School children’s exposure to indoor fine particulate matter

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Abstract

Assessing the exposure of children to indoor fine particulate matter (PM$_{2.5}$) is important because children spend about one third of their day inside early learning microenvironments. Children are more vulnerable to air pollution due to a number of physiological reasons and, therefore, it is crucial to explore the factors that affect indoor (and outdoor) PM$_{2.5}$ levels in these locations to determine appropriate measures to reduce children’s exposure to air pollution. To provide health policy guidance about how to reduce indoor air pollution in schools, this study systematically reviewed the associations between environmental factors and classroom characteristics with indoor PM$_{2.5}$ concentrations or indoor/outdoor (I/O) PM$_{2.5}$ in early learning microenvironments using a PRISMA framework. The systematic literature search reviewed studies that: monitored indoor PM$_{2.5}$ levels in at least one early learning microenvironment; measured outdoor PM$_{2.5}$ levels; and, analysed the influence of relevant factors on PM$_{2.5}$ concentrations or I/O relationships. From an initial search of 1282 results, 66 studies were included in the final review. Overall, these studies showed a lack of robust statistical analyses being performed, inconsistent application of methodological approaches and considerable variation in results. Consequently, these studies demonstrated weak evidence of significant and consistent associations between seasonal, meteorological, activity-based, site-based and ventilation rate variables with indoor PM$_{2.5}$ concentrations. Further large-scale and statistically robust analyses are needed to accurately quantify these associations, with particular attention needed as to how associations between influential variables and indoor PM$_{2.5}$ concentrations or I/O relationships change with seasonal and other factors, and whether these associations vary spatially. Once identified, these factors and relationships could be used to inform policy decisions that would enable better protection of the health of children in early learning microenvironments from chronic and acute exposure to air pollution.

1. Introduction

Fine particulate matter (PM$_{2.5}$) is a common airborne pollutant with well-documented health effects [1]. Exposure to PM$_{2.5}$ has been found to affect many organs in the body [2], but is most strongly, and consistently, associated with increases in respiratory and cardiovascular diseases and mortality [1–4]. Long-term exposure to elevated ambient PM$_{2.5}$ levels is considered a major health concern [3]. The main sources of this ambient air pollution arise from road traffic, industry, agriculture and domestic sources [5, 6]. However, episodic elevated peaks of PM$_{2.5}$ occur during bushfires and dust storms, events which are increasing in intensity and duration due to changing climate extremes [7–9]. A stark example of these changing extremes, and the consequent increased risk to human health, occurred during the ‘Black Summer’ event of 2019–2020 in Australia, during which time more than 400 premature deaths were estimated to have occurred from the inhalation of bushfire smoke [10, 11]. Such events result in acute peaks of PM$_{2.5}$ that are many times above WHO or national air quality guidelines for PM$_{2.5}$. However, current
evidence suggests that there is no ‘safe’ level of PM$_{2.5}$ that is not associated with negative health effects, indicating that even low concentrations of PM$_{2.5}$ pose a significant health threat [12, 13].

The risk of experiencing severe health impacts from airborne fine particulate matter is not uniformly distributed through populations. People with existing health problems, the elderly and young children are more vulnerable [1, 3, 4]. Children have a higher vulnerability because they are very active, they breathe in more air (per body weight) than adults, and their respiratory systems are still developing [3, 4]. For these reasons, it is important to understand children's exposure to PM$_{2.5}$ in environments where they spend significant amounts of time during their formative years [14, 15]. Across high, middle and low-income countries, children spend around one third of their day inside early learning microenvironments [16–20]. Despite this, there is limited guidance for protecting students from hazardous levels of PM$_{2.5}$ and other air pollutants in many countries, aside from keeping students indoors [21]. Although the WHO has published guidelines on acceptable levels of ambient and indoor concentrations of PM$_{2.5}$ [22], they do not provide information on actions that can be undertaken to actively reduce people's exposure when indoor or ambient levels of PM$_{2.5}$ are above guideline levels. Such actions to prevent the infiltration of ambient PM$_{2.5}$ may include immediate actions by staff and students or long-term policy measures, such as updating school buildings and equipment. Such measures are particularly important when levels of fine particulate matter peak acutely, and consistent and scientifically based guidelines are needed to inform proactive interventions and policy measures to protect children from severe levels of exposure [23]. Consequently, it is important to understand how indoor early learning microenvironments protect children from outdoor PM$_{2.5}$, as well as the factors that affect indoor PM$_{2.5}$ levels and the infiltration of outdoor PM$_{2.5}$ into these locations.

To inform appropriate research and policy responses to indoor PM$_{2.5}$ pollution, this systematic review summarises the associations between factors that affect the infiltration or emissions of indoor air pollution, with either indoor PM$_{2.5}$ concentrations or indoor/outdoor (I/O) relationships that are documented in indoor air pollution monitoring studies of early learning microenvironments worldwide.

2. Methods

The PRISMA protocol was used for this review [24]. A literature search was completed using the Web of Science and Scopus databases for studies conducted between August 2001–February 2020 using variations of the following search terms: I/O, indoor, outdoor, PM, school, air pollution, air quality; and, terms for relevant variables including: building, activity and meteorology (the full list is included in supplementary table S1 (https://stacks.iop.org/ERL/15/115003/mmedia)). Studies reviewed in four prior narrative reviews of air quality in indoor microenvironments were included in the list of initial studies for review [25–28].

To filter the initial search results, we used three criteria that each study needed to fulfil for it to be included in the final review. These criteria were that the study had to: measure PM$_{2.5}$ in indoor early learning microenvironments, for example, classrooms, pre-schools, and other rooms within these environments including school gyms, offices and art rooms; measure the relationship between indoor and outdoor PM$_{2.5}$ concentrations; and, investigate the associations between factors affecting the infiltration or emission of indoor air pollution with indoor PM$_{2.5}$ concentrations or I/O relationships of PM$_{2.5}$. After removing duplicate studies, we reviewed the studies' abstracts to ensure they fulfilled these criteria. Only papers that clearly failed to fulfil the criteria, either by failing to monitor a relevant microenvironment, air pollutant particle size fraction, or failing to analyse relevant influencing variables were excluded. We carried out full-text review of the remaining studies. Many of these studies were excluded because they investigated influencing factors irrelevant to our study, inappropriate particle size fractions (only PM$_{10}$ or Ultrafine particles) or lacked investigation of I/O PM$_{2.5}$ relationships. We included studies that measured size fractions that were both finer and overlapping with PM$_{2.5}$, for example, studies that measured concentrations of particulate matter between 0–0.5, 0.5–1, 1–2 and 2–3 micrometers [29, 30]. We also included studies that did not comprehensively measure indoor or outdoor PM$_{2.5}$ but either conducted a relevant controlled intervention study, or applied a high value statistical analysis of variables that were relevant, unique and rarely considered in the literature [31, 32]. Finally, we removed results that were not published journal articles (for example conference papers and lecture notes) and seemingly duplicate studies (or those that provided very similar analyses to each other).

We developed a custom grading system to score these studies as we were unable to use existing grading systems, such as GRADE [33] or EPHPP [34], due to their design which is more applicable to epidemiological studies that typically include randomised trials. In contrast, air pollution monitoring studies are almost entirely observational studies, because they can rarely use control populations due to concerns with data collection and ethics. Our custom grading system is better suited to scoring air pollution monitoring studies, which graded observational studies and controlled interventions based on the value of their statistical analysis, as detailed in table 1. Multiple factors were assessed regarding the value of the analysis presented in each study. Higher
value analyses were defined as either being a controlled intervention or an observational study which included: a large number of monitored rooms; high-quality statistical analysis; analysis of multiple relevant variables; multiple monitoring campaigns across different seasons; and, finer temporal scales of analysis. In contrast, low value analyses were defined as observational studies with: either no statistical analysis or low quality analysis; few rooms monitored, even if in different schools; only one monitoring campaign; and, a coarse temporal analysis scale. Medium value analyses were defined by this system as those that had a combination of high and low value characteristics.

3. Results

The initial search resulted in 1282 papers of which 66 were included in the final review (the full breakdown was based off the PRISMA protocol and is shown in figure 1). These 66 studies were graded according to the system in table 1. Fifteen studies scored level 1, 33 studies scored level 2, and 18 studies scored level 3, as most were observational studies which undertook a medium value statistical analysis of influential factors.

Of the reviewed studies, almost half (31 out of 66) were conducted in European countries, with 16 in Asia (six in India and five in China), eight in the Middle East, seven in North America, and two each in South America and the Pacific region (including one in Australia). The average concentration of indoor PM$_{2.5}$ in early learning microenvironments across all studies was 43.83 µg m$^{-3}$, with over 53% of studies with average PM$_{2.5}$ concentrations above the WHO guideline for 24-h mean PM$_{2.5}$ of 25 µg m$^{-3}$ [22]. The highest concentrations of indoor PM$_{2.5}$ were in the Middle East and Asia and the lowest in the Pacific region and North America, although these continents also had a low number of studies (table 2). In a number of cases, studies within the same country analysed PM$_{2.5}$ levels from the same schools or study area. Most studies also analysed a small number of schools and classrooms, with 43 out of 66 studies monitoring 4 or less schools, and 41 out of 66 studies monitoring less than 10 rooms in early learning microenvironments.

We found that 40 studies used only monitors that applied optical methods to measure PM$_{2.5}$ concentrations, compared to 19 studies that used only gravimetric methods to measure PM$_{2.5}$, five studies which used both, and two studies that used tapered element oscillating microbalance methods. However, many studies calibrated their measurements by comparing them to gravimetric methods first. There was evidence that a large number of studies (32 studies) used high-cost equipment, compared to four studies which used mid or low-cost equipment, although there were a large number of studies (31 out of 66) where the cost or quality of equipment used was unclear, due to a lack of information or discontinued products. Fifty-five studies investigated the influence of various characteristics on indoor PM$_{2.5}$ concentrations. Of these, 41 conducted some form of statistical analyses that measured if there were significant changes in PM$_{2.5}$ concentrations associated with relevant classroom characteristics. Twenty-one studies investigated I/O ratios and/or correlations, including seven which conducted statistical analyses investigating associations between I/O relationships with relevant characteristics. These statistical analyses included measures of linear correlations between continuous variables of classroom characteristics and PM$_{2.5}$ variables, including Spearman’s rank correlation coefficients [35], Pearson’s r correlation coefficients [36] and multivariate linear regressions [37]. In addition, they included methods that measured if there were significant differences in PM$_{2.5}$ levels between categorical variables of classroom characteristics, such as differences in PM$_{2.5}$ levels between occupied and unoccupied classrooms. These methods included t-tests [38], Wilcoxon rank sum tests [39] and Kruskall–Wallis tests [40] among others.

3.1. Seasonality

Twenty-four studies examined associations between seasonality and PM$_{2.5}$ concentrations, I/O ratios or I/O correlations. Five of these studies were level 1 quality, 14 were level 2, 5 were level 3 and nine studies used statistical analysis. Out of the studies that conducted a statistical analysis, six found statistically significant differences in indoor PM$_{2.5}$ concentrations by season [37, 38, 41–43]. Only one study statistically analysed differences in I/O ratios, and it found no significant change in I/O ratios by season [44]. A number of level 2 and 3 studies that did not perform a statistical analysis on seasonality found considerable differences in PM$_{2.5}$ concentrations and I/O ratios between seasons by comparing mean values [45–47]. There was insufficient evidence to determine if associations between season and PM$_{2.5}$ varied by geography.

3.2. Meteorology

Twenty-three studies assessed the associations between meteorological variables and PM$_{2.5}$, with 19 studies analysing them statistically. Seven of these studies were graded as level 1, 14 were level 2 and 2 were level 3. Temperature was the most analysed variable, with similar numbers assessing indoor and outdoor temperature, as shown in table 3. Indoor and outdoor relative humidity and outdoor wind speed were among the most analysed meteorological variables after temperature. Most studies found significant associations between outdoor temperature [38, 40, 41, 48–55], indoor relative humidity [35, 37, 40, 45, 48, 50–53, 56] and wind speed [32, 38, 40, 50–54] with indoor PM$_{2.5}$ concentrations. Approximately half of the statistical analyses
Table 1. Grading system for studies assessed in this review.

| Score | Type of study |
|-------|---------------|
| 1     | Controlled study with statistical analysis of specific interventions with indoor PM$_{2.5}$ concentrations or I/O relationships OR observational study with high value statistical analysis of associations between relevant variables with indoor PM$_{2.5}$ concentrations or I/O relationships |
| 2     | Observational study with medium value statistical analysis of associations between relevant variables with indoor PM$_{2.5}$ concentrations or I/O relationships |
| 3     | Observational study with low value statistical analysis of associations between relevant variables with indoor PM$_{2.5}$ concentrations or I/O relationships OR observational study with quantitative comparison of indoor PM$_{2.5}$ concentrations or I/O relationships with different relevant variables and no statistical analysis |

Figure 1. Flow diagram of review process for selecting and excluding studies.

of indoor temperature [37, 40, 48, 50, 52, 53, 56] and outdoor relative humidity [38, 45, 48, 50, 54, 55] were found significant associations with indoor PM$_{2.5}$ concentrations. The direction (positive or negative) of associations for each of these variables with PM$_{2.5}$ was not consistent across studies, and there was no discernible geographical pattern to these relationships. There was, however, evidence in four studies that associations between these variables on PM$_{2.5}$ concentrations varied with seasonality [50–53]. Wind direction [32, 38, 51], solar radiation [38, 57], ventilation coefficients [45, 55], atmospheric pressure [32, 38] and precipitation [32, 38, 54, 57] were analysed in a small number of studies, with
minimal evidence of significant associations with measures of PM$_{2.5}$.

### 3.3. Activity
Thirty-six studies examined associations between children’s activity inside of early learning microenvironments and PM$_{2.5}$ concentrations or I/O ratios, although of these, only 15 used statistical analyses. Six of these studies were graded as level 1, 14 were level 2 and 16 studies were level 3. Twenty-eight studies (2 graded as level 1, 11 level 2 and 15 level 3) analysed the impact of activity on PM$_{2.5}$ levels by comparing indoor PM$_{2.5}$ concentrations when classrooms were either occupied or unoccupied. Of these 28 studies, eight included statistical analyses. Approaches to measures of occupancy included: comparisons of PM$_{2.5}$ levels between teaching and non-teaching hours [32]; differences between day and night time [58]; weekdays and weekends [46]; or, school days and holidays [59]. There was evidence in some level 2 and level 3 studies that occupancy affected PM$_{2.5}$ concentrations [38, 59, 60], I/O ratios [32, 61] and I/O correlations [32, 62], but there was little significant statistical evidence to confirm these findings. Statistically significant associations were documented between other measures of activity and indoor PM$_{2.5}$ concentrations, including number of students [30, 63] and the cleaning frequency of classrooms [37, 63]. The most frequently used measure of activity was the students’ class/year, which was effectively using students’ ages as a proxy for activity level [37, 40, 63–65]. This proxy was used in five studies, and there was some evidence of statistically significant associations between this measure and indoor PM$_{2.5}$ concentrations in each of them. The direction of this relationship was inconsistent, however, with neither younger nor older children consistently experiencing higher (or lower) indoor PM$_{2.5}$ concentrations. Overall, higher levels of occupancy and activity tended to increase I/O ratios and PM$_{2.5}$ concentrations but decrease the correlation between indoor and outdoor concentrations, although there was weak evidence overall that these associations were statistically significant. In contrast, there was stronger evidence that occupancy affected coarser particulate sizes, such as PM$_{10-2.5}$ [30, 56, 58, 62, 66, 67].

### 3.4. Site characteristics
Forty-two studies analysed the associations between site characteristics and indoor PM$_{2.5}$ concentrations or I/O relationships (15 of these studies were graded as level 1, 18 were level 2 and 11 were level 3). Of these, 26 studies applied statistical analyses, 22 studies (7 level 1, 9 level 2, 6 level 3) assessed the associations between building characteristics and PM$_{2.5}$, and 26 studies (8 level 1, 12 level 2, 6 level 3) assessed the associations between surrounding site characteristics and PM$_{2.5}$, these characteristics and variables are listed in table 4.

At least one variable from all building characteristics was significantly associated with indoor PM$_{2.5}$ concentration. However, each site characteristic and its specific variables were only analysed in a small number of studies. The most analysed building characteristic variables were floor material [37, 63, 70] and floor level [37, 40, 45, 63, 71]. These variables were analysed in three and five studies respectively and each variable had significant associations with PM$_{2.5}$ in two studies. We included two controlled intervention studies in our review which examined the effect of ventilation interventions on indoor PM$_{2.5}$ concentrations [72, 73]. These studies compared indoor air quality when high-quality air filters were installed in classroom ventilation systems and found significant decreases in PM$_{2.5}$ concentrations and I/O ratios as a result of this intervention. Three other observational studies examining the effect of ventilation characteristics, including comparisons of natural and mechanical ventilation systems, did not find significant results [37, 40, 68].

Air pollution source proximity characteristics, such as road traffic, had slightly more consistent associations with PM$_{1.5}$ associations across their analysed variables [31, 37, 42, 54, 74] compared to other surrounding site characteristics such as urbanicity, as shown in table 4. However, these results did not show consistent associations between source proximity characteristics and indoor PM$_{2.5}$ concentrations or I/O relationships. Evidence presented in several studies showed that associations between site characteristics and PM$_{2.5}$ concentrations varied by occupancy [30, 37, 72, 73], but these results were not sufficient to demonstrate consistent patterns.

### 3.5. Ventilation
Ventilation rates are measures of the movement of outdoor air to indoors. Sixteen studies assessed the association between ventilation rates and PM$_{2.5}$ concentration or I/O ratios, with nine studies applying statistical analyses (five of these studies were level 1, 8 were level 2 and 3 were level 3). The

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**Table 2. Mean indoor PM$_{2.5}$ concentrations.**

| Continent     | Mean PM$_{2.5}$ (µg m$^{-3}$) | Number of studies |
|---------------|-------------------------------|-------------------|
| Asia          | 71.76                         | 14 (16)$^a$       |
| Europe        | 33.98                         | 26 (31)           |
| Middle East   | 78.31                         | 8 (8)             |
| North America | 9.72                          | 7 (7)             |
| Pacific       | 6.7                           | 1 (2)             |
| South America | 12.03                         | 1 (2)             |
| Overall       | 43.83                         | 57 (66)           |

$^a$ The number of studies which explicitly included their mean concentration and, therefore, were used to calculate the mean indoor PM$_{2.5}$ concentration are listed in each cell, with the total number of studies from each continent listed in brackets.
### Table 3. Results of statistical analyses of associations between meteorological variables and measures of PM$_{2.5}$ concentrations or I/O ratios.

| Study author(s)       | Grading | Dependent Variable | Notes                                | Methods | T\(_{in}\) | T\(_{out}\) | RH\(_{in}\) | RH\(_{out}\) | WS | WD | AP | Prec. | VC | SR |
|-----------------------|---------|--------------------|--------------------------------------|---------|-----------|-----------|-----------|-----------|----|----|----|-------|----|----|
| Canha et al 2016 [68] | 1       | Indoor PM$_{2.5}$  | Specific humidity measured instead of relative humidity | BC      | X\(^a\)   | X         |           |           |     |    |    |       |    |    |
| Branco et al 2019 [37]| 1       | Indoor PM$_{2.5}$  | Direction of Associations not shown in results | BC (non-occupied) | ✓          | ✓         |           |           |     |    |    |       |    |    |
|                       |         |                    |                                       | BC (occupied)    | X          | ✓         |           |           |     |    |    |       |    |    |
|                       |         |                    |                                       | MVR (non-occupied) | X          | X         |           |           |     |    |    |       |    |    |
|                       |         |                    |                                       | MVR (occupied)   | X          | X         |           |           |     |    |    |       |    |    |
| Madureira et al 2016 [35] | 1     | Indoor PM$_{2.5}$  |                                       | BC      | X         | ✓        | ✓         |           |     |    |    |       |    |    |
| Alves et al 2013 [36]  | 1       | Indoor PM$_{2.5}$  |                                       | BC      | X         | ✓        | ✓         |           |     |    |    |       |    |    |
| Majd et al 2019 [40]   | 1       | Indoor PM$_{2.5}$  |                                       | BC      | ✓+        | ✓+       | ✓+        | X         | ✓   |    |    |       |    |    |
| Dorizas et al 2013 [48]| 1       | Indoor PM$_{2.5}$  | T\(_{in}\) and T\(_{out}\) not measured as separate variables | MVR     | X         | X         |           |           |     |    |    |       |    |    |
| Halek et al 2013 [69]  | 2       | Indoor PM$_{2.5}$  | T\(_{in}\)—T\(_{out}\) the specific variable measured | MVR     | X         | X         |           |           |     |    |    |       |    |    |
| Mohammadyan et al 2017 [49] | 2     | Indoor PM$_{2.5}$  |                                       | MVR     | ✓         | ✓         | ✓         | X         |     |    |    |       |    |    |
| Elbayoumi et al 2015 [50] | 2     | Indoor PM$_{2.5}$  |                                       | MVR     | ✓         | ✓         | ✓         | X         |     |    |    |       |    |    |
|                       |         |                    |                                       | BC (Fall) | X         | X         | X         | X         | ✓   |    |    |       |    |    |
|                       |         |                    |                                       | BC (Winter)   | ✓         | ✓         | ✓         | ✓         |     |    |    |       |    |    |
|                       |         |                    |                                       | BC (Spring)   | X         | X         | ✓         | X         |     |    |    |       |    |    |
|                       |         |                    |                                       | MVR (Fall)    | X         | X         | ✓         | X         |     |    |    |       |    |    |
|                       |         |                    |                                       | MVR (Winter)  | ✓         | X         | X         | ✓         |     |    |    |       |    |    |
|                       |         |                    |                                       | MVR (Spring)  | X         | X         | X         | X         |     |    |    |       |    |    |
| Lv et al 2019 [51]    | 2       | Indoor PM$_{2.5}$  | Variables with the most influence in the | MVR (non-heating season) | X         | X         | ✓         | ✓         | X   |    |    |       |    |    |
|                       |         |                    |                                       | MVR (heating season) | X         | ✓         | ✓         | X         | X   |    |    |       |    |    |
| Raysoni et al 2016 [57]| 2     | Indoor PM$_{2.5}$  | MVR listed in green—statistical significance was not measured | BC      | X         | ✓        | ✓         | ✓         | X   |    |    |       |    |    |
|                       |         |                    |                                       | BC (Fall)    | X         | X         | ✓         | ✓         | X   |    |    |       |    |    |
|                       |         |                    |                                       | BC (Spring)  | X         | X         | ✓         | X         |     |    |    |       |    |    |
| Elbayoumi et al 2014 [52] | 2     | Indoor PM$_{2.5}$  |                                       | MVR (Overall) | ✓         | ✓         | ✓         | X         |     |    |    |       |    |    |
|                       |         |                    |                                       | MVR (Fall)   | ✓         | ✓         | ✓         | X         |     |    |    |       |    |    |
|                       |         |                    |                                       | MVR (Winter) | ✓         | ✓         | ✓         | X         |     |    |    |       |    |    |
|                       |         |                    |                                       | MVR (Spring) | X         | X         | X         | X         |     |    |    |       |    |    |
### Table 3. (Continued.)

| Study author(s)                  | Grading | Dependent Variable | Notes                                                                 | Methods                        | $T_{\text{in}}$ | $T_{\text{out}}$ | RH$_{\text{in}}$ | RH$_{\text{out}}$ | WS | WD | AP | Prec. | VC | SR |
|----------------------------------|---------|--------------------|----------------------------------------------------------------------|-------------------------------|-----------------|-----------------|-----------------|-----------------|----|----|----|------|----|----|
| Branis et al 2009 [53]           | 2       | Indoor PM$_{2.5}$  |                                                                       | BC (Overall)                  | $X$             | $\checkmark$   | $\checkmark$   | $X$             |    |    |    | $X$   |    |    |
|                                  |         |                    |                                                                       | BC (Heating season)            | $X$             | $\checkmark$   | $X$             | $X$             | $\checkmark$ |    |    |    |      |    |    |
|                                  |         |                    |                                                                       | BC (Non-heating season)        | $\checkmark$     | $\checkmark$   | $\checkmark$   | $X$             |    |    |    | $X$   |    |    |
| Ward et al 2013 [54]             | 2       | Indoor PM$_{2.5}$  |                                                                       | BC (Elementary School)         | $\checkmark$     | $\checkmark$   | $\checkmark$   | $\checkmark$   |    |    |    | $X$   |    |    |
|                                  |         |                    |                                                                       | BC (Middle School)             | $X$             | $X$             | $X$             | $X$             | $X$ |    |    | $X$   | $X$ |    |
| Chithra and Nagendra 2014 [38]   | 2       | Indoor PM$_{2.5}$  | Statistical significance not measured—only strength of associations with PM$_{2.5}$ | BC                            | $\checkmark$     | $\checkmark$   | $\checkmark$   | $X$             |    |    |    | $X$   |    | $X$ |
| Razali et al 2015 [56]           | 2       | Indoor PM$_{2.5}$  |                                                                       | BC                            | $\checkmark$     | $\checkmark$   | $\checkmark$   | $\checkmark$   |    |    |    | $X$   |    |    |
| Kovačević et al 2015 [32]        | 2       | Outdoor PM$_{2.5}$ |                                                                       | BC                            | $X$             | $\checkmark$   | $\checkmark$   | $\checkmark$   |    |    |    | $X$   |    |    |
| Wang et al 2017 [55]             | 2       | Indoor PM$_{2.5}$  |                                                                       | BC                            | $\checkmark$     | $\checkmark$   | $\checkmark$   | $\checkmark$   |    |    |    | $X$   |    | $X$ |

Number of studies examined (number of studies with statistically significant results):

|                       | 12(6) | 14(10) | 12(10) | 12(6) | 11(8) | 3(0) | 3(0) | 4(1) | 2(1) | 2(0) |

**Abbreviations:** $T_{\text{in}}$—Indoor Temperature; $T_{\text{out}}$—Outdoor Temperature; RH$_{\text{in}}$—Indoor Relative Humidity; RH$_{\text{out}}$—Outdoor Relative Humidity; WS—Wind Speed; WD—Wind Direction; AP—Atmospheric Pressure; Prec.—Precipitation; VC—Ventilation Coefficient; SR—Solar Radiation; I/O PM$_{2.5}$—Indoor/Outdoor ratio of PM$_{2.5}$; BC—Bivariate Correlation; MVR—Multivariate Regression

* $X$—Not statistically significant; $\checkmark$—Statistically significant; $\checkmark+$—Positive association; $\checkmark-$—Negative association; Empty cells indicate variables were not analysed in that study.
most analysed variable was carbon dioxide (CO₂) concentration, which was used as an inverse measure of ventilation rates and was statistically analysed in nine studies, as shown in table 3. Seven of these nine studies found statistically significant associations between indoor CO₂ and PM₂.₅ concentrations [36, 37, 50, 52, 56, 63, 68]. In three of them, associations between indoor CO₂ and PM₂.₅ varied depending on season and whether classrooms were occupied or not [37, 50, 52]. Overall, the associations between indoor CO₂ and PM₂.₅ concentrations were generally positive and statistically significant. Other measures of ventilation, including ventilation rates and ‘air stuffiness’ (which is defined by the amount of time that levels of CO₂ in a room are above or below defined threshold values) [68] were significantly associated with PM₂.₅ concentration. These associations were either investigated in a very small number of studies or were affected by season, with the direction of these associations found to be inconsistent between the studies [50, 52, 75]. Air exchange rates were also analysed in one study, but no significant associations were found between any of the three measures of air exchange rates and indoor PM₂.₅ concentrations [68].

4. Discussion

Historically, outdoor air pollution measurements have been used to inform decisions regarding exposure to indoor air pollution, despite the obvious shortcomings of this approach. With a significant body of evidence building that identifies health impacts from exposure to increasingly lower levels of air pollution, policy-makers and decision-makers must have reliable evidence-based guidance about how best to reduce indoor air pollution. This advice is particularly important for early learning microenvironments because children spend a significant percentage of their developmental years inside school buildings and they are highly vulnerable to air pollution. In order to provide such evidence enabling effective measures to reduce children’s exposure to indoor air pollution, this systematic review sought to document factors impacting indoor air quality in early learning microenvironments. This review focused on factors related to the emission, infiltration and re-suspension of air pollution indoors, and their associations with indoor PM₂.₅ concentrations and I/O relationships, documented by existing research.

This systematic review found that there is weak evidence that seasonality, meteorology, activity, site characteristics and ventilation are associated with indoor PM₂.₅ concentrations, and very weak evidence of associations with I/O ratios or I/O correlations. Results from the current body of research on air quality in early learning microenvironments show insufficient and inconsistent evidence of associations between relevant factors with measures of indoor PM₂.₅.

Weak evidence of associations overall is partly due to the small number of studies with high-quality statistical analysis, which is exacerbated by variation and inconsistencies in methodologies and variables analysed. There is also evidence from a small number of studies that associations between microenvironment characteristics and PM₂.₅ levels may vary with the influence of season, activity or other factors. This may relate to the influence of contextual factors as associations between environmental or building factors and PM₂.₅ likely vary between countries, and to some extent, within countries as seasonal conditions, building standards and sources will vary considerably between and within countries. However, too few studies were conducted and results were too inconsistent for these patterns to be adequately examined.

Despite these shortcomings, these findings still provide some guidance to decision-makers seeking to reduce children’s exposure to air pollution. There were certain variables that had stronger evidence of associations with indoor PM₂.₅ concentrations compared to others. For example, although there was some variation in results across different measures, there was evidence that ventilation, particularly measured by indoor CO₂ concentrations, was inversely associated with indoor PM₂.₅ concentrations. There was also some robust evidence that the installation of high-quality filters in ventilation systems reduced indoor PM₂.₅ concentrations and I/O ratios, which was found in two controlled intervention studies, the only non-observational studies reviewed. These findings indicate that increased ventilation in early learning environments is likely to reduce indoor air pollution. There was also relatively consistent evidence of significant associations between certain meteorological variables with indoor PM₂.₅ concentrations, specifically outdoor temperature, indoor relative humidity and outdoor wind speed, although the direction of these associations were inconsistent across studies. Associations between indicators of activity and PM₂.₅ concentrations or I/O ratios, in contrast, had a notably consistent positive direction, suggesting that increased indoor activity increases air pollution levels through the re-suspension of air pollution deposited indoors. Despite this, there was weak evidence of statistically significant associations. In addition, even for variables with the most substantial evidence of associations with PM₂.₅, there was still insufficient evidence of consistent and significant associations between these variables with indoor PM₂.₅ concentrations in early learning microenvironments.

Beyond these general insights, the shortcomings of this current body of research highlights an important, if underappreciated, area of air pollution research that can be partly addressed with the relatively recent
Table 4. Statistically analysed site characteristics and the variables used to measure them.

| Category of characteristic | Characteristic                      | Variables analysed<sup>ab</sup>                                                                 |
|-----------------------------|-------------------------------------|-----------------------------------------------------------------------------------------------|
| Building characteristics    | Floor                               | Floor material ( Carpets v non-carpets )<sup>+</sup>                                          |
|                             | State of room/building              | Signs of dampness, building defects, Signs of cracks, Age of building<sup>+</sup>; Building type |
|                             | Ventilation type                    | Ventilation intervention ( upgraded mechanical ventilation )<sup>+</sup>; Ventilation system (mechanical v. natural); Air purifier<sup>−</sup>; Room AC; Number of open windows; Total area of windows; Total area of doors |
|                             | Room size                           | Classroom volume<sup>−</sup>; Classroom area; Number of students<sup>+</sup>                   |
|                             | Blackboard                          | Board type (black v whiteboard); Presence of blackboard<sup>✓</sup>                           |
|                             | Room position                       | Floor level<sup>+</sup>; Adjacent to playground; Adjacent to street; Distance to outdoor; Distance to inside door |
|                             | Other room features                 | Roof type (Green v. Concrete roof); Playroom inside room; Age group<sup>±</sup>; Heating     |
|                             | Proximity to sources—Traffic        | Distance to roads; Distance to major roads<sup>−</sup>; Time downwind to major roads; Traffic density; Truck density<sup>+</sup>; Car density |
|                             | Proximity to sources—Other          | Proximity to Industrial sites; Surrounding Greenspace<sup>−</sup>; Residential stovereplacement intervention (measured in years)<sup>−</sup> |
|                             | Urbanicity                          | Urban v semi-rural; Urban v suburban                                                        |
|                             | Other surroundings                  | Spatial variation<sup>✓</sup>; School type (Elementary v. Nursery)                          |

<sup>a</sup> Bold variables are those that were found to have a statistically significant association in at least one study

<sup>b</sup> (+) — positive association; (−) — negative association; (√) — direction not given;

<sup>c</sup> Significantly associated with indoor PM<sub>2.5</sub> concentration

<sup>d</sup> Significantly associated with I/O ratio
of air purifiers, mechanical ventilation systems and children's exposure to air pollution, such as the use of various measures for reducing children's air pollution levels can be reduced by increasing mechanical ventilation with a filter and decreasing children's levels of activity in classrooms (although contextual factors, there was weak evidence of associations between seasonal and other factors, and whether these associations vary spatially. Once identified, these factors and relationships could be used to inform policy decisions that would enable better protection of the health of children in early learning microenvironments from chronic and acute air pollution episodes.

5. Conclusion

As shown by this review, such analyses are also needed to address limitations in our current understanding of the associations between various factors and indoor PM$_{2.5}$ levels in early learning environments. Particular attention is needed as to how associations between variables and indoor PM$_{2.5}$ or I/O relationships change with seasonal and other factors, and whether these associations vary spatially. Once identified, these factors and relationships could be used to inform policy decisions that would enable better protection of the health of children in early learning microenvironments from chronic and acute air pollution episodes.

Table 5. Statistically calculated associations between ventilation measures and indoor PM$_{2.5}$ concentrations.

| Study author(s) | Grading | Methods | CO$_2$ (in) | CO$_2$ (out) | VR | Other Measures |
|-----------------|---------|---------|------------|-------------|-----|----------------|
| Canha et al 2016 [68] | 1 | BC | ✓ + | ✓ − | ICONE ✓ +; AER X; nAER X; wAER X |
| Branco et al 2019 [37] | 1 | BC (occupied) | X | | |
| | | BC (non-occupied) | ✓ | | |
| | | MVR (occupied) | NA | | |
| | | MVR (non-occupied) | ✓ | | |
| Madureira et al 2016 [35] | 1 | BC | X | | |
| Alves et al 2013 [36] | 1 | BC | ✓ + | | |
| Dorizas et al 2013 [48] | 1 | BC | X | | |
| Habil and Taneja 2011 [75] | 2 | BC (Winter) | ✓ + | | |
| | | BC (Summer) | ✓ + | | |
| Elbayoumi et al 2015 [50] | 2 | BC (Fall) | ✓ − | X | ✓ − |
| | | BC (Winter) | ✓ − | X | ✓ + |
| | | BC (Spring) | ✓ − | X | ✓ |
| | | MVR (Fall) | X | X | X |
| | | MVR (Winter) | X | X | ✓ + |
| | | MVR (Spring) | ✓ − | X | |
| Abdel-Salem 2019 [63] | 2 | BC | ✓ + | | |
| Elbayoumi et al 2014 [52] | 2 | BC | ✓ + | ✓ + | ✓ − |
| | | MVR (Winter) | X | X | ✓ + |
| | | MVR (Spring) | X | ✓ − | X |
| | | MVR (Overall) | X | X | ✓ + |
| Razali et al 2015 [56] | 2 | BC | ✓ + | | |

Abbreviations: CO$_2$ (in) — Indoor CO$_2$; CO$_2$ (out) — Outdoor CO$_2$; VR — Ventilation Rates; ICONE — ICONE (Indice de CONfinement d’air dans les Ecoles) air stuffiness index; AER — Air Exchange Rate; nAER — Night time Air Exchange Rate; wAER — Average School Week Air Exchange Rate; BC — Bivariate Correlation; MVR — Multivariate Regression

a ✓ — Statistically significant; ✓ + — Positive association; ✓ − — Negative association; X — Not statistically significant

b NA — Not tested in MVR due to lack of statistical significance in bivariate analysis

development of smaller, low-cost air pollution monitors that could be deployed inside and outside early learning environments [76]. A considerable hurdle in previous air quality research has been the deployment of indoor and outdoor monitors across multiple locations because, historically, monitors have been prohibitively expensive and therefore typically deployed sparingly in indoor environments. With low-cost monitors becoming increasingly accessible and reliable, there is a greater ability to develop a real-time network of indoor and outdoor air pollution sensors in early learning microenvironments using comprehensive statistical analyses for validation. This in turn provides the means for air quality researchers to accurately assess children's air pollution exposure on a population-wide level and for policy-makers to develop locally relevant guidance for decision-makers.

While population-wide measures of children’s exposure to air pollution are important for public health policy, the use of low-cost sensors could be especially important for conducting a large number of robust analyses of associations between influential factors and indoor and outdoor PM$_{2.5}$ concentrations. Such analyses are necessary for assessing the suitability of various measures for reducing children's exposure to air pollution, such as the use of air purifiers, mechanical ventilation systems and classroom floor materials, among other measures.
acknowledging the difficulty of decreasing this latter measure), which may be of use to policy-makers and decision-makers. However, more robust indoor monitoring studies, using larger monitoring networks and more comprehensive statistical analyses, are needed to accurately quantify associations between classroom characteristics and indoor air quality, before reliable guidance can be provided to decision-makers about reducing children's exposure to PM_{2.5}. The need for these studies, which has become increasingly viable through the greater accessibility of low-cost sensors, is likely to be of growing importance as climate extremes may increase acute episodes of outdoor air pollution, which, if unchecked are likely to increase this health burden.

Data availability statement

No new data were created or analysed in this study.

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Author contributions

NC had full access to all of the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis. Concept and design: NC, DG. Acquisition, analysis, or interpretation of data: NC. Drafting of the manuscript: NC, DG. Critical revision of the manuscript for important intellectual content: NC, DG, YG, SV. Administrative, technical, or material support: DG, YG, SV. Supervision: DG

Conflicts of interest

There are no conflicts of interest to report.

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