Effects of Meeting Type on Indoor Environmental Conditions in Shared Spaces

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ABSTRACT

Meetings are a major driver of occupancy in shared indoor spaces, yet little is known about how different meeting types contribute to short-term changes in indoor air quality (IAQ). This study analyzed environmental sensor data linked with 10,255 validated meetings held in the University of Virginia's Living Link Lab from 2018-2025. A rule-based classifier assigned meetings to six categories: Admin/Leadership /Programs, Events/Outreach/Social, Instruction/Student Support, Research/Lab/Project, Walkup, and Other. Nonparametric statistical tests were used to evaluate the differences in peak changes of CO_2 and volatile organic compounds (VOCs) relative to pre-meeting baselines. Results showed statistically significant but generally small differences in peak CO_2 increases across categories, with substantial overlap in distributions. VOC responses showed clearer differentiation. Instruction/Student Support and Events/Outreach/Social meetings tended to produce larger VOC peaks, whereas Walkup and Research/Lab/Project meetings showed smaller changes. These patterns indicate that meeting type provides meaningful structure for describing IAQ variability, particularly for VOCs, but explains only a portion of the overall variation. Overall, meeting type information may serve as a uesful input for IAQ-aware building management, although practical control strategies will require integrating meeting classification with occupancy, ventilation conditions, and room characteristics. This study provides an empirical foundation for future work on IAQ-driven scheduling and ventilation planning in shared indoor environments.

1 INTRODUCTION

Modern organizations, ranging from educational institutions to businesses, rely heavily on meetings as a primary mechanism for communication, coordination, brainstorming, problem-solving, training, and decision-making [1]. White-collar workplace managers spend most of their working day in meetings [2], and the amount of time spent in meetings continues to increase each year [3]. Inefficiencies in meetings due to their poor facilitation or administration have been shown to cause considerable losses in time and money for both corporations and workers [4]. Due to the prevalence of poorly planned or run meetings, most white-collar workers around the world tend to view meetings as irrelevant to their work or a waste of their personal time [2]. Thus, understanding the structure and characteristics of meetings, particularly successful ones, is becoming increasingly important to corporations.

Prior research has shown that meeting types differ substantially in structure, purpose, and format [5]. Corporate studies indicate that staff meetings, task force meetings, information-sharing sessions, brainstorming sessions, and other formats occur at different frequencies and serve distinct organizational functions [3]. Meetings can also be classified using various binary distinctions, such as scheduled vs. unscheduled [6], stand-up vs. sit-down [7], or public vs. private [8]. Past work has therefore emphasized the importance of developing taxonomies to categorize meetings based on their intended goals and activities [9]. In this research, the purpose of a meeting was shown to be one of the most important taxonomic factors for classification. For example, one study divided corporate meetings into staff meetings, task force, information sharing, brainstorming, ceremonial, and other [3].

Almost all white-collar meetings take place indoors, with 74% of in-person meetings being held in company conference rooms [3]. Moreover, individuals spend nearly 90% of their lives inside buildings [10]. Thus, meeting participants are exposed to various indoor environmental conditions such as temperature, humidity, CO_2, VOC levels, particulate matter, and acoustic factors. Previous studies have shown that these environmental factors can influence the quality of a meeting experience and affect cognitive performance, task engagement, and worker productivity [11–14]. A healthy and secure environment may increase comfort and minimize outside distractions for meeting attendees, increasing their focus and boosting meeting productivity [15].

These findings suggest that different types of meetings, each with unique activity levels, purposes, group sizes, and interaction patterns, may impose different environmental loads on shared spaces, and poor environmental preparation may negatively impact the effectiveness of a meeting. Despite this, most meeting research has focused on organizational effectiveness and participant experience rather than how different meeting types contribute to indoor environmental loads such as CO_2 and volatile organic compounds (VOCs). Little work has connected meeting types with measurable indoor air quality (IAQ) changes, despite the fact that CO_2, VOCs, and particulate matter are direct byproducts of occupant activity in shared spaces.

2 PROBLEM STATEMENT

Past research has shown that meetings vary widely in structure, purpose, and degree of interaction. They can be categorized using a variety of taxonomies. At the same time, work in the building sciences has examined how indoor environmental conditions and human activity contribute to pollutant generation, thermal load, and resource consumption. However, there has been a lack of research in combining these two fields to explore how the different types of meetings influence the environmental conditions and resource usage of the rooms in which they occur.

This paper seeks to address this gap by examining the relationship between meeting category and environmental impact, focusing specifically on short-term changes in CO_2 and VOCs during meetings. Meetings within the University of Virginia's Link Lab will be categorically classified using Machine Learning (ML). The central question of this study is: Which types of meetings have the greatest impact on CO_2 and VOC levels? By linking meeting classifications with real sensor data, this work provides actionable insights that can help building managers and building management systems better anticipate resource demand and understand how different types of meetings contribute to indoor environmental load.

3 MOTIVATION

Buildings contribute substantially to global emissions and energy consumption. In the United States alone, buildings account for 40% of primary energy use and 72% of electricity consumption, with HVAC systems responsible for nearly half of that demand [16]. Numerous studies have documented the large role buildings play in CO_2 emissions worldwide [17].

Given these trends, identifying new methods for understanding and predicting the environmental effects of building usage is increasingly important. As the prevalence and frequency of meetings continue to rise in white-collar workplaces [3], meetings represent a substantial component of building occupancy and, by extension, IAQ-related environmental load.

Understanding how different types of meetings affect indoor environmental metrics, such as temperature, CO_2 concentration, VOC levels, particulate matter, and power consumption, can provide building managers with valuable insights. For example, if certain meeting types are consistently associated with higher pollutant generation or slower IAQ recovery, managers may adjust ventilation schedules or increase air-change rates during those periods. In this way, meeting-type-based analytics can help describe patterns in IAQ demand over time and support future work on targeted ventilation strategies. Because healthier indoor conditions are linked with improved attendee focus and cognitive performance [15], using meeting-type insights to guide scheduling and ventilation strategies may also enhance overall meeting productivity. However, establishing control policies will require quantifying not only statistical significance but also the magnitude and consistency of these differences across buildings and operating conditions.

4 METHODOLOGY

4.1 Data Sources

Minute-level environmental data were retrieved from an InfluxDB time-series database. The data included sensor streams for CO_2, VOCs, fine particulate matter with an aerodynamic diameter 2.5 micrometers or smaller ($PM_{2.5}$), temperature, relative humidity, sound level, illumination, passive infrared (PIR) motion, and electrical measurements. Data were extracted for three Link Lab conference rooms from the University of Virginia's Olsson Hall (rooms 211, 217, and 225) from January 1, 2018, to November 11, 2025. These streams were combined into a single long-format dataset indexed by timestamp and room.

Calendar data were obtained from the Link Lab-managed Google Calendar feeds associated with the same rooms. All scheduled events, including recurring meetings, were expanded to individual occurrences. Calendar entries were converted to a standardized iCalendar (ICS) format as defined in RFC 7986 [18]. Metadata extracted from ICS fields included the meeting summary, description, organizer (when available), and start and end times. All timestamps were standardized and converted to UTC to align with the sensor data.

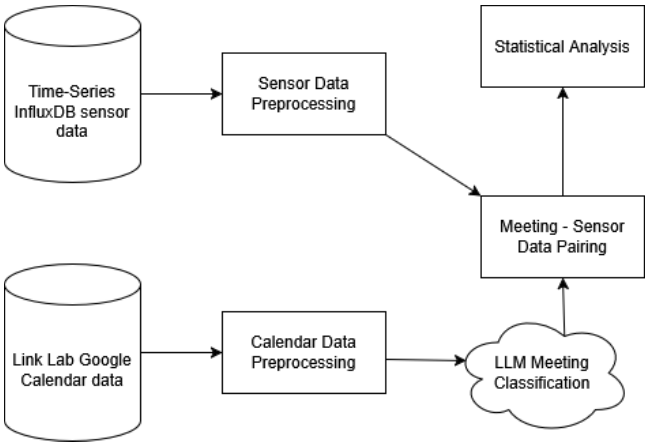

Figure 1: Data Transformation and Flow Through the Designed System

4.2 Data Preprocessing

Sensor column names were cleaned and normalized for consistency. Timestamps were converted to UTC, and the dataset was sorted chronologically. Short gaps in sensor availability were addressed using a two-stage method. First, forward-fill and backward-fill were applied for gaps of up to 10 minutes to preserve continuity at window edges. Second, linear interpolation was applied within the same limit to smooth transitions without fabricating long stretches of artificial data. Duplicate timestamps were removed. A search for long missing periods was performed; however, none overlapped with meeting times.

Calendar data were cleaned by removing all-day events and entries without valid start or end times. All timestamps were converted to UTC to match the sensor records. Events were then sorted by room and time. Figure 1 provides an overview of the data collection, processing, and analysis pipeline.

4.3 Meeting Classification

Meeting categories were assigned using the summary field, which typically contained the event title. Summaries were lower-cased, stripped of punctuation, and whitespace was normalized. A rule-based classification method was applied using regular expressions to assign each event to one of six categories: (1) Research/Lab/Project, (2) Admin/Leadership/Programs, (3) Instruction/Student Support, (4) Events/Outreach/Social, (5) Walkup, and (6) Other. Keyword patterns were iteratively refined using domain knowledge and a language-model-based review of common summary terms. A CO_2-based validation rule was used to identify meetings that had likely occurred.

Meetings were excluded when CO_2 did not increase by at least 10 parts per million (ppm) during the scheduled meeting window and the baseline median CO_2 concentration remained low, suggesting no occupancy. Meetings with elevated pre-meeting CO_2 baselines were retained to accommodate possible back-to-back events. This filtering procedure removed 4,690 unrealized meetings, leaving 10,255 validated meetings for analysis.

4.4 Feature Engineering

For each validated meeting, sensor data were extracted for multiple windows. These windows included: pre-meeting (30 minutes before the start), during meeting (from start to end), post-meeting (0-30 minutes and 30-60 minutes after the end), and snapshot values (nearest readings within 5 minutes of the end, 30 minutes after the end, and 60 minutes after the end). Within each window and for each metric, descriptive statistics were computed, including mean, median, minimum, maximum, and linear slope. Snapshot values at each post-meeting time point were also recorded. Event duration was included as an additional variable.

To quantify IAQ changes attributable to meetings, impact metrics were computed relative to pre-meeting baselines. These included the peak delta (maximum during-meeting value minus the pre-meeting mean), post-window deltas (subtracting the pre-meeting mean from the post-window mean), and snapshot deltas (the instantaneous deltas at the end, 30 minutes after, and 60 minutes after the meeting). This process generated a feature table containing approximately 240 engineered variables per meeting.

4.5 Statistical Analysis

Impact metrics were winsorized at the 1st and 99th percentiles to limit the effect of extreme outliers. Differences in IAQ impact across the six meeting categories were assessed using Kruskal-Wallis tests. Pairwise differences were assessed using Mann-Whitney U tests with Holm correction. Visualization methods included box plots and plots showing group means with 95% confidence intervals.

Post-meeting recovery analysis was conducted to estimate how long it took each IAQ metric to return to its baseline. The baseline for each metric was defined as the mean value during the 15 minutes before the meeting began. A metric was considered recovered when the post-meeting metric returned to within 2% of its baseline. Recovery was assessed up to 180 minutes after the meeting ended. Only meetings where the metric was elevated at the end of the meeting, the metric increased from the start to the end, and a measurable recovery point existed were included in the recovery calculations. Recovery times were summarized and visualized for CO_2, temperature, relative humidity, VOCs, and $PM_{2.5}$.

Kruskal-Wallis tests were used to assess differences in recovery duration across meeting categories.

Although $PM_{2.5}$, temperature, relative humidity, and power data were collected, these metrics did not show statistically meaningful variation across meeting categories and were therefore omitted from the main analysis.

5 RESULTS

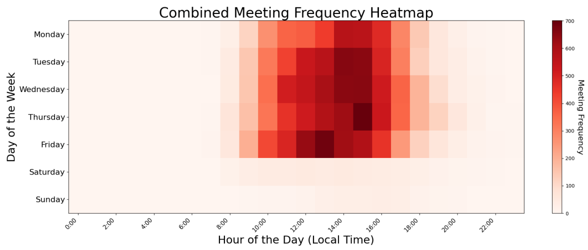

Figure 2: Heatmap of Most Common Weekdays and Times of Meetings in the Link Lab

5.1 Data Overview

Across the three monitored rooms, 14,489 meetings were recorded, and 10,255 remained after filtering unrealized events, duplicates, and periods with missing sensor data. Figure 2 shows the frequency of meetings by day of the week and hour. The majority of meetings occurred between 9:00 AM and 6:00 PM. These meetings were assigned to one of six defined categories based on their normalized calendar metadata. Table 1 shows the distribution of meetings across categories. Meetings were unevenly distributed across categories, with Walkup and Research/Lab/Project meetings accounting for more than 70% of all validated meetings. This imbalance influenced confidence intervals and the interpretation of group differences. Because the primary interest of this study was whether meeting type is associated with short-term IAQ changes, the analysis focuses on peak CO_2 and VOC increases relative to pre-meeting baselines.

Table 1: Counts and percentages of verified meetings by category after filtering unrealized events.

Meeting Category	Count	Percent
Walkup	4204	41.0%
Research/Lab/Project	3018	29.4%
Other	1309	12.8%
Instruction/Student Support	828	8.1%
Admin/Leadership/Programs	792	7.7%
Events/Outreach/Social	104	1.0%
Total	10255	100%

5.2 Impact on IAQ

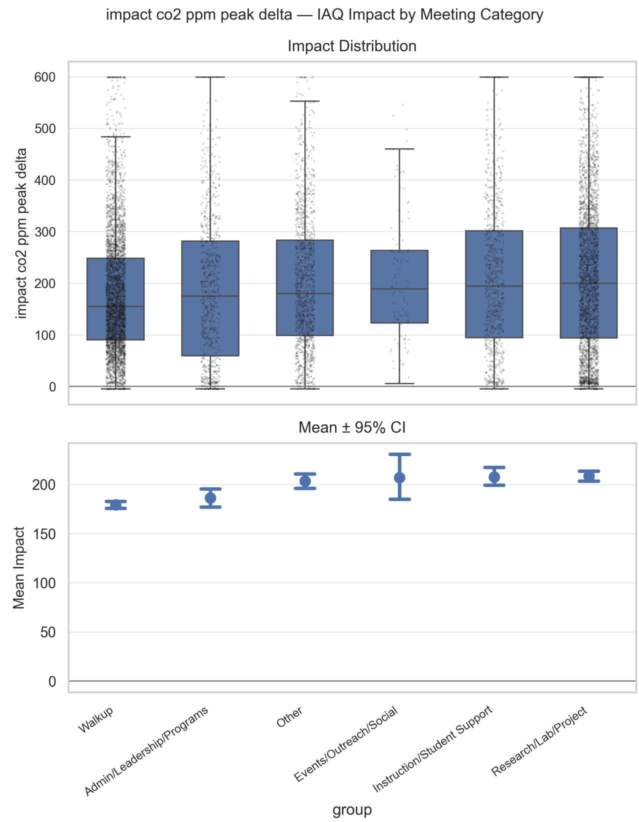

Figure 3: Average Meeting Impact on CO_2 with 95% Confidence Interval

To evaluate whether meeting category was associated with variation in indoor air quality changes, two primary outcomes were examined: the peak change in CO_2 relative to the pre-meeting baseline and the peak change in VOC concentration relative to baseline. A Kruskal-Wallis test examining differences in peak CO_2 changes across categories revealed a significant effect of meeting type ($H = 112.95$, $p < 10^{-21}$). To further characterize this pattern, pairwise Mann-Whitney U tests with Holm correction were conducted for all comparisons. Several pairwise differences were statistically significant after Holm correction. However, the effect sizes were small ($|r|$=0.08-0.12), and the differences in central tendency were small relative to the large within-category variability. Categories with the largest sample sizes (Walkup and Research/Lab/Project) had the narrowest confidence intervals. Figure 3 shows the average impact of different meeting types on CO_2 concentration, defined as the change from the pre-meeting baseline to the meeting's peak value.

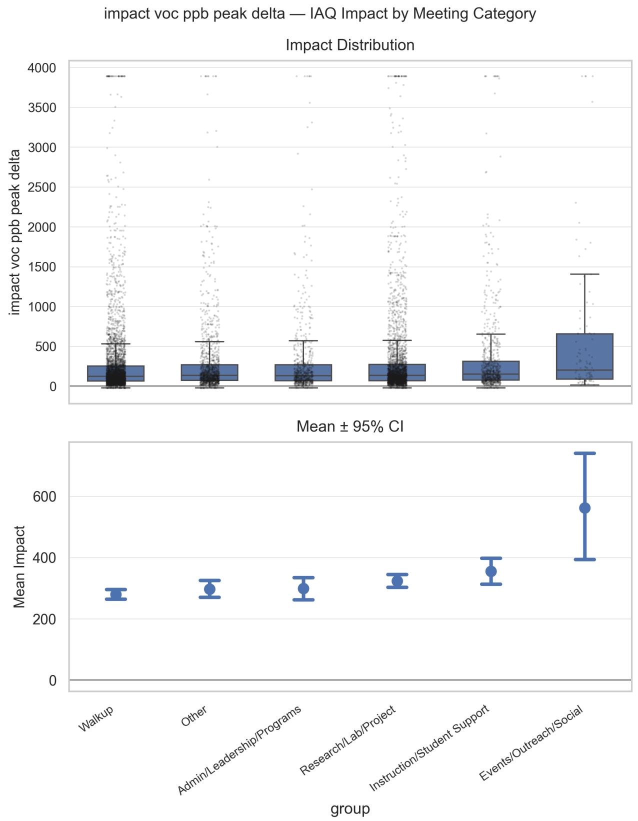

Figure 4: Average Meeting Impact on VOCs with 95% Confidence Interval

For VOCs, Mann-Whitney U tests were run to assess pairwise differences between meeting categories. Several contrasts were statistically significant after Holm correction. Instruction/Student Support, Research/Lab/Project, Other, and Events/Outreach/Social meetings all showed higher peak VOC increases than Walkup meetings (adjusted $p < 0.05$; $|r| = 0.05\text{-}0.23$), and Events/Outreach/Social meetings also had higher peaks than Admin/Leadership/Programs, Research/Lab/Project, and Other meetings. Effect sizes were small to moderate and the distributions overlapped substantially across categories. Confidence intervals were again wider for Events/Outreach/Social, which had a much smaller sample size. Figure 4 shows the average impact of meeting types on VOC concentration, defined as the difference between the baseline VOC concentration and the peak VOC concentration during the meeting.

Figure 5 shows the mean change in CO_2 concentration over time, aligned to meeting start and normalized to each meeting's 30-minute pre-meeting baseline. Overall, all meeting types showed an increase in CO_2 relative to baseline once

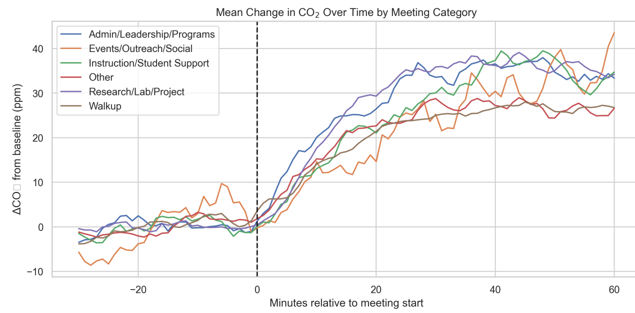

Figure 5: Mean CO_2 Pattern Over Time. Values are normalized to the 30-minute pre-meeting baseline.

the meeting began, but the magnitude and rate of increase differed across categories.

Instruction/Student Support meetings showed the most rapid and consistent CO_2 increase, rising steadily across the first hour of the meeting. Admin/Leadership/Programs and Research/Lab/Project meetings showed moderate increases with a similar trajectory but at a lower magnitude. Walkup meetings displayed the smallest and flattest CO_2 response, remaining close to baseline throughout most of the meeting duration.

Events/Outreach/Social meetings showed more variability, but the central trend remained lower than the instructional categories. Across categories, the normalized curves show clearer separation in accumulation rates than the raw peak-delta analysis alone, suggesting that meeting type influences not only the maximum increase but also the temporal pattern of build-up.

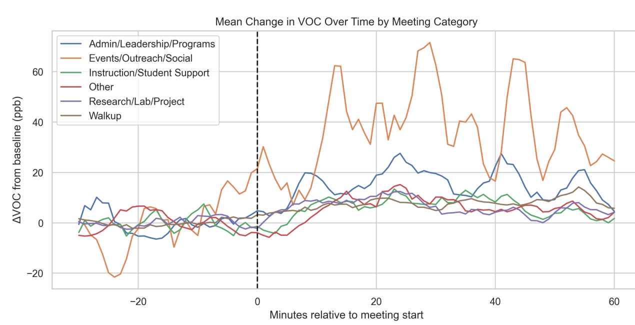

Figure 6: Mean VOC Pattern Over Time. Values are normalized to the 30-minute pre-meeting baseline.

Figure 6 shows the mean change in VOC concentration over time, aligned to meeting start and normalized to each meeting's 30-minute pre-meeting baseline. VOC responses showed stronger differentiation across meeting types than CO_2. Instruction/Student Support and Events/Outreach/Social meetings displayed the largest sustained increases, with multiple short spikes visible throughout the meeting window. These sharper changes reflect the sensitivity of VOCs to occupant activity.

Admin/Leadership/Programs and Research/Lab/Project meetings showed comparatively modest VOC changes, staying close to baseline with mild fluctuations. Walkup meetings remained the lowest across categories, showing almost no VOC deviation. The Other category retained the widest spread, consistent with it varying composition. Overall, time-course curves highlight the larger dynamic range of VOC responses relative to CO_2 and reinforce that meeting type provides a stronger signal for VOC variation than for CO_2.

6 DISCUSSION

The meeting schedule and category distribution help contextualize the IAQ patterns. Figure 2 shows that most meetings occurred on weekdays between 9:00 AM and 6:00 PM, particularly in the hours of 12:00PM to 4:00 PM, reflecting typical academic use of the conference rooms. As shown in Table 1, Walkup and Research/Lab/Project meetings accounted for 41 and 29.4%, respectively, which influenced the precision of estimates across categories with much smaller percentages and were considered when interpreting confidence intervals and effect sizes.

For CO_2 concentration, the meeting category was statistically associated with differences in peak increases relative to pre-meeting baseline, but the effect sizes were small and distributions overlapped substantially between categories. This suggests that factors such as occupancy level, duration, and ventilation state may play a larger role in CO_2 building than meeting purpose alone, although meeting type still provides some signal. As shown in Figure 5, CO_2 concentration tended to increase as meetings progressed. This makes sense, because more time spent in a room will result in more CO_2 emitted. The steepest increases in CO_2 were observed for Events/Outreach/Social meetings, which is consistent with expectations of higher and more sustained attendance. Across categories, baseline CO_2 levels varied from meeting to meeting, while the rate of CO_2 change remained fairly similar across meeting types. The Kruskal-Wallis test produced a large test statistic, indicating that at least some meeting categories differed in their distribution of peak CO_2 increases. However, because the Kruskal-Wallis test does not identify which specific categories differ, pairwise testing was necessary to determine where these differences occurred. Taken together, these analyses showed that although several contrasts were statistically significant, meeting type explained only a limited portion of overall variation in peak CO_2 buildup.

VOC patterns showed clearer differentiation between meeting types than CO_2. Events/Outreach/Social meetings exhibited the highest VOC peaks and more frequent sharp increases, while all remaining categories showed differentiating peaks and changes than the more steady VOC levels found in Walkup meetings. These differences align with the expectation that VOC emissions are more sensitive to short-lived, activity-dependent sources, such as the use of materials, food, or movement within the room. However, because the data set does not directly capture behavioral or material-use information, these mechanisms cannot be confirmed as fact, requiring further investigation. The broader variability and sharper peaks observed for certain categories also reflect the higher dispersion in VOC data, suggesting that meeting type provides stronger differentiation for VOC behavior than for CO_2, but still explains only part of the overall variability. As with CO_2, additional contextual factors likely contribute to the observed patterns and can improve future investigation.

Taken together, these results indicate that meeting type can help characterize IAQ demand profiles over time, especially for VOCs, but it is not always the primary driver of CO_2 buildup in this setting. For building managers, this means that meeting-type information could be one input to IAQ-aware scheduling, such as flagging high-VOC meeting categories for additional ventilation checks, rather than a stand-alone control variable. Additional information, including occupancy counts, room volume, and baseline ventilation rates, is required to translate these findings into applicable systems.

7 LIMITATIONS

The results of this paper demonstrated a statistically significant impact of the type of a meeting on indoor environmental conditions. However, there are some aspects of this research into the environmental effects of a meeting that could not be fully covered by this paper. Due to project constraints, all meeting data came from the conference room data in the University of Virginia's Link Lab in Olsson Hall. A more thorough analysis of could have considered meetings conducted across multiple buildings and outside academic environments.

The available data contributed to other key limitations. As Olsson Hall is primarily an academic building, the vast majority of meetings within the Link Lab took place within standard working hours between 9:00 AM and 6:00 PM on weekdays. Meetings during standard working hours took place during a period of increased air changes per hour due to the preset policies of the Olsson Hall HVAC system. This limited the ability to study the longer-term effects of IAQ of a single meeting on future meetings. If more meetings during non-standard working hours were included in the dataset, the effect of meetings on the IAQ of future meetings could have been studied further.

Another key limitation was the strong imbalance in meeting categories. Walkup and Research/Lab/Project meetings dominate the dataset, while Events/Outreach/Social meetings are rare. This imbalance affects the width of confidence intervals and the stability of estimates, particularly for categories with small sample sizes. In addition, although several effects were statistically significant, the corresponding effect sizes were generally small, which limits the strength of any practical recommendations that rely solely on meeting type.

Finally, there was potential for inaccuracies in the data. The occupancy estimates for certain conference rooms were known to be inaccurate or unavailable at certain times, and many scheduled meetings did not actually take place. To account for the potential for inaccurate occupancy data, CO_2 estimates were used as a secondary source to determine human presence. More accurate occupancy data over time would have eliminated the need for roundabout estimates and would have further guaranteed data integrity.

7.1 Future Work

This work provides an initial foundation for understanding the effects of meeting type on indoor environmental factors such as IAQ, and is not intended to be the final research conducted into the emerging field. Future studies should expand upon the limitations imposed on this paper by broadening the scope of study to meetings outside of academia. Meetings that occur in the white-collar, or even blue-collar, workplace will likely require a different set of classifications than those observed in the Link Lab.

In addition, future studies should integrate IAQ-driven predictive algorithms to adjust HVAC schedules based on upcoming meeting classifications, enabling proactive ventilation and resource management. Research in environments such as corporate offices or community centers would also allow for broader validation of these models. Finally, expanding the analysis to additional metrics beyond IAQ, including electrical power usage, may provide a more comprehensive understanding of how different meetings affect building resources. This research would allow building managers and building management systems to dynamically control important systems within a building, such as the HVAC, for more efficient and comfortable usage.

8 CONCLUSION

The findings of the research in this paper demonstrated that different meeting types have measurable effects on IAQ, although CO_2 effects were generally minimal. Walkup meetings and Research/Lab/Project meetings generally had lower VOC level increases compared to other meeting types. Differences in CO_2 buildup across categories were statistically significant but small, with substantial overlap across meeting types. The change in VOC over time had more variation for most meeting types except Walkup meetings.

Overall, the findings showed that categorizing meetings by type is useful for describing IAQ patterns, especially for VOCs, but meeting type alone explains only a portion of the variation in CO_2 and VOC changes. In practice, meeting-type information is best viewed as one component of a broader IAQ-aware building management strategy that also incorporates occupancy, ventilation schedules, and room characteristics. Future work can build on these results to design and evaluate targeted interventions. This study presents exploratory research to guide future implementations.

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