomes. While a large percentage of children are in some form of non-parental care, there is a lack of research and measurements of such a soundscape. Measurement of the daycare acoustic environment highlighted high background noise levels and high peak values were often exceeded. From the staff's perception, sound can overwhelm staff and increase difficulty in communicating. Four different statistical clustering techniques were utilized and allowed for analysis of several acoustic features such as the difference between active and nonactive cluster centers and well as percent active. Of the four clustering models analyzed, Agnes did not seem to work well with this acoustic data, while K-means, Pam, and Diana gave similar and reasonable results. Future work includes better understanding the discrepancies with Agnes, analyzing collected language data in one of the measured daycares, and understanding the relationship between machine learning results and perception.

5. ACKNOWLEDGMENTS

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