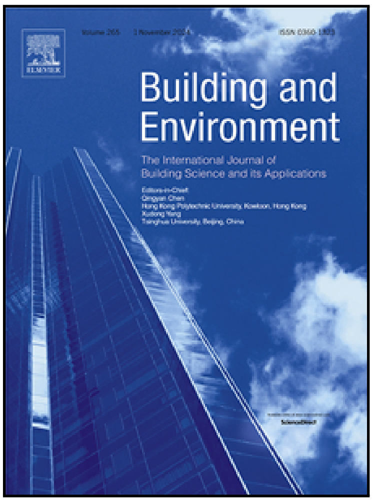

Positive Pressure Ventilation Systems and Indoor Air Quality: $PM_{2.5}$ Outcomes in Residential Buildings

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Highlights

- PPV systems reduced indoor $PM_{2.5}$ by 38-62% in homes across New Zealand
- $PM_{2.5}$ reductions were generally larger during peak periods than non-peak periods
- $PM_{2.5}$ reductions were larger with greater indoor-outdoor temperature differentials
- Living rooms generally exhibited higher $PM_{2.5}$ concentrations than master bedrooms

Positive Pressure Ventilation Systems and Indoor Air Quality: $PM_{2.5}$ Outcomes in Residential Buildings

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Abstract

Fine particulate matter ($PM_{2.5}$) presents a risk to residential indoor environments, particularly during winter, when occupancy is high and natural ventilation is reduced. Evidence from intervention-based field studies is limited, especially under real-world, continuously occupied conditions.

This study investigates the effects of positive pressure ventilation (PPV) systems on indoor $PM_{2.5}$ concentrations in 24 homes across New Zealand. Using a pre-post intervention design, $PM_{2.5}$ concentrations, temperature and relative humidity were measured in living rooms and master bedrooms over six week periods before and after PPV installation during winter.

Following PPV installation, mean indoor $PM_{2.5}$ concentrations decreased across all homes, with reductions ranging from 38% to 62%. Linear mixed effects regression modelling supported the observed reductions while accounting for outdoor $PM_{2.5}$ and building characteristics. Indoor $PM_{2.5}$ concentrations were higher in living rooms than in bedrooms, although post-intervention reductions were similar between rooms. Indoor-outdoor (I/O) ratios exceeded 1.0 in half of the homes prior to PPV installation and fell below 1.0 in most homes post-installation, indicating reduced dominance of indoor sources.

Post-PPV reductions in indoor $PM_{2.5}$ were larger during peak activity periods than non-peak periods and tended to be greater in homes with larger indoor-outdoor temperature differentials, suggesting that building envelope performance influences PPV effectiveness.

This study presents field-based evidence that PPV systems can reduce indoor $PM_{2.5}$ in homes during winter, especially where initial indoor concentrations are high and thermal separation from outdoors is greater. The findings highlight the combined importance of ventilation, envelope performance, and occupant behaviour in reducing indoor $PM_{2.5}$ exposure.

Keywords

Indoor Air Quality, Fine Particulate Matter, Positive Pressure Ventilation.

1 Introduction

Exposure to airborne fine particulate matter, $PM_{2.5}$, has been associated with adverse health effects including respiratory and cardiovascular diseases, and increased mortality [1–4]. The World Health Organization (WHO) identifies $PM_{2.5}$ as one of the most harmful air pollutants due to its ability to penetrate easily deep into the lungs and enter the bloodstream [4]. There is clear evidence that indoor exposure to $PM_{2.5}$ is key to explaining the air pollution-related burden of disease worldwide [5]. Past studies have found that on average people spend 90% of their time indoors, where PM concentrations often exceed ambient levels [6–11].

Indoor air quality (IAQ) can be influenced by numerous factors including internal pollutant sources (e.g. heating, cooking and other human activities), infiltration of outdoor pollutants, and ventilation performance [12–16]. Ventilation in particular plays an essential role in maintaining healthy IAQ by helping to dilute indoor pollutant concentrations [17–19]. Inadequate ventilation can lead to the accumulation of indoor-generated PM, especially in airtight buildings designed to minimise cooling and heating energy consumption [7,20–22].

While typically low ambient $PM_{2.5}$ levels present a lesser impact on indoor concentrations, such as in countries like New Zealand, indoor environments remain a major contributor due to the dominance of indoor sources and occupant activity. Such outdoor conditions provide an opportunity to assess ventilation with a lower confounding influence from ambient pollution, offering greater insight into indoor $PM_{2.5}$ source control and interactions between ventilation and building envelope. The effectiveness of natural ventilation (NV), involving passive air exchange via windows, doors and vents (as distinct from infiltration via building cracks and leaks), is often compromised in colder periods, when occupants tend to keep them closed to maintain indoor temperatures [23,24]. Accordingly, occupant behaviour and ambient conditions can substantially influence NV performance, resulting in significant wintertime IAQ variability between homes.

Mechanical ventilation (MV) systems are therefore often utilised to maintain adequate air exchange inside the home, by introducing external air and displacing stale indoor air [17–19]. In some cases, MV systems are equipped with filters that can reduce the ingress of particulate matter (PM), although high efficiency filtration capable of substantially removing $PM_{2.5}$ is less common in residential buildings. While MV can provide improved air exchange over NV, the extent of $PM_{2.5}$ reduction achievable in practice can vary between houses.

Despite growing recognition of the importance of ventilation for IAQ, several documented gaps regarding its impact in residential settings remain in the literature [25–27]. Multiple reviews report that many IAQ studies either focus on short-duration air quality monitoring or report only long-term averages, limiting the ability to characterise day-to-day and room-to-room variations in PM exposure [22,28–32]. Although both NV and MV have been widely studied, reviews identify there is limited research directly comparing the two systems within the same building under comparable conditions [19,33,34]. This gap is particularly evident during winter, when hours of occupancy, ventilation patterns and the contribution of outdoor sources can differ substantially from warmer months [35–37]. While large scale IAQ studies across multiple homes exist, they often identify broad trends across multiple homes, rather than detailed house- or room-level analyses, failing to gain insights into the influence of building characteristics such as envelope performance on IAQ [38,39]. Additionally, ventilation performance in regions subject to relatively high ambient PM levels is well covered in the literature [28,35,40–43], while studies in cleaner air contexts, becoming increasingly more relevant in developed countries, are less common. Furthermore, reviews of residential IAQ research suggest that relatively few studies employ advanced statistical modelling approaches, such as mixed effects models, or evaluate their findings against health-based standards such as WHO indoor air guidelines (2010) and ASHRAE Standard 62.2 [30,44,45].

This study forms part of a larger, ongoing research programme investigating the performance of positive pressure ventilation (PPV) systems, a form of supply-only MV, on IAQ in New Zealand homes. Earlier phases of the project presented preliminary results, focussing on IAQ benefits of PPV under high occupancy, and seasonal multi-pollutant improvements in individual regions [46,47]. The present paper extends this work by analysing a larger dataset across Auckland, Hamilton, and Dunedin to assess PPV performance under diverse climatic and housing conditions.

Monitoring was undertaken during winter to evaluate the performance of PPV systems under conditions of reduced NV and higher rates of occupancy and indoor particle generation. Sensors recorded $PM_{2.5}$, temperature and relative humidity (RH) across multiple rooms, while outdoor monitoring enabled evaluation of infiltration and source contributions. This design enabled direct comparison of NV and PPV under the same household and seasonal conditions, with each home acting as its own control.

This article specifically evaluates the real-world house-level impact of PPV on indoor $PM_{2.5}$ relative to pre-installation conditions in occupied homes under low ambient PM2.5 conditions using empirical analysis and applying linear mixed effects regression (LMER) modelling to corroborate the observed reductions. The study investigates how PPV performance varies at house-level, across rooms, and over the diurnal cycle, and examines whether indoor-outdoor temperature differentials (ΔT_{I-O}) are associated with PPV-related reductions. Finally, by interpreting the results against health-based air quality benchmarks, including the US EPA Air Quality Index (AQI), this article characterises the observed changes in IAQ associated with PPV operation.

2 Methodology

2.1 Study design and overview

This study examines the impact of PPV systems on PM concentrations in residential homes in different cities in New Zealand under winter conditions. The experimental campaign was conducted over three separate phases: Phase 1 in 2021 (Auckland and Hamilton), Phase 2 in 2023 (Auckland), and Phase 3 in 2024 (Dunedin) (Figure 1). The study adopts a pre-post intervention design, where each home acts as its own control. All analyses are performed at house-level, while campaign-level grouping reflects the field campaigns conducted in different phases. Temporal variation in indoor $PM_{2.5}$ is characterised by examining diurnal patters within each individual home.

New Zealand is home to several cities with diverse climate and geography. Auckland, a coastal, harbour city, experiences mild winters (average daily maximum of 18.0 °C), and relatively high winter humidity (92% RH) [48,49]. Hamilton is an inland city with slightly lower temperatures (17.7°C) and winter humidity (87% RH) than Auckland [50,51]. Dunedin, also a coastal city, is cooler (17.3°C) and dryer (80% RH) than the other two cities [52,53]. Campaign-level mean temperature and RH values for each city over the study period are presented in Table 1.

Table 1 – House-level outdoor temperature and RH, grouped by campaign sample

Campaign	Temperature °C		RH %	
	Mean	SD	Mean	SD

Auckland 2021	10.9	1.7	75.8	15.3
Hamilton 2021	13.6	0.2	74.7	1.3
Auckland 2023	10.9	4.1	81.5	8
Dunedin 2024	11.1	1.4	73.5	3.5

A diversity in typical house construction also exists in these cities. Auckland and Hamilton generally have a newer and more recently renovated housing stock, while Dunedin has a higher proportion of older homes pre-dating insulation standards that were first introduced in New Zealand in 1978, and are known to suffer from draughts and dampness [54,55].

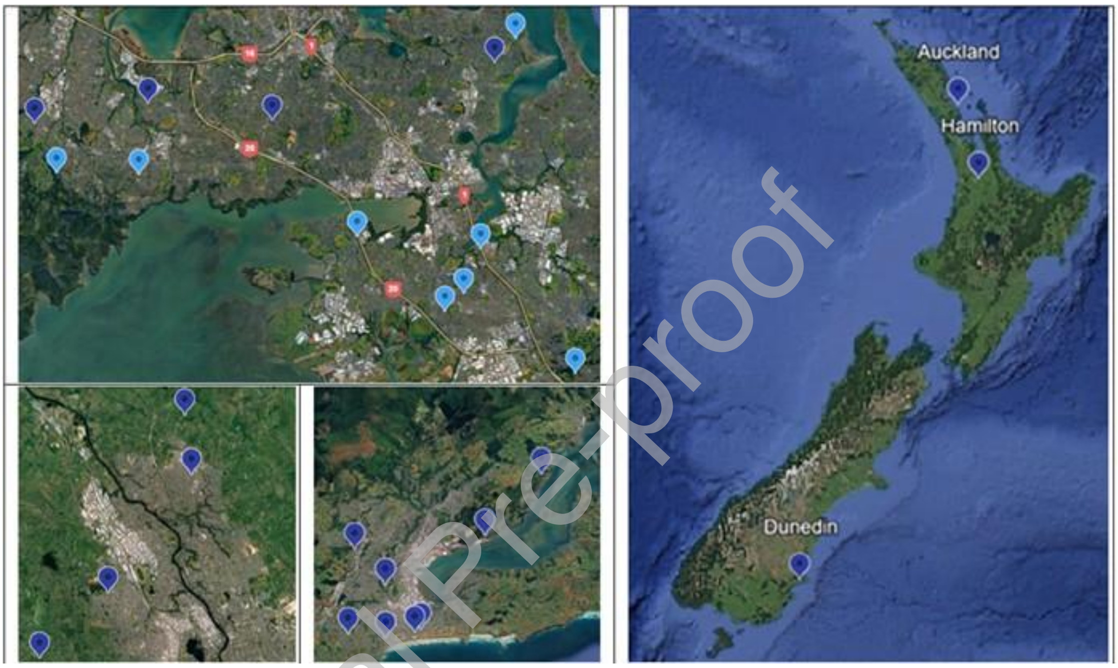

Figure 1 - Study and house locations across New Zealand (top: Auckland -12-; bottom right: Hamilton -4-; bottom left: Dunedin -8-)

Each phase of the campaign extended over a three-month period in each city, six weeks either side of a planned PPV Installation (Figure 2). While each phase was implemented in different years, seasonal comparability was maintained. The 2021 campaign coincided with a strict COVID-19 lockdown, potentially resulting in higher occupancy and elevated pollutant levels [56–60].

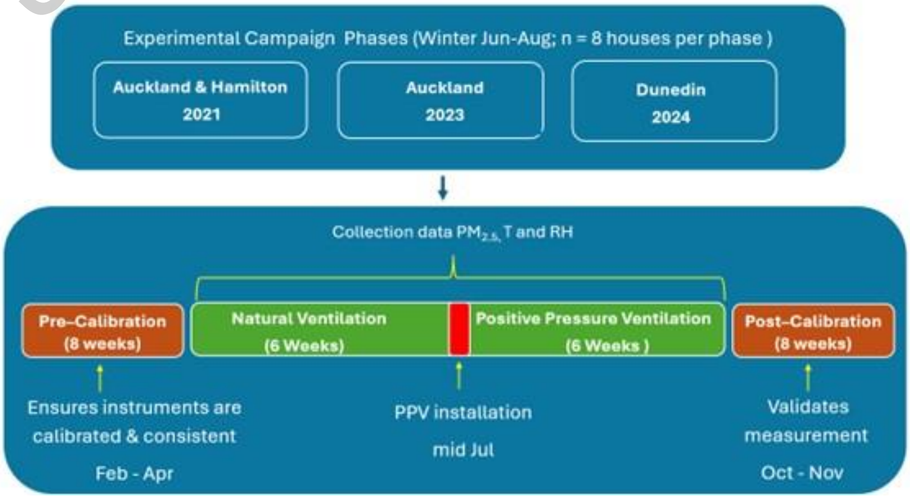

Figure 2 - Conceptualisation of the experimental campaign

Each phase of the experimental campaign commenced with a pre-calibration step to ensure accuracy and consistency of monitoring across each campaign sample, for each device. This was followed by a six-week period of monitoring without a PPV system to establish a baseline under NV conditions. A PPV system (described in Section 2.2) was then installed, followed by a second six-week monitoring period under PPV conditions. Finally, post-calibration of the monitors was performed to verify that the accuracy and consistency of each device were maintained throughout the study phase.

The study was structured around three key field visits. The initial visit took place at the start of winter, where air quality monitors were set up, the condition of the house was evaluated, and baseline data was gathered. The second visit occurred mid-winter, aligning with the installation of the PPV system. The final visit, conducted six weeks later, involved retrieving the monitors and evaluating the effects of the PPV system, thereby concluding the data collection process.

2.2 Positive pressure ventilation system

PPV systems deliver filtered external air into the building's living spaces to create a slightly positive indoor pressure. Each study house was retrofitted with a commercially available PPV system which filters and supplies air from the roof cavity to the indoor environment. This type of system is commonly used in New Zealand.

Each PPV installation comprises two core components: a fan and a filter. The fan is mounted within the roof cavity, delivering supply air via insulated ducting and a ceiling diffuser. The replaceable filter includes a multilayer system including an electrospun nanofibre layer, with a nominal F8 efficiency rating, in line with Eurovent and ASHRAE guidelines [61–63]. Such high efficiency filters (F7-F8) are commonly adopted in residential PPV systems in New Zealand and are consistent with guidance on residential ventilation in Europe and the UK, where a minimum F7 filtration grade is recommended [64,65].

PPV systems were operated in Automatic mode, where the internal system controller regulates the operation of the fan. While the system typically adjusts fan speed and operation according to differences in roof and indoor temperatures, specific details of the control algorithm were not available to the research team. For consistency, occupants were instructed to leave the system in Automatic mode for the duration of the post-installation period of the study and to keep all windows and external doors closed while the system was running.

Direct measurements of air change rate and infiltration rates were not performed in this study. The airflow data used in this study is based on the maximum rated airflow of each installed system, as specified by the manufacturer, divided by the internal volume of the house. These values represent the upper performance limit under ideal test conditions within each home.

For each home, the fan-filter assembly was positioned in the roof cavity and connected to ceiling-mounted diffusers via insulated ducting, as shown in Figure 3. Standard installation procedures occasionally required localised adjustments to insulation or duct routing to accommodate the system.

Figure 3 - Typical schematic of PPV home installation, showing details of (L-R) fan/filter assembly, ducting, and diffuser.

2.3 Selection of dwellings

Homes for this study were carefully selected for uniformity in construction and layout and to represent typical New Zealand homes [66–68]. A total of 24 non-smoking, pet-free households were selected, with distribution across Auckland, Hamilton, and Dunedin. The nominated homes were all free-standing, with a range of three to five bedrooms, and an open-plan kitchen and living area. While the number of homes limits population-scale inferences, the pre-post intervention study design with continuous monitoring focuses on house-level indoor $PM_{2.5}$ reductions following PPV installation.

Floor areas varied between 80 m^2 and 270 m^2, and they were occupied by two to five people, including at least two adults. This is comparable with that of other developed countries such as Australia, while being 60% larger, on average, than EU homes (similar room sizes, but more purpose-specific rooms in NZ homes) [69]. Table 2 provides details of relevant house features .

Table 2 – House-level building characteristics, grouped by campaign sample

Campaign	No. of homes	Occupants	Floor Area, m^2	Year of construction	Building construction	Heating system
Auckland 2021	4	3-4	95-150	1920-2015	Timber / concrete	Heat pump*
Hamilton 2021	4	3-4	90-170	1990-2015	Timber / brick	Heat pump*
Auckland 2023	8	2-4	80-270	1950-2010	Timber / concrete	Heat pump*
Dunedin 2024	8	2-4	110-222	1900-2010	Timber weatherboard	Heat pump* / Wood burner

* *non-ducted heat pumps*

2.4 Data collection and measurement

To evaluate indoor and outdoor air quality in the study homes, time-resolved measurements were taken. Each home was equipped with three air quality monitors, strategically placed in the master bedroom, the living area, and outdoors. Living areas were chosen as the most occupied room of the house[70,71], while master bedrooms were selected to provide an indoor comparison and to evaluate spatial distribution of indoor pollutants. Outdoor monitors were placed to investigate the influence of outdoor concentrations on indoor levels, enabling assessment of how external pollution sources and environmental conditions contributed to PPV performance.

Three different types of monitoring device were utilised to gather air quality data throughout the experimental campaign: Airly PM [72], uRAD [73], and EdiGreen Home AI-2002W [74]. These monitors continuously measured and recorded PM$_{2.5}$ concentrations, as well as thermal comfort parameters such as temperature and RH. PM$_{2.5}$ concentrations were measured and recorded under ambient temperature and pressure conditions, representing the direct output of the monitors, without correction for standard temperature or pressure.

To maintain consistency in measurements, each monitor was positioned at a height of approximately 1.5 metres above the floor, avoiding direct exposure to heat sources and windows, when possible, for each of the experimental campaigns. Details of these monitors and the pollutant measurement methods of each is as detailed in Table 3. Monitor locations were generally as shown in the table, with Edimax monitors used for Phase 1 campaign only, and uRAD and Airly monitors used for Phases 2 and 3.

All three monitor types have been comprehensively field-evaluated by South Coast Air Quality Management District in Southern California, USA, alongside Federal Reference Method (FRM), Federal Equivalent Methods (FEM) air monitoring equipment [75,76]. The Airly PM monitor indicated strong correlation for PM, temperature and RH (R^2 for 5-min averages of 0.83, 0.92, and 0.89, respectively), with high data recovery (>93%) and low variability (0.29 µg/m^3 for PM$_{2.5}$) [77]. uRAD monitor exhibited strong correlation for PM$_{2.5}$ (R^2 for 1-hour averages of 0.7-0.78), with high data recovery (99%) and moderate variability (19-25%) [78]. The Edimax monitors showed strong correlation for PM, temperature and RH (R^2 for 5-minute averages of 0.82, 0.97, and 0.98 respectively), with high data recovery (99.6%) and low variability (4.7% for PM$_{2.5}$) [79].

Table 3 - Air quality monitor details

Make/ Model	Location / Duration / Measurement frequency	Parameter	Range / Accuracy	Measurement Method
Airly PM	Living Area, Outside	Temp.	Range: -40°C – +80°C ± Accuracy: 0.1°C	Laser scattering sensor
	12 weeks (pre/ post-PPV)	RH	Range: 0 – 100% Accuracy: ± 1%	
	Every 5 min	PM$_{2.5}$	Range: 0 – 1000 µg/m^3 Accuracy: ±1 µg/m^3	
Magnasci SRL uRADMonitor INDUSTRIAL (HW103)	Bedrooms (2023-24)	Temp.	Range: -40°C – +125°C Accuracy: ± 0.3°C	Laser scattering sensor
	12 weeks (pre/post-PPV)	RH	Range: 0 – 100% Accuracy: ± 2%	
	Every 5 min	PM$_{2.5}$	Range: 0 – 1000 µg/m^3 Accuracy: ±1 µg/m^3	
Edimax EdiGreen Home AI-2002W 7-in-1 Multi-Sensor[	Bedrooms (2021)	Temp.	Range: 0°C – +80°C Accuracy: ± 1.0°C	Laser scattering sensor
	12 weeks (pre/post-PPV)	RH	Range: 0 – 100% Accuracy: ± 5%	
	Every 5 min	PM$_{2.5}$	Range: 0 – 500 µg/m^3 Accuracy: 0.3 µm	

2.5 Calibration

All study sensors were calibrated by using council air quality monitoring (AQM) stations (Thermo Scientific FH 62 C14 Continuous Particulate Monitor, range: 0 to 5,000 µg/m^3, accuracy: ± 1 µg/m^3, utilising beta ray attenuation [81]) as regulatory-grade reference monitors. Three calibration sensors were co-located with AQM stations in each of the study cities for a minimum three-month period: a research-grade PM monitor (Aeroqual Dust Sentry Pro, MCERTs-certified and SCAQMD-pre-approved [82]), a low-cost PM sensor, and a temperature and humidity logger. This setup allowed for cross-calibration and validation of the three devices.

Pre- and post-calibration was undertaken before and after each monitoring period, whereby all study sensors were calibrated at the Unitec Institute of Technology campus by co-locating with the three calibration sensors. The Aeroqual Dust Sentry Pro was used as the transfer standard, while the low-cost sensor and T/RH logger acted as arbitrary references to reduce uncertainty and maintain consistency across the monitors. This method aligns with methods used in other studies, including Kang et al [28], and were successfully applied for similar research purposes [47,83]. Calibrations were performed in a laboratory room with open windows to allow NV. This environment was select to emulate the conditions of the field deployment (indoor household setting with NV), with the aim of capturing particle characteristics representative of the study environment.

Pre- and post- calibrations were performed on an hourly basis. Following calibration of sensors prior to each monitoring period, sensors exhibiting R^2 values below 0.8, or substantial divergence between pre- and post-PPV calibration coefficients were discarded from further analysis. These thresholds were selected to balance data quality with sample retention, and are in line with previous studies, and exceeds the minimum target (0.7) set by US EPA standards for field testing using $PM_{2.5}$ sensors [84–87]. The remaining study monitors demonstrated strong correlations with the Aeroqual Dust Sentry Pro (accuracy of ±5 µg/m³ ±15% of reading) for $PM_{2.5}$ (R^2 = 0.80–0.87).

The observed R^2 values align with those from previous studies [88–90]. In contrast, some studies calibrating low-cost PM sensors against reference devices have reported weaker correlations (R^2 = 0.55-0.72) [91,92]. No significant differences were observed between the pre- and post-calibration R^2 values, indicating that monitoring accuracy was constant throughout the experimental campaigns. Mutual co-location also confirmed strong linear relationships, with R^2 values averaging 0.88 for $PM_{2.5}$. The R^2 values for temperature and RH ranged from (0.80-0.96) and (0.80-087), respectively.

Once calibration was complete, outliers were identified and removed from the data using the software programme R[93] using the ‘rstandard(model)’ function from the ‘stats’ package, together with visual inspection to highlight anomalous points, including negative values.

2.6 Analysis

The statistical analysis has been structured to address the study objectives: quantifying the impact of PPV on indoor $PM_{2.5}$, testing differences across peak and non-peak periods and study locations, evaluating the role of outdoor and building factors, and interpreting outcomes against AQI benchmarks.

PM analysis focussed on $PM_{2.5}$, due to its significant impact on human health[94,95]. Statistical analysis and identification of trends in diurnal peaks were undertaken using R[93] to asses IAQ before and after PPV installation. Time series analysis used the hour() and ymd_hms() functions from the ‘lubridate’ package, while visualisation of the data was performed using the ggplot(), geomline(), and facet_wrap() functions from the ‘ggplot2’ package [96,97]. Indoor-outdoor (I-O) ratios were calculated to explore the relationship between indoor and outdoor PM levels. Spearman’s rank correlation was used, with the Spearman’s coefficient (r_s) indicating the strength and correlation between pairs of variables [98].

The Mann-Whitney U Test and rank-biserial correlation were used to assess the statistical significance and strength (effect size) of the calculated reductions between pre-PPV and post-PPV $PM_{2.5}$ concentrations, for both peak and non-peak periods [99,100]. Rank-biserial correlation was used as a non-parametric effect size measure to test whether the direction of change was consistent across all paired pre- and post-PPV values, beyond the house-level means. Analysis of the $PM_{2.5}$ data showed peak concentrations consistently occurred between 7-10am and 6-9pm, with all other times classified as non-peak.

A linear mixed-effects regression (LMER) model was developed to analyse changes in indoor $PM_{2.5}$ concentrations before and after PPV installation [101]. A similar approach has been adopted by other studies to support the statistical analysis and to isolate environmental factors [47,102–104]. The model results are interpreted as house-level effects, where each dwelling is treated as its own control, and forms the unit of analysis. The model evaluates indoor $PM_{2.5}$ controlling for outdoor $PM_{2.5}$ concentrations, outdoor temperature, house area, and normalised air delivery capacity (NADC). NADC was calculated for each home by dividing the maximum rated airflow of the PPV system (m^3/h), by the internal volume of the dwelling (m^3). This value represents the theoretical maximum clean air delivery capacity of the system. Pre-PPV conditions were treated as the baseline for each home, accounting for variability between homes through random effects. Therefore, the model distinguishes between an uncontrolled, variable baseline (NV) and a controlled intervention. $PM_{2.5}$ concentrations (indoor and outdoor) were log-transformed in the LMER models due to their skewed distribution [103]. Additional parameters, such as RH, indoor-outdoor temperature differential, construction materials, year of construction, and occupancy were initially included in the model. Occupancy was modelled at house-level, based on number of occupants and typical occupancy hours (as reported by participants at commencement of the campaign). None of these additional parameters showed statistical significance and were therefore excluded from the final model. The model includes house-specific random intercepts and a house-specific random slope for PPV: 1 + PPV | house, to capture house-to-house differences, which may partially include contributions from occupancy and other parameters. The model outputs represent fitted values to the study dataset, and therefore represent observed changes in indoor $PM_{2.5}$.

Model reliability was confirmed through a series of diagnostic tests. Residual plots were used to test model assumptions (normality, homoscedasticity, and random effects structure). Analysis of residual vs fitted plots showed an even scatter around zero, while Normal Q-Q plots indicated the residuals generally followed a normal distribution, and relative uniformity in residuals for varying modelled values was demonstrated using Scale-location plots. The inclusion of random slopes was validated using the Likelihood-ratio test [105], which yielded a highly significant χ^2 statistic ($\chi^2(2) = 1561.6$, with p-value $< 2.2 \times 10^{-16}$). Histograms of random slopes for fixed values such as NADC were shown to be symmetrically distributed around zero.

Spearman’s rank correlation was performed to compare rank-order agreement between observed and modelled $PM_{2.5}$, providing a validity check, independent of linearity. Due to sample size constraints, the data was not partitioned into training and test sets. Instead, model robustness was evaluated by fitting the model to the full dataset, and repeating the evaluation for each campaign sample. Consistent effects observed across individual houses within all campaign samples supported the broader applicability of the findings. 95% confidence intervals have been added for all fixed-effect coefficients to quantify uncertainty. Further comparisons were made by generating probability-density functions for each campaign sample using kernel density estimation (KDE).

As a further qualitative measure of PPV impacts on indoor pollutant levels, each pre-PPV and post-PPV indoor $PM_{2.5}$ measurement was classified against the U.S. EPA AQI [106]. This index categorises $PM_{2.5}$ concentrations into six different bands: Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy, Very Unhealthy, and Hazardous (Table 4). These categories represent different levels of health risk from airborne pollutants. For each campaign sample, each category is expressed as the percentage of $PM_{2.5}$ measurements that fell within that category.

Table 4 - Air Quality Index (Source: US EPA (2014) [106])

AQI Values	**Levels of Health Concern**	**Colour**
0 to 50	Good	Green
51 to 100	Moderate	Yellow
101 to 150	Unhealthy for sensitive groups	Orange
151 to 200	Unhealthy	Red
201 to 300	Very Unhealthy	Purple
301 to 500	Hazardous	Maroon

Temperature and RH were monitored to investigate their relationship with IAQ and PPV performance. Changes in indoor temperature and RH following PPV installation were analysed at house-level, with measurements collected in the living rooms of all study homes, and results grouped by campaign sample. Temperature differentials (ΔT), calculated as the difference between indoor and outdoor values, were compared with observed $PM_{2.5}$ reductions following PPV installation. These differentials, which suggest there may be a more tightly controlled indoor environment, have been adopted as an indicator to assess the relationship between building envelope and PPV performance.

3 Results and Discussion

3.1 Indoor particulate matter

3.1.1 Pre-PPV and post-PPV installation

The following results are presented according to the pre-post intervention study design, with each home functioning as its own control. All analyses are performed at house-level, with campaign-level grouping applied to reflect the differing contexts of each field campaign.

The statistical metrics shown in Table 5 summarise the observed spread of living area $PM_{2.5}$ concentrations at house-level, grouped by campaign sample, collected before and after PPV installation. Statistical uncertainty in pre-post changes is quantified by the LMER model (χ^2, p, r_s). 'Pre-PPV' and 'Post-PPV' metrics have been calculated for each house and then averaged to obtain the campaign-level values as presented. The campaign sample values are used to calculate the ‘Change (mean)’ and ‘Overall’ values, as shown in the table.

Table 5 - Statistical summary of house-level Indoor PM$_{2.5}$ data, grouped by campaign sample

	Pre-PPV				Post-PPV				Change (mean)		LMER Model output
Campaign	mean µg/m^3	SD µg/m^3	5th %ile µg/m^3	95th %ile µg/m^3	mean µg/m^3	SD µg/m^3	5th %ile µg/m^3	95th %ile µg/m^3	Abs. Chg µg/m^3	Perc. Chg %	Perc. Chg %
Auckland 2021	8.6	12.4	1.2	23.2	3.6	6.9	0.3	11.6	-5.0	-58	-62
Hamilton 2021	7.7	13.8	1.8	30.0	2.9	7.5	0.5	11.3	-4.8	-62	-66
Auckland 2023	3.9	11.8	0.3	12.7	1.8	7.2	0.1	5.7	-2.0	-52	-46
Dunedin 2024	4.9	10.4	0.7	18.3	3.1	7.5	0.4	12.1	-1.8	-38	-36
Overall	**6.3**	**12.1**			**2.9**	**7.3**			**-3.4**	**-52**	**-52**
Stats Metrics	$\chi^2 = 1561.6$ $p < 2.2 \times 10^{-16}$ $r_s = 0.75$										

Prior to PPV installation, the six-week mean PM$_{2.5}$ concentrations per house ranged from 4.7-14.5 µg/m^3 for Auckland 2021, 3.9-16.4 µg/m^3 for Hamilton 2021, 1.7-8.2 µg/m^3 for Auckland 2023, and 2.9-8.2 µg/m^3 for Dunedin 2024. Concentrations were generally higher for the 2021 campaigns, potentially due to the higher levels of occupancy resulting from COVID lockdowns which coincided with these field campaigns. Similar observations have been made in other studies focusing on periods of increased occupancy [107,108]. Pre-PPV concentrations varied between dwellings across each field campaign, reflecting house-level differences within each phase of the study. Only one house during the study (in Hamilton 2021) exhibited mean PM$_{2.5}$ levels above the WHO 24-hour guideline limit of 15 µg/m^3 [109].

The pre-PPV indoor concentrations were similar to those reported by Kang et al. (2022) and Lim et al. (2021) for naturally ventilated residential buildings in cities experiencing comparable outdoor PM$_{2.5}$ levels (Chicago 16.1 µg/m^3, Seoul 17.4 µg/m^3, respectively) [28,35]. Other studies in cities observing outdoor concentrations significantly higher (Krakow 43 µg/m^3, Nanjing 75 µg/m^3), reported higher indoor concentrations under NV (21 µg/m^3 and 64.9 µg/m^3, respectively) [42,110].

Following PPV installation, the six-week mean PM$_{2.5}$ concentrations per house ranged from 1.3-7.0 µg/m^3 for Auckland 2021, 1.4-4.3 µg/m^3 for Hamilton 2021, 0.7-4.3 µg/m^3 for Auckland 2023, and 1.6-4.6 µg/m^3 for Dunedin 2024. Post-PPV concentrations were lower across dwellings in all campaigns, with variability between houses remaining evident within each phase. In contrast with the pre-PPV period, no 24-hour mean indoor PM$_{2.5}$ concentrations above the WHO guideline were detected post-PPV (15 µg/m^3). The observed reductions align with previous studies on PPV systems [28,35,111].

Reductions were observed across all houses following PPV installation. Campaign averages, based on the individual house pre-and post-PPV mean reductions, were Auckland 2021 52-73%; Hamilton 2021 31-82%; Auckland 2023 42-77%; and Dunedin 2024 21-64%. Within each campaign, the level of pre-post reduction varied between houses. Building characteristics typical to a given campaign sample, such as envelope leakage in older homes, may help to explain the varying magnitude of observed reductions. Uncontrolled envelope leakage can dissipate positive pressures before they effectively drive out polluted indoor air, reducing the pollutant removal efficiency of the system.

From Table 5, the campaign pre-PPV mean concentrations were highest (nearly double) in Auckland 2021 and Hamilton 2021. Across campaigns, higher pre-intervention concentrations were associated with larger pre-post reductions within dwellings, suggesting that PPV systems may achieve greater reductions in homes with higher initial $PM_{2.5}$ levels.

Statistical analysis using the Mann-Whitney U test indicated that the distributions of hourly $PM_{2.5}$ concentrations differed significantly between pre- and post-PPV periods across all study sites: Auckland 2021 ($p = 0.048$), Hamilton 2021 ($p = 0.0077$), Auckland 2023 ($p = 0.0077$), and Dunedin 2024 ($p = 0.043$). To complement the house-level summary, a paired non-parametric test was also performed. The resulting rank-biserial correlation coefficients were consistently -1.0 across all comparisons, indicating that every post-PPV measurement was lower than its corresponding pre-PPV distribution, showing complete consistency in the direction of change. Together, these results demonstrate that PPV installation was associated with systematic reductions in indoor $PM_{2.5}$ concentrations.

To test whether these observed changes could be explained by key environmental and building factors, a linear mixed-effects regression (LMER) model was fitted to the dataset. The LMER model outputs closely followed observed reductions, as indicated in Table 5. The model indicated that outdoor $PM_{2.5}$, outdoor temperature, floor area, and ventilation rate explained most of the variation in indoor $PM_{2.5}$. Parameters representing indoor sources, such as occupancy, did not have statistical significance, so were not included in the model. The mixed-effects model was specified at the house level and included dwelling-specific random effects, such that each house was compared to itself before and after PPV installation. The model is used to support and quantify the field observed pre-post indoor $PM_{2.5}$ reductions at a house level.

To further support the model interpretation, the probability density functions in Figure 4 comparing the LMER model outputs against observed data, shows that fitted reductions align closely with the measured house-level values across all campaign samples. Model outputs were generated for the full time-series dataset (hourly indoor measurements) for each home. For comparison, percentage reductions were first calculated for each home as the change between the pre- and post-PPV modelled means, then pooled by campaign sample to capture location-specific conditions while maintaining sufficient sample sizes for reliable density estimation. The density curves indicate close alignment between the observed and modelled reductions across campaigns, with distributions centred around similar levels of reduction. The left-bias and narrower curves for Auckland 2021 and Hamilton 2021 likely reflect the smaller sample sizes in these campaign samples, where fewer data points produce smoother KDEs with less apparent variability. The LMER model slightly underestimated $PM_{2.5}$ concentrations both pre-PPV and post-PPV, consistently by around 0.52 $\mu g/m^3$. However, percentage reductions were estimated reliably, indicating accurate magnitude estimation despite some bias in the model.

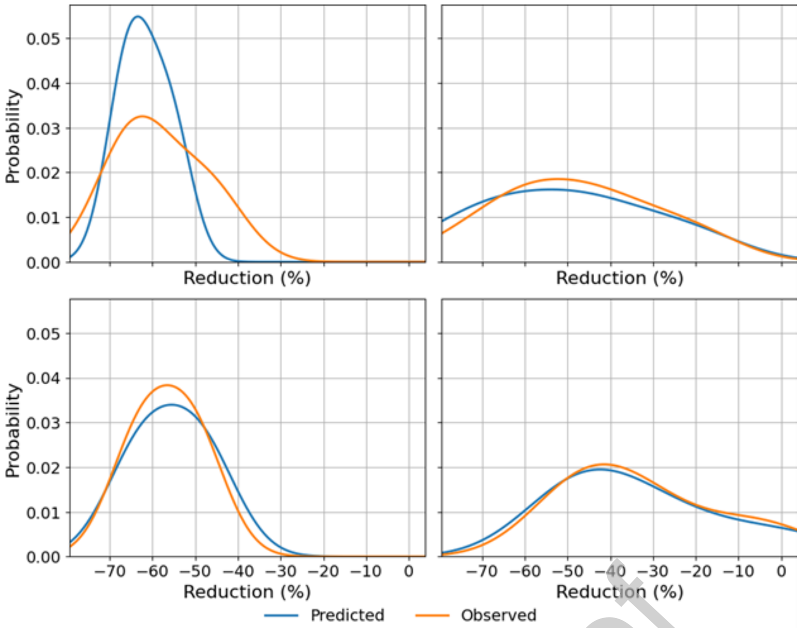

Figure 4 - Probability density curves comparing modelled and observed house-level percentage reductions, grouped by campaign sample. (top left: Auckland 2021; top right: Hamilton 2021; bottom left: Auckland 2023; bottom right: Dunedin 2024)

3.1.2 In-house spatial variability

PM concentrations recorded within each house were compared for each field campaign phase to investigate the relationship between different rooms. Indoor $PM_{2.5}$ concentrations were generally higher in living rooms than in bedrooms, both before and after PPV installation. This potentially reflects the typically higher PM-generating activities associated with living areas, such as cooking and resuspension of settled PM due to movement. Across all homes, living room concentrations averaged 1.3 $\mu g/m^3$ higher than master bedrooms, consistent with prior studies [112,113]. Before PPV installation, 60% of homes had higher $PM_{2.5}$ in the living room; this increased to 72% post-PPV, indicating a consistent room-based differential.

Figure 5 shows the percentage change in $PM_{2.5}$ concentrations, between pre-PPV and post-PPV periods, for each home in each campaign sample, comparing living rooms and master bedrooms. Four houses were omitted from the analysis (two in Auckland 2023, two in Dunedin 2024) due to sensors not meeting minimum performance requirements, post-calibration. $PM_{2.5}$ levels consistently decreased across all houses in all campaign samples following PPV installation.

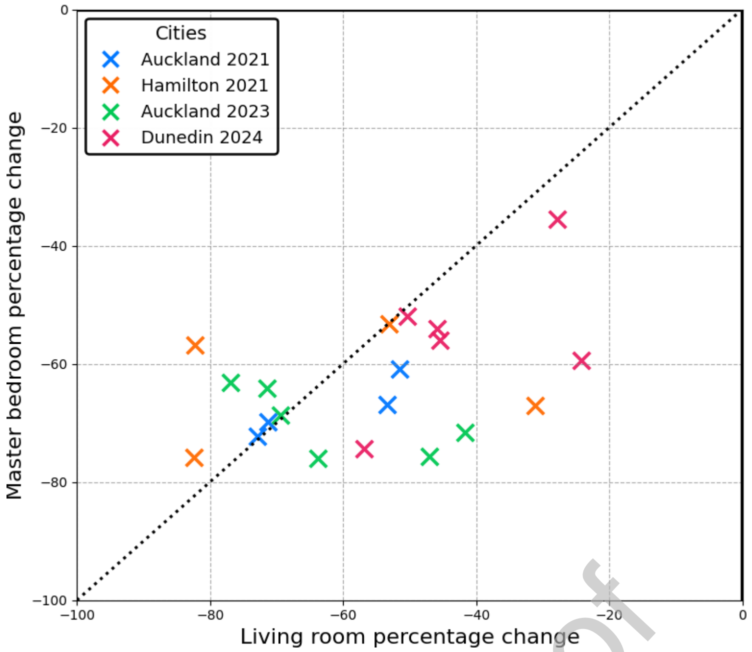

Figure 5 - House-level PM2.5 percentage change in living rooms and master bedrooms, grouped by campaign sample

Campaign-level average reductions ranging from 43-62% and 47-67% were observed in living rooms and master bedrooms, respectively, indicating consistent house-level reductions following PPV installation. These results indicate that both rooms exhibited significant reductions following PPV installation, with variability in the level of reduction between dwellings. The majority of houses experienced greater reductions in master bedrooms than in living rooms, as indicated in the scatter plot in Figure 5. The greater reductions observed in bedrooms post-PPV may reflect more stable airflow and lower pollutant activity (e.g. cooking), as well as the presence of dedicated supply vents.

Spearman's Rank analysis confirmed moderate correlations between living room and bedroom $PM_{2.5}$ values (pre-PPV: r_s = 0.4; post-PPV: r_s = 0.48), indicating that pollutant trends within a house were aligned but varied by room function. COVID-19 lockdowns may have affected occupancy patterns, however no behavioural data were collected to validate this assumption.

3.1.3 Diurnal variation

Diurnal profiles of $PM_{2.5}$ concentrations were analysed for each campaign sample for both the pre-PPV and post-PPV periods. For each hour of the day, the corresponding hourly values for every day within the period and every house within the campaign sample were averaged. Morning and evening peaks were identified in diurnal profiles, aligning with common household activities (e.g. cooking, indoor fireplaces) and outdoor pollution sources such as peak traffic volumes or wood smoke from neighbourhood home heating [114–116]. The results as summarised in Figure 6 indicate a reduction in average $PM_{2.5}$ concentrations between the pre-PPV and post-PPV periods, with variations observed across the 24-hour period.

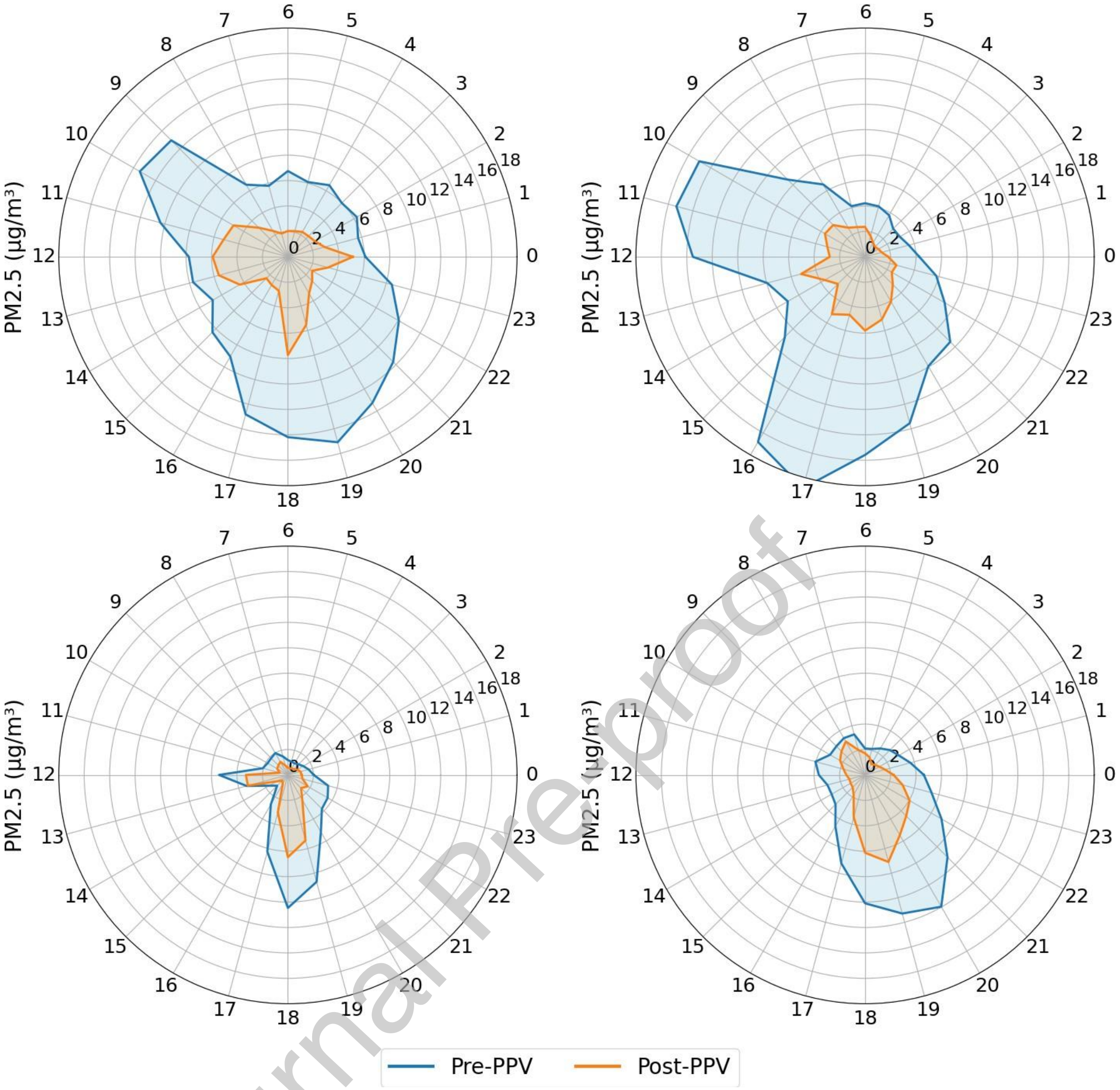

Figure 6 – Campaign-average house-level indoor $PM_{2.5}$ diurnal concentrations: Auckland 2021 (top left); Hamilton 2021 (top right); Auckland 2023 (bottom left); Dunedin 2024 (bottom right).

Across dwellings, reductions were observed during both peak and non-peak activity periods. Houses monitored during 2021, showed higher $PM_{2.5}$ reductions during peak periods of indoor $PM_{2.5}$ than non-peak periods. Peak period reductions averaged 71% and 63% for Hamilton 2021 and Auckland 2021 homes, respectively. Non-peak period reductions were 10% and 45%, respectively, for these campaign samples. For Auckland 2023 and Dunedin 2024 homes, there was a smaller difference between $PM_{2.5}$ reductions during peak and non-peak periods, with some peak period reductions slightly lower than non-peak periods. Peak period reductions were 58% and 53% for Auckland 2023 and Dunedin 2024 homes, respectively. Meanwhile, non-peak period reductions for these campaign samples were 64% and 56%, respectively. These results indicate that PPV achieved comparable house-level reductions during both peak and non-peak activity periods, with differences reflecting house-level variability within each campaign context. The higher peak reductions in 2021 may reflect elevated background concentrations resulting from higher occupancy and associated activity during lockdown.

The results of the Mann-Whitney U Test, comparing the difference between pre-PPV and post-PPV concentrations during peak and non-peak intervals for each house, indicate statistically significant results, with p-values consistently below 0.01. These results support the observation that, within dwellings, PPV generally performed the same or slightly better during peak periods, when initial concentrations were high, than in non-peak periods. The rank-biserial correlation results further support these findings, with effect sizes up to 0.73 for peak period reductions and 0.66 for non-peak period reductions. For all houses across all campaign samples, the Mann-Whitney U p-values were all well below 0.01 for both the pre-PPV and post-PPV periods, indicating strong statistical significance.

3.1.4 Air quality index (AQI)

Indoor (living room) $PM_{2.5}$ measurements were classified against US EPA's AQI for each campaign period, before and after PPV installation. The number of readings that fell into each category, expressed as a percentage of the total number of readings for each campaign sample, are presented in Figure 7. Overall, AQI classifications improved across all campaign samples following PPV installation.

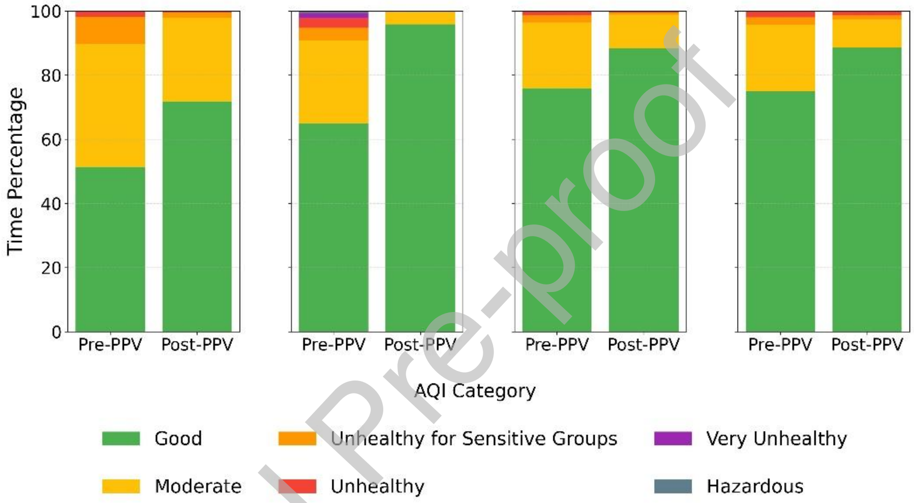

Figure 7 – House-level indoor $PM_{2.5}$ concentrations, expressed in terms of US EPA AQI, grouped by campaign sample (L-R: Auckland 2021, Hamilton 2021, Auckland 2023, Dunedin 2024)

The pre-PPV distributions across campaigns indicated compromised IAQ, with substantial proportions of readings falling outside the "Good" AQI category. Only 50%, approximately, of readings in Auckland 2021 were classified as "Good", with the remainder falling into either "Moderate" or unhealthy levels. The other three campaign samples also experienced discernible proportions of their readings falling into "Moderate" or unhealthy levels. A small proportion of readings reached "Hazardous" levels within the Hamilton 2021 campaign. These results show a consistent pattern of elevated $PM_{2.5}$ concentrations, likely due to a combination of poor air exchange, accumulation of indoor-originating pollutants (e.g. cooking, cleaning products), and potentially infiltration of contaminants from outdoors.

Post-PPV, a consistent improvement in $PM_{2.5}$ concentrations is observed across campaigns. The percentage of "Good" readings increased by between 16% and 50%, with some campaigns showing "Good" classifications exceeding 90% of total observations. More severe classifications, including "Unhealthy," "Very Unhealthy," and "Hazardous" disappeared almost entirely across all campaign samples. These improvements highlight the effectiveness of PPV systems in maintaining and enhancing IAQ. The post-PPV data demonstrates how these systems can bring pollutant concentrations down to within US EPA AQI "Good" classifications, mitigating health risks and enhancing the indoor environmental quality in a measurable and sustained manner. These findings align with the diurnal analysis, that $PM_{2.5}$ reductions tend to be higher at times of peak occupant activity.

3.1.5 Outdoor contributions

Indoor-Outdoor (I-O) $PM_{2.5}$ ratios were calculated for each house across each campaign sample. Figure 8 presents the comparison of I-O ratios between the pre-PPV and post-PPV periods for each individual house. I-O ratios greater than 1.0 indicate that indoor $PM_{2.5}$ concentrations exceeded outdoor levels. The relatively low outdoor levels observed in this study indicate that the substantial post-PPV indoor reductions are unlikely to be explained solely by dilution of contaminants from outdoors. Instead, these reductions highlight the role of indoor source control, building envelope, and pressurisation.

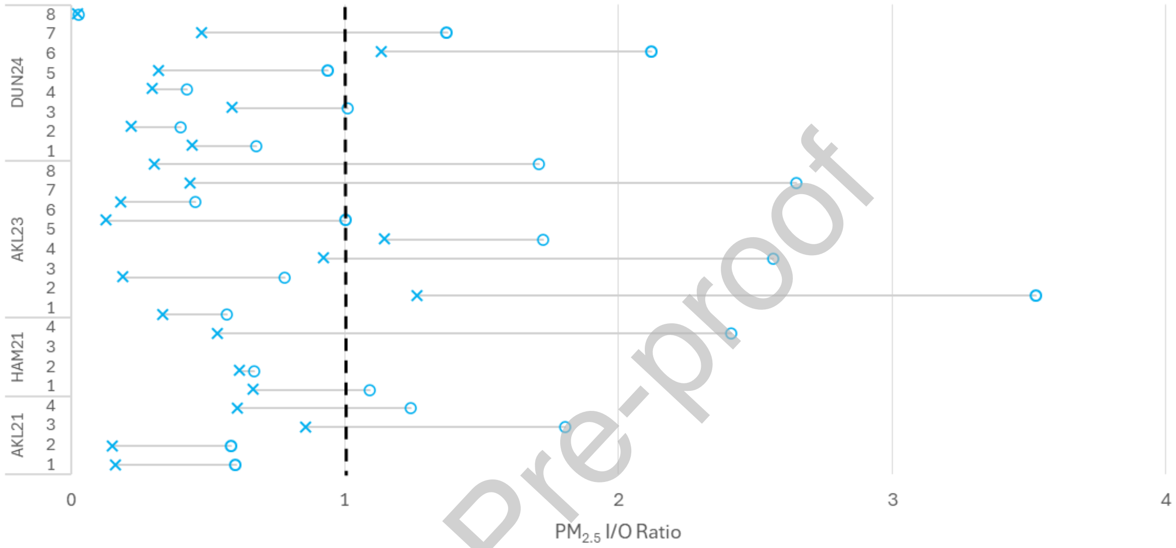

Figure 8 – House-level $PM_{2.5}$ Indoor-outdoor ratios, grouped by campaign sample (O = pre-PPV, X = post-PPV)

Pre-PPV I-O ratios were greater than 1.0 in 50% of the homes in Auckland 2021 and Hamilton 2021, 75% in Auckland 2023, and 25% in Dunedin 2024. Post-PPV, indoor concentrations fell below outdoor levels in most homes. No I-O ratios exceeded 1.0 for Auckland 2021 or Hamilton 2021 homes, while the percentage of Auckland 2023 homes exceeding 1.0 fell to 25%, with Dunedin 2024 homes remaining unchanged at 25%. These results support the notion that the PPV system can effectively reduce PM levels from indoor sources, while also reducing indoor concentrations toward or below outdoor levels, consistent with reduced dominance from indoor sources with PPV operation.

I/O ratios reduced by averages of 0.6, 0.7, 1.2, and 0.2 in Auckland 2021, Hamilton 2021, Auckland 2023, and Dunedin 2024, respectively. Auckland 2023 houses were notable for their relatively high pre-PPV I-O ratios (average 1.8). However, campaign-average post-PPV ratios were similar across all campaign samples (0.4-0.6), reflecting the higher I/O reductions observed for Auckland 2023 homes. The observed I-O reductions align with the 0.2-0.6 range reported in previous studies for PPV [28,35,111].

The LMER model used to evaluate the effect of PPV systems on indoor $PM_{2.5}$ was run both with and without outdoor $PM_{2.5}$ concentrations as a fixed effect [47]. Both models showed significant $PM_{2.5}$ reductions post-PPV. When outdoor $PM_{2.5}$ was included as a fixed effect, the estimated effect was 10.3% reduction ($p < 0.001$). Ignoring the effect of outdoor $PM_{2.5}$, the model estimated an effect of 11.2% reduction ($p < 001$). The estimated effects were virtually unchanged after adjustment to the original $PM_{2.5}$ scale. These results indicate that, within the observed range of ambient $PM_{2.5}$ during winter monitoring, PPV was associated with lower indoor levels of $PM_{2.5}$.

3.1.6 Temperature and RH

Changes in indoor (living room) temperature and RH following installation of the PPV system, for each campaign sample, are summarised in Table 6. Prior to PPV installation, indoor temperature and RH varied across houses and campaigns. Campaign-level trends remained broadly similar post-PPV, suggesting that PPV operation did not dominate environmental conditions in governing indoor thermal comfort parameters.

Table 6 - Statistical summary of house-level indoor temperature & RH data, grouped by campaign sample

		Pre-PPV		Post-PPV		Abs. Change
	Campaign	mean	SD	mean	SD	mean
Temp (°C)	Auckland 2021	17.9	2.6	17.7	2.6	-0.2
	Hamilton 2021	19.6	3.4	20.7	2.3	1.0
	Auckland 2023	18.0	2.1	17.0	2.6	-1.1
	Dunedin 2024	11.3	1.8	11.7	2.5	0.4
RH (%)	Auckland 2021	61.5	4.7	57.3	4.4	-4.3
	Hamilton 2021	52.7	5.7	52.1	4.2	-0.6
	Auckland 2023	64.8	5.1	61.7	6.4	-3.1
	Dunedin 2024	74.6	5.9	71.1	7.2	-3.5

The temperatures observed within the Dunedin campaign sample were notably lower than for the other campaign samples, consistent with findings from previous studies [117,118]. This likely reflects the colder outdoor climate and differences in building stock (typically older homes with substandard airtightness).

The introduction of PPV resulted in reductions in RH levels (1-4%), while variable temperature effects were observed (5% increase to 6% reduction) across campaign samples. Within the two Auckland campaigns, mean indoor temperatures exhibited slight reductions, while modest increases were observed within the Hamilton and Dunedin campaign samples. Temperature impacts were likely influenced by external factors such as occupant preferences and local climate. These findings are similar to those reported in previous studies [35,119].

3.1.7 Thermal differential

Temperature differentials (calculated as indoor minus outdoor temperature, ΔT_{I-O}) were analysed before and after PPV installation across all study houses to investigate their relationship with indoor $PM_{2.5}$ reductions. Figure 9 depicts this relationship for each study house over the pre-PPV period. The graph also highlights patterns within each campaign sample by fitting ellipses that capture the variability of the relationship, illustrating how houses cluster within the sampled regime. Similar trends were observed over the post-PPV period, as supported by findings from the Spearman's Rank analysis, discussed below.

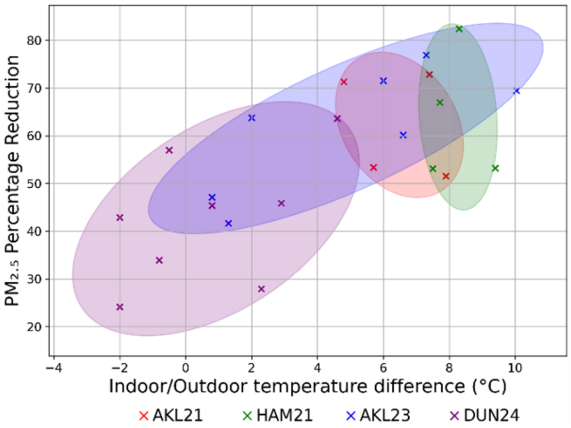

Figure 9 – House-level temperature differential vs $PM_{2.5}$ reduction, grouped by campaign sample

$\Delta T_{I\text{-}O} > 0$ indicates homes with warmer conditions indoors than outdoors. Figure 9 shows the majority of homes maintained warmer indoor conditions relative to outdoors, with the exception of four homes in Dunedin, which were cooler indoors than outdoors. A general trend can be observed, where homes with the more positive temperature differential exhibit a greater level of $PM_{2.5}$ reduction.

Across houses, larger positive $\Delta T_{I\text{-}O}$ values were associated with larger house-level reductions in $PM_{2.5}$, consistent with reduced indoor-outdoor exchange driven by improved thermal separation. Average $\Delta T_{I\text{-}O}$ values were higher for Auckland 2021 and Hamilton 2021 campaign samples, with corresponding average $PM_{2.5}$ reductions of 58% and 62%, respectively. These findings suggest that greater thermal separation enhances the effectiveness of PPV systems in reducing indoor PM concentrations. Within the Dunedin campaign sample, $\Delta T_{I\text{-}O}$ values were lower on average, with corresponding average $PM_{2.5}$ reductions of 38%. These observations may reflect envelope leakage in older housing stock influencing the level of house-level reductions [120,121].

Spearman's Rank analysis confirms these trends. $PM_{2.5}$ reductions were positively correlated with $\Delta T_{I\text{-}O}$ (pre-PPV: $r_s = +0.64$; post-PPV: $r_s = +0.65$). The strength and direction of the relationship did not alter significantly following the PPV intervention, indicating that the influence of thermal differential on $PM_{2.5}$ reduction did not change once PPV systems were installed. These results highlight that higher temperature differentials can be an important indicator of PPV system effectiveness in reducing indoor particulate concentrations.

4 Conclusions

This study provides field-based evidence of house-level wintertime PPV system performance in an urban setting with low outdoor $PM_{2.5}$. Using a pre-post intervention framework, mean indoor $PM_{2.5}$ concentrations exhibited consistent reductions, with campaign averages between 38% and 62%. The statistics and mixed-effects modelling both support these observations.

Spatial analysis of indoor $PM_{2.5}$ within the home shows that concentrations were generally higher in the living room than in the master bedroom, while post-intervention reductions tended to be similar. I/O ratios exceeded 1.0 in half of the homes prior to PPV installation, falling below 1.0 in most homes post-PPV. I/O reductions correlated strongly with pre-PPV I/O ratios ($r_s = 0.90$), suggesting that PPV systems are more effective at reducing indoor $PM_{2.5}$ when indoor sources dominate.

Larger campaign-average reductions in indoor $PM_{2.5}$ were observed in campaigns where pre-intervention levels were higher, in particular during the 2021 monitoring periods, likely reflecting greater indoor particle generation associated with the COVID-19 lockdown. In line with this, diurnal analysis shows post-PPV reductions were greater during peak activity periods than during non-peak periods. Combined, these results suggest that PPV systems can achieve larger $PM_{2.5}$ reductions when initial levels are higher and indoor source activity is more prominent.

PPV installation resulted in modest shifts in indoor temperature (-6% to +5%) and humidity (-4% to -1%). Analysis of indoor-outdoor temperature differentials showed that these values were closely linked to the effectiveness of PPV systems in reducing $PM_{2.5}$ concentrations. These findings suggest that indoor-outdoor temperature differentials may serve as a useful indirect indicator of building envelope performance.

Within the Dunedin 2024 campaign sample, $PM_{2.5}$ reductions were of lower average magnitude, which may reflect the predominance of older homes in this campaign which are often associated with greater envelope leakage. In line with this interpretation, the lower thermal separation observed in the Dunedin sample suggests that PPV effectiveness may be influenced by envelope performance.

5 Limitations and future work

The limitations experienced in this study offer valuable opportunities for future research to improve and expand on these findings. These results should be interpreted as campaign-specific house-level effects rather than direct city-to-city comparisons, due to campaigns being conducted in different years.

The pre-post intervention study design with continuous monitoring provides statistical power for detecting changes at house-level. However, the modest number of houses limits the ability to make city or regionwide inferences. Increasing the sample size would therefore enhance the reliability of the results, providing a more comprehensive understanding of household pollution.

Detailed occupant behaviour was not monitored during this study and could not be included in the statistical modelling, despite their known influence on IAQ. The house-level pre-post design compares the same dwelling and occupants before and after PPV installation, which reduces, but does not eliminate, the likelihood that systematic behavioural changes drive the observed reductions in $PM_{2.5}$ concentrations. Future studies would benefit from collaboration with participants to collect more detailed information about occupant behaviours (e.g. day-today occupancy hours, household activities, ventilation behaviours, as well as heating/cooling behaviours) during the monitoring campaign that may contribute to pollutant levels, as well as closer monitoring or control of window and door openings.

While the winter focus of this study was intended to evaluate PPV performance under conditions of limited NV, higher occupancy and indoor particle emissions, it does not represent year-round performance. Future studies should consider year-round monitoring campaigns to sufficiently capture seasonal variation in ventilation behaviour, meteorological conditions, and occupant activities.

Finally, this study did not include measurements of in-situ airflow or building airtightness. Measurement of household air exchange and blower door testing should therefore be considered for future studies.

6 Credit authorship contribution statement

German Hernandez Herrera: conceptualisation, methodology, investigation, data curation, formal analysis, writing – original draft, visualisation. Rafael Borge: conceptualisation, writing – review and editing, supervision. Terri-Ann Berry: conceptualisation, methodology, resources, writing – review and editing, supervision, funding acquisition.

7 Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

8 Funding sources

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9 Data availability

Data will be made available on request.

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11 References

1. Pope, C. A., & Dockery, D. W. (2006). Health Effects of Fine Particulate Air Pollution: Lines that Connect. *Journal of the Air & Waste Management Association*, *56*(6), 709–742. https://doi.org/10.1080/10473289.2006.10464485

2. Brook, R. D., Rajagopalan, S., Iii, C. A. P., Brook, J. R., Bhatnagar, A., Diez-Roux, A. V., Holguin, F., Hong, Y., Luepker, R. V., Mittleman, M. A., Peters, A., Siscovick, D., Smith, S. C., Whitsel, L., & Kaufman, J. D. (2010). *Particulate matter air pollution and cardiovascular disease: An update to the scientific statement from the American Heart Association*. https://pubmed.ncbi.nlm.nih.gov/20458016/

3. Schraufnagel, D. E. (2020). The health effects of ultrafine particles. *Molecular Medicine*.

4. World Health Organization. (2024). *Ambient (outdoor) air pollution*. https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health

5. Lelieveld, J., Pozzer, A., Poschl, U., Fnais, M., Haines, A., & Munzel, T. (2020). Loss of life expectancy from air pollution compared to other risk factors: A worldwide perspective. *Cardiovascular Research*, *116*, 1910–1917. https://doi.org/10.1093/cvr/cvaa025

6. Jones, A. P. (1999). Indoor air quality and health. *Atmospheric Environment*.

7. Chen, C., & Zhao, B. (2011). Review of relationship between indoor and outdoor particles: I/O ratio, infiltration factor and penetration factor. *Atmospheric Environment*, *45*, 275–288.

8. Sundell, J. (2004). On the history of indoor air quality and health. *Indoor Air*, *14*(7), 51–58.

9. Klepeis, N. E., Nelson, W., Ott, W., Robinson, J., Tsang, A., Switzer, P., Behar, J., Hern, S., & Engelmann, W. (2001). The National Human Activity Pattern Survey (NHAPS). *Exposure Science & Environmental Epidemiology*, *11*, 231–252. https://doi.org/10.1038/sj.jea.7500165

10. Ouyang, Z., Mao, R., Hu, E., Xiao, C., Yang, C., & Guo, X. (2022). The indoor exposure of microplastics in different environments. *Gondwana Research*, *108*, 193–199. https://doi.org/10.1016/j.gr.2021.10.023

11. Wallace, L. (2000). *Real-Time Monitoring of Particles, PAH, and CO in an Occupied Townhouse*. https://pubmed.ncbi.nlm.nih.gov/10660987/
12. Hussein, T., Glytsos, T., Ondracek, J., Dohanyosova, P., Zdımal, P., Hameri, K., Lazaridis, M., Smolık, J., & Kulmala, M. (2006). Particle size characterization and emission rates during indoor activities in a house. *Atmospheric Environment*, *40*, 4285–4307.
13. He, C., Morawska, L., & Taplin, L. (2007). Particle Emission Characteristics of Office Printers. *Environmental Science & Technology*, *41*(17), 6039–6045.
14. Wang, Y., Koutrakis, P., Michanikou, A., Kouis, P., Panayiotou, A., Kinni, P., Tymvios, F., Chrysanthou, A., Neophytou, M., Mouzourides, P., Savvides, C., Vasiliadou, E., Papasavvas, I., Christophides, T., Nicolaou, R., Avraamides, P., Kang, C., Papatheodorou, S., Middleton, N., … Achilleos, S. (2024). Indoor residential and outdoor sources of PM2.5 and PM10 in Nicosia, Cyprus. *Air Quality, Atmosphere & Health*, *17*, 485–499.
15. Alonso-Blanco, E., Gómez-Moreno, F., Diaz-Ramiro, E., Fernández, J., Coz, E., Yagüe, C., Román-Cascón, C., Narros, A., Borge, R., & Artíñano, B. (2023). Real-Time Measurements of Indoor–Outdoor Exchange of Gaseous and Particulate Atmospheric Pollutants in an Urban Area. *Environmental Research and Public Health*, *20*(19), 6823.
16. Rivas, E., Santiago, J., Martin, F., Martilli, A., Diaz, E., Gomerz-Moreno, F., Artinano, B., Roman-Cascon, C., Yague, C., de la Paz, D., & Borge, R. (2024). Indoor-outdoor NOX modelling in a single-side naturally ventilated room in a real building in Madrid. *Building Engineering*, *84*, 108403.
17. Awbi, H. (1991). *Ventilation of Buildings*.
18. Nilsson, H. (2007). Thermal comfort evaluation with virtual manikin methods. *Building and Environment*, *42*(12), 4000–4005. https://doi.org/10.1016/j.buildenv.2006.04.027
19. Dimitroulopoulou, C. (2012). Ventilation in European dwellings: A review. *Building and Environment*, *47*, 109–125. https://doi.org/10.1016/j.buildenv.2011.07.016

20. Milner, J. T., Dimitroulopoulou, C., & ApSimon, H. M. (2004). *Indoor concentrations in buildings from sources outdoors*. https://www.researchgate.net/profile/James-Milner-5/publication/266409126_Indoor_concentrations_in_buildings_from_sources_outdoors/links/551aae1a0cf251c35b4e7ec6/Indoor-concentrations-in-buildings-from-sources-outdoors.pdf
21. Ormandy, D., & Ezratty, V. (2012). Health and thermal comfort From WHO guidance to housing strategies. *Energy Policy*. https://core.ac.uk/download/pdf/1389329.pdf
22. Mucha, W., Mainka, A., & Bragoszewska, E. (2024). Impact of ventilation system retrofitting on indoor air quality in a single-family building. *Building and Environment*, *262*, 111830. https://doi.org/10.1016/j.buildenv.2024.111830
23. Ward, I. (2008). The Potential Impact of the New (UK) Building Regulations on the Provision of Natural Ventilation in Dwellings—A Case Study of Low Energy Social Housing. *International Journal of Ventilation*, *7*(1), 77–88. https://doi.org/10.1080/14733315.2008.11683801
24. Hu, H., Huang, X., Zhao, Y., Qian, H., & Liu, C. (2022). A new PM2.5-based PM-up method to measure non-mechanical ventilation rate in buildings. *Journal of Building Engineering*, *52*, 104351. https://doi.org/10.1016/j.jobe.2022.104351
25. Kumar, A., Moreno-Rangel, A., Khan, M. A. I., & Piasecki, M. (2022). Ventilation and Indoor Air Quality. *Atmosphere*, *13*(10), 1730. https://doi.org/10.3390/atmos13101730
26. Allen, J. G. (2024). Recommitting to Ventilation Standards for Healthy Indoor Air Quality. *American Journal of Public Health*, *114*(10), 991–993.
27. Morawska, L., Li, Y., & Salthammer, T. (2024). Lessons from the COVID-19 pandemic for ventilation and indoor air quality. *Science*, *385*(6707), 396–401.
28. Kang, I., McCreery, A., Azimi, P., Gramigna, A., Baca, G., Abromitis, K., Wang, M., Zeng, Y., Scheu, R., Crowder, T., Evens, A., & Stephens, B. (2022). Indoor air quality impacts of residential mechanical ventilation system retrofits in existing homes in Chicago, IL. *Science of The Total Environment*, *804*, 150129. https://doi.org/10.1016/j.scitotenv.2021.150129

29. Bekö, G., Weschler, C. J., Wierzbicka, A., Karottki, D. G., Toftum, J., Loft, S., & Clausen, G. (2013). Ultrafine Particles: Exposure and Source Apportionment in 56 Danish Homes. *Environmental Science & Technology*, 130904150722005. https://doi.org/10.1021/es402429h
30. Baeza_Romero, M. T., Dudzinska, M. R., Amouei Torkmahalleh, M., Barros, N., Coggins, A. M., Ruzgar, D. G., Kildsgaard, I., Naseri, M., Rong, L., Saffell, J., Scutaru, A. M., & Staszowska, A. (2022). A review of critical residential buildings parameters and activities when investigating indoor air quality and pollutants. *Indoor Air*, *32*(11). https://doi.org/10.1111/ina.13144
31. Kumar, A., Moreno-Rangel, A., Khan, M. A. I., & Piasecki, M. (2022). Ventilation and Indoor Air Quality. *Atmosphere*, *13*(10), 1730. https://doi.org/10.3390/atmos13101730
32. Chen, C., & Zhao, B. (2011). Review of relationship between indoor and outdoor particles: I/O ratio, infiltration factor and penetration factor. *Atmospheric Environment*, *45*(2), 275–288. https://doi.org/10.1016/j.atmosenv.2010.09.048
33. Zaniboni, L., & Albatici, R. (2022). Natural and Mechanical Ventilation Concepts for Indoor Comfort and Well-Being with a Sustainable Design Perspective: A Systematic Review. *Buildings*, *12*(11), 1983. https://doi.org/10.3390/buildings12111983
34. Kumar, P., Morawska, L., Martani, C., Biskos, G., Neophytou, M., Di Sabatino, S., Bell, M., Norford, L., & Britter, R. (2015). The rise of low-cost sensing for managing air pollution in cities. *Environment International*, *75*, 199–205. https://doi.org/10.1016/j.envint.2014.11.019
35. Lim, A.-Y., Yoon, M., Kim, E.-H., Kim, H.-A., Lee, M. J., & Cheong, H.-K. (2021). Effects of mechanical ventilation on indoor air quality and occupant health status in energy-efficient homes: A longitudinal field study. *Science of The Total Environment*, *785*, 147324.
36. Liu, S., Song, R., & Zhang, T. (Tim). (2021). Residential building ventilation in situations with outdoor PM2.5 pollution. *Building and Environment*, *202*, 108040. https://doi.org/10.1016/j.buildenv.2021.108040
37. Stamp, S., Burman, E., Shrubsole, C., Chatzidiakou, L., Mumovic, D., & Davies, M. (2022). Seasonal variations and the influence of ventilation rates on IAQ: A case study of five low-energy

London apartments. *Indoor and Built Environment*, *31*(3), 607–623. https://doi.org/10.1177/1420326X211017175

38. Liu, H.-Y., Schneider, P., Haugen, R., & Vogt, M. (2019). Performance Assessment of a Low-Cost PM2.5 Sensor for a near Four-Month Period in Oslo, Norway. *Atmosphere*, *10*(2), 41. https://doi.org/10.3390/atmos10020041
39. Weschler, C. J. (2009). Changes in indoor pollutants since the 1950s. *Atmospheric Environment*, *43*(1), 153–169. https://doi.org/10.1016/j.atmosenv.2008.09.044
40. Ścibor, M., Balcerzak, B., Galbarczyk, A., Targosz, N., & Jasienska, G. (2019). Are we safe inside? Indoor air quality in relation to outdoor concentration of PM10 and PM2.5 and to characteristics of homes. *Sustainable Cities and Society*, *48*, 101537. https://doi.org/10.1016/j.scs.2019.101537
41. Choi, D. H., & Kang, D. H. (2017). Infiltration of Ambient PM2.5 through Building Envelope in Apartment Housing Units in Korea. *Aerosol and Air Quality Research*, *17*(2), 598–607. https://doi.org/10.4209/aaqr.2016.06.0287
42. Wang, F., Meng, D., Li, X., & Tan, J. (2016). Indoor-outdoor relationships of PM2.5 in four residential dwellings in winter in the Yangtze River Delta, China. *Environmental Pollution*, *215*, 280–289. https://doi.org/10.1016/j.envpol.2016.05.023
43. Yin, H., Zhai, X., Ning, Y., Li, Z., Ma, Z., Wang, X., & Li, A. (2022). Online monitoring of PM2.5 and CO2 in residential buildings under different ventilation modes in Xi’an city. *Building and Environment*, *207*(A), 108453. https://doi.org/10.1016/j.buildenv.2021.108453
44. World Health Organization. (2010). *WHO Guidelines for Indoor Air Quality: Selected Pollutants*. https://www.who.int/publications/i/item/9789289002134
45. ASHRAE. (2022). *Standards 62.1 & 62.2—Ventilation and Acceptable Indoor Air Quality*. https://www.ashrae.org/technical-resources/bookstore/standards-62-1-62-2

46. Hernandez, G., Borge, R., Blanchon, D., & Berry, T.-A. (2025). Effects of Positive Pressure Ventilation System on Indoor Particulate Matter Concentrations in a Subtropical Climate. *Indoor Air*.
47. Hernandez, G., Borge, R., Blanchon, D., & Berry, T.-A. (2025). Impact of positive pressure ventilation systems on indoor air quality in residential settings. *Building and Environment*, *283*, 113323.
48. MetService. (2025). *Past Weather for Auckland*. https://www.metservice.com/towns-cities/regions/auckland/locations/auckland/past-weather
49. Chappell, P. (2013). *The Climate and Weather of Auckland* (No. 60; NIWA Science and Technology Series). NIWA. https://webstatic.niwa.co.nz/static/Auckland%20ClimateWEB.pdf
50. MetService. (2025). *Past Weather for Hamilton*. https://www.metservice.com/towns-cities/regions/waikato/locations/hamilton/past-weather
51. Chappell, P. (2013). *The Climate and Weather of Waikato* (No. 61; NIWA SCIENCE AND TECHNOLOGY SERIES). https://webstatic.niwa.co.nz/static/Waikato%20ClimateWEB.pdf
52. MetService. (2025). *Past Weather for Dunedin*. https://www.metservice.com/towns-cities/regions/dunedin/locations/dunedin/past-weather
53. Macara, G. (2015). *The Climate and Weather of Otago* (No. 67; NIWA SCIENCE AND TECHNOLOGY SERIES). NIWA. https://webstatic.niwa.co.nz/library/NIWAsts67.pdf
54. Otago Daily Times. (2008). *Mould a "significant problem" in New Zealand houses*. https://www.odt.co.nz/news/dunedin/mould-significant-problem-new-zealand-houses
55. Presbyterian Support Otago. (2005). *Old, Cold, and Costly? A Survey of Low Income Private Rental Housing In Dunedin 2004*. https://psotago.org.nz/assets/Documents/d3585e01f2/Old-Cold-and-Costly-0.pdf
56. Patel, H., Talbot, N., Salmond, J., Dirks, K., Xie, S., & Davy, P. (2020). Implications for air quality management of changes in air quality during lockdown in Auckland (New Zealand) in response to the 2020 SARS-CoV-2 epidemic. *Science of the Total Environment*.

57. Ezani, E., Brimblecombe, P., Asha'ari, Z. H., Fazil, A. A., Ismail, S. N. S., Ramly, Z. T. A., & Khan, F. (2021). *Indoor and Outdoor Exposure to PM2.5 during COVID-19 Lockdown in Suburban Malaysia*. *21*(3), 200476. https://doi.org/10.4209/aaqr.2020.07.0476
58. University of Auckland. (2023). *Covid-19 Timeline 2021 | Auckland Policy Commons*. https://www.ppi.auckland.ac.nz/covid-19-policy-resources/covid-19-timeline/covid-19-timeline-2021/
59. Du, W., Wang, J., Wang, Z., Lei, Y., Huang, Y., Liu, S., Wu, C., Ge, S., Chen, Y., Bai, K., & Wang, G. (2021). Influence of COVID-19 lockdown overlapping Chinese Spring Festival on household PM2.5 in rural Chinese homes. *Chemosphere*, *278*, 130406. https://doi.org/10.1016/j.chemosphere.2021.130406
60. Mousavi, A., & Wu, J. (2021). Indoor-Generated PM2.5 During COVID-19 Shutdowns Across California: Application of the PurpleAir Indoor–Outdoor Low-Cost Sensor Network. *Environ. Sci. Technol.*, *55*(9), 5648–5656. https://doi.org/10.1021/acs.est.0c06937
61. Courtey, S. (2017). Definition of filtration performance – from EN 779 to ISO 16890. *REHVA*, 16–19.
62. Eurovent. (2018). *SELECTION OF EN ISO 16890 RATED AIR FILTER CLASSES FOR GENERAL VENTILATION APPLICATIONS* (No. 4/23; Version Second Edition). https://www.eurovent.eu/wp-content/uploads/news-files/eurovent-rec-4-23-selection-of-en-iso-16890-rated-air-filter-classes-2018-english-web.pdf
63. HRV New Zealand. (2021). *NZ's Leading Home Ventilation System*. https://www.hrv.co.nz/ventilation
64. Courtey, S. (2017). Residential Air Handling Units for better indoor air quality and energy efficiency. *REHVA European HVAC Journal*, *54*(1), 27–31.
65. Passivhaus Trust. (2018). *Good Practice Guide: MVHR for single dwellings*. https://www.passivhaustrust.org.uk/UserFiles/File/Technical%20Papers/2018%20MVHR%20Good%20Practice%20Guide%20rev%201.1.pdf

66. Khajehzadeh, I., & Vale, B. (2017). How New Zealanders distribute their daily time between home indoors, home outdoors and out of home. *Kōtuitui: New Zealand Journal of Social Sciences Online*, *12*(1), 17–31.

67. Stats NZ. (2024). *2023 Census household, family, and extended family highlights*. https://www.stats.govt.nz/information-releases/2023-census-household-family-and-extended-family-highlights/

68. Stats NZ. (2024). *Data sources and imputation for cigarette smoking behaviour in the 2023 Census*. https://www.stats.govt.nz/methods/data-sources-and-imputation-for-cigarette-smoking-behaviour-in-the-2023-census/

69. Khajehzadeh, I., & Vale, B. (2016). *LARGE HOUSING IN NEW ZEALAND: ARE BEDROOM AND ROOM STANDARDS STILL GOOD DEFINITIONS OF NEW ZEALAND HOUSE SIZE?* The 9th Australasian Housing Researchers Conference. https://www.auckland.ac.nz/assets/creative/our-research/doc/urban-research-network/khajehzadeh-vale-definition-of-house-size.pdf

70. Wigzell, E., Kendall, M., & Nieuwenhuijsen, M. (2000). The spatial and temporal variation of particulate matter within the home. *Exposure Analysis and Environmental Epidemiology*, *10*(3), 307–314.

71. Kao, H., Chang, T., Hiseh, Y., Wang, C., & Hsieh, C. (2009). Comparison of airflow and particulate matter transport in multi-room buildings for different natural ventilation patterns. *Energy and Buildings*, *41*(9), 966–974.

72. Airly. (2023). *Air Quality Sensors | Air Quality Monitoring. Monitor in UK & Europe. Airly Data Platform and Monitors*. https://airly.org/en/features/air-quality-sensors/

73. uRAD. (2017). *uRADMonitor » Products*. https://www.uradmonitor.com/products/

74. Edimax. (2019). *EdiGreen Plus 7-in-1 Multi-Sensor Indoor Air Quality Detector*. https://www.edimax.com/edimax/mw/cufiles/files/download/datasheet/AI-2003W_datasheet_EN.PDF

75. AQ-SPEC. (2025). *AQ-SPEC Air Quality Sensor Performance Evaluation Center—Field Evaluations*. https://www.aqmd.gov/aq-spec/evaluations/criteria-pollutants/field

76. Polidori, A., Papapostolou, V., Feenstra, B., & Zhang, H. (2017). *AQ-SPEC - Field Evaluation of Low-Cost Air Quality Sensors—Field Setup and Testing Protocol*. https://www.aqmd.gov/docs/default-source/aq-spec/protocols/sensors-field-testing-protocol.pdf?sfvrsn=5824c061_0

77. AQ-SPEC. (2015). *Field Evaluation Airly* [Field Evaluation]. South Coast AQMD. https://www.aqmd.gov/docs/default-source/aq-spec/field-evaluations/airly---field-evaluation.pdf?sfvrsn=df93d361_8

78. AQ-SPEC. (2015). *Field Evaluation Magnasci SRL uRADMonitor INDUSTRIAL (version HW103) Sensor*. South Coast AQMD. https://www.aqmd.gov/docs/default-source/aq-spec/field-evaluations/uradmonitor_industrial---field-evaluationde40a0efc2b66f27bf6fff00004a91a9.pdf?sfvrsn=e3f6cf61_12

79. AQ-SPEC. (2018). *Field Evaluation—Edimax EdiGreen Home* [Field Evaluation]. South Coast AQMD. https://www.aqmd.gov/docs/default-source/aq-spec/field-evaluations/edimax-edigreen-home---field-evaluation.pdf?sfvrsn=fc63f561_12

80. Magnasci. (2018). *uRADMonitor INDUSTRIAL*. https://www.uradmonitor.com/wp-content/uploads/2018/12/datasheet_industrial_104.pdf

81. Thermo Scientific. (2013). *Thermo Scientific FH 62 C14 Continuous Particulate Monitor—Product Specifications*. https://assets.thermofisher.com/TFS-Assets/LSG/Specification-Sheets/D19629~.pdf

82. Aeroqual. (2025). *Dust Sentry Specification Sheet*. https://hydroterra.com.au/wp-content/uploads/2024/07/54435_DAeroqual-Dust-Sentry-Spec-Sheet-1.pdf

83. Hernandez, G., Borge, R., Blanchon, D., & Berry, T.-A. (2025). Effects of Positive Pressure Ventilation System on Indoor Particulate Matter Concentrations in a Subtropical Climate. *Indoor Air (in Press)*.

84. Duvall, R. M., Clements, A. L., Hagler, G., Kamal, A., Kilaru, V., Goodman, L., & Frederick, S. (2021). *Performance testing protocols, metrics, and target values for fine particulate matter air sensors: Use in ambient, outdoor, fixed site, non-regulatory supplemental and informational monitoring applications* (No. EPA/600/R-20/280). US EPA. https://nepis.epa.gov/Exe/ZyPDF.cgi/P1012RCE.PDF?Dockey=P1012RCE.PDF\

85. Kelly, K. E., Whitaker, J., Petty, A., Widmer, C., Dybwad, A., Sleeth, D., Martin, R., & Butterfield, A. (2017). *Ambient and laboratory evaluation of a low-cost particulate matter sensor*. https://pmc.ncbi.nlm.nih.gov/articles/PMC10625486/pdf/nihms-1815660.pdf

86. Badura, M., Batog, P., Drzeniecka-Osiadacz, A., & Modzel, P. (2018). Evaluation of Low-Cost Sensors for Ambient PM2.5 Monitoring. *Journal of Sensors*, *2018*, 5096540.

87. Sousan, S., Koehler, K., Thomas, G., Park, J., Hillman, M., Halterman, A., & Peters, T. (2016). Inter-comparison of low-cost sensors for measuring the mass concentration of occupational aerosols. *AEROSOL SCIENCE AND TECHNOLOGY*, *50*(5), 462–473. https://doi.org/10.1080/02786826.2016.1162901

88. Cavaliere, A., Carotenuto, F., Di Gennaro, F., Gioli, B., Gualtieri, G., Martelli, F., Matese, A., Toscano, P., Vagnoli, C., & Zaldei, A. (2018). Development of Low-Cost Air Quality Stations for Next Generation Monitoring Networks: Calibration and Validation of PM2.5 and PM10 Sensors. *Sensors*, *18*(9), 2843. https://doi.org/10.3390/s18092843

89. Stavroulas, I., Grivas, G., Michalopoulos, P., Liakakou, E., Bougiatioti, A., Kalkavouras, P., Fameli, K., Hatzianastassiou, N., Mihalopoulos, N., & Gerasopoulos, E. (2020). Field Evaluation of Low-Cost PM Sensors (Purple Air PA-II) Under Variable Urban Air Quality Conditions, in Greece. *Atmosphere*, *11*(9), 926. https://doi.org/10.3390/atmos11090926

90. Wang, Li, J., Jing, H., Zhang, Q., Jiang, J., & Biswas, P. (2015). Laboratory Evaluation and Calibration of Three Low-Cost Particle Sensors for Particulate Matter Measurement. *Aerosol Science and Technology*, *49*(11), 1063–1077. https://doi.org/10.1080/02786826.2015.1100710

91. Liu, Schneider, P., Haugen, R., & Vogt, M. (2019). Performance Assessment of a Low-Cost PM2.5 Sensor for a near Four-Month Period in Oslo, Norway. *Atmosphere*, *10*(2), 41. https://doi.org/10.3390/atmos10020041
92. Mallia, D., Kochanski, A., Kelly, K., Whitaker, R., Xing, W., Mitchell, L., Jacques, A., Farguell, A., Mandel, J., Gaillardon, P., Becnel, T., & Krueger, S. (2020). Evaluating Wildfire Smoke Transport Within a Coupled Fire-Atmosphere Model Using a High-Density Observation Network for an Episodic Smoke Event Along Utah's Wasatch Front. *Atmospheres*, *125*. https://doi.org/10.1029/2020JD032712
93. R Core Team. (2022). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. https://www.R-project.org
94. Hodas, N., Meng, Q., Lunden, M. M., Rich, D. Q., Özkaynak, H., Baxter, L. K., Zhang, Q., & Turpin, B. J. (2012). Variability in the fraction of ambient fine particulate matter found indoors and observed heterogeneity in health effect estimates. *Journal of Exposure Science & Environmental Epidemiology*, *22*(5), 448–454. https://doi.org/10.1038/jes.2012.34
95. Ostro, B., Hu, J., Goldberg, D., Reynolds, P., Hertz, A., Bernstein, L., & Kleeman, M. J. (2015). Associations of Mortality with Long-Term Exposures to Fine and Ultrafine Particles, Species and Sources: Results from the California Teachers Study Cohort. *Environmental Health Perspectives*, *123*(6), 549–556. https://doi.org/10.1289/ehp.1408565
96. Wickham, H. (with Sievert, C.). (2016). *ggplot2: Elegant graphics for data analysis* (Second edition). Springer.
97. Grolemund, G., & Wickham, H. (2024). Dates and Times Made Easy with lubridate. *Journal of Statistical Software*, *40*(3), 1–25. https://doi.org/10.18637/jss.v040.i03
98. Gauthier, T. (2001). Detecting Trends Using Spearman's Rank Correlation Coefficient. *Environmental Forensics*, *2*(4), 359–362. https://doi.org/10.1006/enfo.2001.0061
99. de la Rubia, J. (2022). Note on Rank-Biserial Correlation when There Are Ties. *Open Journal of Statistics*, *12*(5), 597–622.

100. Conover, W. (1999). *Practical nonparametrics* (3rd ed.).

101. Brown, V. (2021). An Introduction to Linear Mixed-Effects Modeling in R. *Advances in Methods and Practices in Psychological Science*, *4*(1), 1–19. https://doi.org/10.1177/2515245920960351

102. Cordero, J. M., Hingorani, R., Jimenez-Relinque, E., Grande, M., Cutillas, F., Martinez, E., Borge, R., Narros, A., & Castellote, M. (2021). Challenges in quantification of photocatalytic NO2 abatement effectiveness under real world exposure conditions illustrated by a case study. *Science of The Total Environment*, *766*, 144393. https://doi.org/10.1016/j.scitotenv.2020.144393

103. Hassan, H., Mishra, A. K., Wemken, N., O'Dea, P., Cowie, H., McIntyre, B., & Coggins, A. M. (2024). Deep energy renovations' impact on indoor air quality and thermal comfort of residential dwellings in Ireland – ARDEN project. *Building and Environment*, *259*, 111637. https://doi.org/10.1016/j.buildenv.2024.111637

104. Huang, C.-H., Xiang, J., Austin, E., Shirai, J., Liu, Y., Simpson, C., Karr, C. J., Fyfe-Johnson, A. L., Kronborg Larsen, T., & Seto, E. (2021). Impacts of using auto-mode portable air cleaner on indoor PM2.5 levels: An intervention study. *Building and Environment*, *188*, 107444. https://doi.org/10.1016/j.buildenv.2020.107444

105. Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using **lme4**. *Journal of Statistical Software*, *67*(1). https://doi.org/10.18637/jss.v067.i01

106. US EPA. (2014). *Air Quality Index—A Guide to Air Quality and Your Health* (No. EPA-456/F-14-002). https://www.airnow.gov/sites/default/files/2018-04/aqi_brochure_02_14_0.pdf

107. Cowell, N., Chapman, L., Bloss, W., Srivastava, D., Bartington, S., & Singh, A. (2023). Particulate matter in a lockdown home: Evaluation, calibration, results and health risk from an IoT enabled low-cost sensor network for residential air quality monitoring. *Environmental Science: Atmospheres*, *3*(1), 65–84. https://doi.org/10.1039/d2ea00124a

108. Laltrello, S., Amiri, A., & Lee, S.-H. (2022). Indoor Particulate Matters Measured in Residential Homes in the Southeastern United States: Effects of Pandemic Lockdown and Holiday Cooking. *Aerosol and Air Quality Research*, *22*(5), 210302. https://doi.org/10.4209/aaqr.210302

109. World Health Organization. (2021). *WHO global air quality guidelines—Particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide*. https://iris.who.int/bitstream/handle/10665/345329/9789240034228-eng.pdf?sequence=1

110. Ścibor, M., Balcerzak, B., Galbarczyk, A., Targosz, N., & Jasienska, G. (2019). Are we safe inside? Indoor air quality in relation to outdoor concentration of PM10 and PM2.5 and to characteristics of homes. *Sustainable Cities and Society*, *48*, 101537. https://doi.org/10.1016/j.scs.2019.101537

111. Wang, Meng, D., Li, X., & Tan, J. (2016). Indoor-outdoor relationships of PM2.5 in four residential dwellings in winter in the Yangtze River Delta, China. *Environmental Pollution*, *215*, 280–289. https://doi.org/10.1016/j.envpol.2016.05.023

112. Shen, H., Hou, W., Zhu, Y., Zheng, S., Ainiwaer, S., Shen, G., Chen, Y., Cheng, H., Hu, J., Wan, Y., & Tao, S. (2021). Temporal and spatial variation of PM2.5 in indoor air monitored by low-cost sensors. *Science of the Total Environment*, *770*, 145304.

113. Zhu, Y. (2021). Spatiotemporal variation in residential PM2.5 and PM10 concentrations in China: National on-site survey. *Environmental Research*.

114. Manning, M. I., Martin, R. V., Hasenkopf, C., Flasher, J., & Li, C. (2018). Diurnal Patterns in Global Fine Particulate Matter Concentration. *Environmental Science & Technology Letters*, *5*(11), 687–691. https://doi.org/10.1021/acs.estlett.8b00573

115. Wallis, S. L., Hernandez, G., Poyner, D., Birchmore, R., & Berry, T.-A. (2019). Particulate matter in residential buildings in New Zealand: Part I. Variability of particle transport into unoccupied spaces with mechanical ventilation. *Atmospheric Environment: X*, *2*, 100024.

116. Zhang, Y.-L., & Cao, F. (2015). Fine particulate matter (PM2.5) in China at a city level. *Scientific Reports*, *5*(1), 14884. https://doi.org/10.1038/srep14884

117. Povey, D. M., & Harris, U. (2005). *Old, cold and costly?: A survey of low income private rental housing in Dunedin 2004*. Presbyterian Support Otago. https://psotago.org.nz/assets/Documents/d3585e01f2/Old-Cold-and-Costly-0.pdf

118. French, L. J., Camilleri, M. J., Isaacs, N. P., & Pollard, A. R. (2007). Temperatures and heating energy in New Zealand houses from a nationally representative study—HEEP. *Energy and Buildings*, *39*(7), 770–782. https://doi.org/10.1016/j.enbuild.2007.02.004

119. Zhao, Y., Sun, H., & Tu, D. (2018). Effect of mechanical ventilation and natural ventilation on indoor climates in Urumqi residential buildings. *Building and Environment*, *144*, 108–118. https://doi.org/10.1016/j.buildenv.2018.08.021

120. Stephenson, J., Brown, C., & McDonald, H. (2020). *Dunedin Household Energy Study* [Technical Report]. Dunedin City Council. https://www.researchgate.net/publication/342877240_Dunedin_Household_Energy_Study

121. Otago Daily Times. (2018). *Renovating Dunedin's reputation*. https://www.odt.co.nz/opinion/editorial/renovating-dunedins-reputation

Declaration of interests

☐ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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