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Ventilation indices for evaluation of airborne infection risk control performance of air distribution

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A R T I C L E   I N F O

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A B S T R A C T

Air distribution is an effective engineering measure to fight against respiratory infectious diseases like COVID-19. Ventilation indices are widely used to indicate the airborne infection risk of respiratory infectious diseases due to the practical convenience. This study investigates the relationships between the ventilation indices and airborne infection risk to suggest the proper ventilation indices for the evaluation of airborne infection risk control performance of air distribution. Besides the commonly used ventilation indices of the age of air (AoA), air change effectiveness (ACE), and contaminant removal effectiveness (CRE), this study introduces two ventilation indices, i.e., the air utilization effectiveness (AUE) and contaminant dispersion index (CDI). CFD simulations of a hospital ward and a classroom served by different air distributions, including mixing ventilation, displacement ventilation, stratum ventilation and downward ventilation, are validated to calculate the ventilation indices and airborne infection risk. A three-step correlation analysis based on Spearman’s rank correlation coefficient, Pearson correlation coefficient, and goodness of fit and a min-max normalization-based error analysis are developed to qualitatively and quantitatively test the validity of ventilation indices respectively. The results recommend the integrated index of AUE and CDI to indicate the overall airborne infection risk, and CDI to indicate the local airborne infection risk respectively regardless of the effects of air distribution, supply airflow rate, infectivity intensity, room configuration and occupant distribution. This study contributes to airborne transmission control of infectious respiratory diseases with air distribution.

1. Introduction

Indoor air quality influences human health. The biological contaminants compose a part of the indoor environment [1], thus leading to consequences on the health of the occupants who expose to the indoor environment, e.g., allergy, asthma [2], and the transmission of SARS-CoV-2 [3], etc. Air distribution (ventilation) greatly influences indoor air quality and has been recognized as a valid engineering approach for the COVID-19 pandemic control [4]. Therefore, evaluating the airborne infection risk control performance of air distribution has become necessary.

The assessment of the infection risk control performance of air distribution can proceed from the exposure-based methods and the ventilation index-based methods. The exposure-based methods evaluate the airborne infection risk control performance by comparing the exposure-based values, such as airborne infection risk and intake fraction under different air distributions. The dose-response and Wells-Riley models [5] are widely used to predict airborne infection risk, requiring the epidemiological parameters, e.g., infectious dose data and the quantum generation rate, respectively. The intake fraction is the ratio of the inhaled bioaerosol quantity to that exhaled by the infector [5]. Xu et al. [6] investigated the performance of intake fraction and airborne infection risk for COVID-19 control assessment of personal ventilation. Compared with the intake fraction, the dose-response model can indicate the infection risk growth with the cumulative exposure time and increased infectious dose data. However, acquiring infectious dose data for the dose-response model is difficult because it needs high-risk animal experiments, and there are differences among airways of different species.

Abbreviations: ACE, Air change effectiveness; AoA, Age of air; AUE, Air utilization effectiveness; CDI, Contaminant dispersion index; CRE, Contaminant removal effectiveness; DV, Displacement ventilation; DWV, Downward ventilation; MAE, Mean absolute error; MV, Mixing ventilation; SV, Stratum ventilation.

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The Wells-Riley model and its variations are commonly used for evaluating infection risk in ventilated rooms [8–10]. The quantum generation rate for the Wells-Riley model can be estimated with the known number of infectors, the number of susceptible infection cases, room ventilation rate, pulmonary ventilation rate, and exposure time [11] in an outbreak. However, the quantum generation rate is highly dependent on the activity levels and the virus properties [12]. For example, there is a wide range instead of a specific value for the SARS-CoV-2 quantum generation rate, e.g., 14-48 h⁻¹ estimated by Dai & Zhao [13] and 970 ± 390 h⁻¹ estimated by Miller et al. [14].

The ventilation index-based methods use ventilation indices to indicate the airborne infection risk control performance of air distribution in practice. The ventilation indices are influenced by the airflow pattern and supply airflow rate, in essence, requiring no epidemiological parameters, and thus are convenient to implement in practice [15,16]. There are common ventilation indices to evaluate the efficacy of air distribution, including the age of air (AoA), air change effectiveness (ACE), and contaminant removal effectiveness (CRE). The AoA and ACE quantify the air renewal ability of the ventilation system. The CRE quantifies the performance of the air distribution to exhaust contaminants from the breathing zone.

Although ventilation indices are widely used to indicate the airborne infection risk control performance of air distribution in practice because of their convenience, their applicability in evaluating the airborne infection risk control performance of air distribution is not yet clear. The monotonic relationship between the ventilation indices and airborne infection risk, particularly a linear relationship, makes the ventilation indices effectively indicate the airborne infection risk control performance of air distribution [19–23]. Novoselac and Srebric [17] found that ACE was less suitable for evaluating the air distribution with the known contaminated sources. The multi-indicator evaluation of Tian et al. [18] showed that the CRE outperformed the ACE in evaluating the overall indoor air quality. Zhang et al. [19] found a good correlation between the CRE and reciprocal of airborne infection risk. Villafuerta et al. [20] investigated the ventilation indices to evaluate both the overall and local airborne infection risk control performances of air distribution. The results showed a poor correlation between the ACE and the overall airborne infection risk and no correlation between the ACE and the local airborne infection risk. The CRE had monotonous correlations to the overall and local airborne infection risks, but the correlations were non-linear [20]. However, Villafuerta et al. [20] only considered two ventilation indices and two air distribution modes (with the supply air inlets at the floor level and exhausted air outlets at the ceiling level or supply air outlets at the ceiling level and exhausted air outlets at the floor level).

This study further validates the ventilation indices for airborne infection risk control performance evaluation and air distribution. Compared with the existing studies [19–23], the contributions of this study are as follows. First, as the ventilation indices are widely used to evaluate the airborne infection control performance of the air distribution, this study investigates the validity of using ventilation indices to indicate the airborne infection risk through the qualitative and quantitative analyses. Second, besides the common ventilation indices of AoA, ACE and CRE, this study introduces two more ventilation indices, i.e., the air utilization effectiveness (AUE) and contaminant dispersion index (CDI). Third, to assure the robustness of the ventilation indices in indicating the airborne infection control performance, this study considers different air distribution modes, i.e., mixing ventilation, displacement ventilation, stratified ventilation, and downward ventilation, under different supply airflow rates, different infectivity intensities, different room configurations and occupancy distributions. This study justifies that compared with the common ventilation indices of AoA, ACE and CRE, the AUE and CDI are more competent for airborne infection risk control performance evaluation of air distribution because of their high linearity with the airborne infection risk.

In Section 2.1, the AUE, CDI, and other commonly used ventilation indices are briefly explained, as well as the dilution-based expansion of the Wells-Riley model for airborne infection risk calculation. In Sections 2.3 and 2.4, a three-step correlation analysis and a min-max normalization-based error analysis are introduced to qualitatively and quantitatively analyze the relationship between the ventilation indices and airborne infection risk, respectively. In Section 2.4, the CFD model of a patient ward is developed for the calculation of the ventilation indices and airborne infection risk under different air distributions, supply airflow rates and infectivity intensities. Sections 3 presents the qualitative and quantitative analysis results. In Section 4, the validity of the ventilation indices for airborne infection risk control performance evaluation is discussed.

2. Methodology

2.1. Ventilation indices and airborne infection risk

This study develops the air utilization effectiveness (AUE) as an analogy to the thermal utilization effectiveness (a ventilation index regarding energy performance) [21]. AUE is the ratio of contaminant concentration change between the air exhaust and breathing zone to the contaminant concentration change between the air exhaust and air supply (Eq. (1)). AUE shows the efficiency of utilizing the fresh air to clean the breathing zone. A lower concentration in the breathing zone means better use of the clean air and a higher AUE.

\[
AUE = \frac{C_e - C_b}{C_i - C_e}
\]

Where \(C_i\) is the contaminant concentration of the exhausted air, ppm; \(C_b\) is the contaminant concentration of the breathing zone, ppm; \(C_e\) is the contaminant concentration of the supply air, ppm.

The contaminant dispersion index (CDI) is defined as the ratio of the standard deviation of the contaminant concentration at sampling points to the contaminant concentration of the contaminant source (Eq. (2)). A smaller CDI indicates a better contaminant dispersion ability.

\[
CDI = \frac{1}{C_{\text{source}}} \sqrt{\frac{\sum_{i=1}^{n} (C_i - \overline{C})^2}{n - 1}}
\]

Where \(C_{\text{source}}\) is the contaminant concentration of the contaminant source, ppm; \(C_i\) is the contaminant concentration at the \(i\)th sampling point, ppm; \(\overline{C}\) is the average contaminant concentration of the \(n\) sampling points, ppm.

The local mean age of air (AoA) is the average time needed for the air to reach the measured point from the air inlet [22]. The AoA is a straightforward indicator showing the freshness of the air. The AoA at the air inlet is zero. Lower age of air is preferred [23].

\[
AoA = \frac{1}{C_i(0)} \int_{0}^{\infty} C_i(t) dt
\]

Air change effectiveness (ACE) is the ratio of the volume-averaged air age of piston flow to the actual volume-averaged air age of the room [20].

\[
ACE = \frac{V}{2Q \cdot AoA}
\]

Where \(V\) is the room volume, m³; \(Q\) is the supply airflow rate, m³/s; \(AoA\) is the volume-averaged age of air of the investigated location.

The contaminant removal effectiveness (CRE) in the breathing zone (also termed zone air distribution effectiveness [24]) is the ratio of contaminant concentration change between the air supply and air exhaust to the contaminant concentration change between the air supply and the breathing zone.
\[ CRE = \frac{C_i - C_s}{C_s} \]  

Table 1 shows the implications of the ventilation indices. For AUE, if multiple breathing zones are of interest, the contaminant concentration of the breathing zone is represented by the average concentration of the multiple breathing zones. AUE less than zero indicates that the breathing zone is bypassed by the fresh air, resulting in the contaminant recirculating in the breathing zone. The negative AUE value closer to zero means the breathing zone is less bypassed, and the air distribution tends to be well-mixed. The value of AUE between zero and unity is preferable for the air distribution. A positive AUE value closer to unity indicates more clean air is supplied to the breathing zone. The AUE of the idealized personal ventilation is unity. The value of CDI shows the ratio of the standard deviation of the contaminant concentration at sampling points to the contaminant concentration at the source. CDI evaluates the air distribution from the perspective of the contaminant distribution uniformity. In a confined space, a higher value of CDI means a more drastic change in the contaminant concentration spatially, indicating a higher local contaminant concentration.

Knowing the mean and the maximum airborne infection risks in an indoor environment can capture the panorama of the airborne infection risk control performance of air distribution. The mean airborne infection risk shows the overall infection control performance of air distribution. The maximum airborne infection risk gives the highest probability of an occupant getting infected and shows the local infection control performance of the ventilation \[20\]. These two indices reflect the general risk control performance of air distribution.

With the known source concentration and target concentration, the airborne infection risk (\(P_i\)) can be predicted by the expansion of the Wells-Riley model based on the dilution ratio \[25\] (Eqs. (6) and (7)). The exponential term in Eq. (6) represents the inhaled quanta of the susceptibles.

\[ P_i = 1 - \exp \left( - \int S_i(t) \cdot q(t) dt \right) \]  

Where \(S_i\) is the penetration factor of the personal protection equipment such as masks; \(q\) is the rate of quantum generation of the infector, \(s^{-1} \cdot p\), and \(p\) are the breathing rate of the susceptible and infector respectively, \(m^3/s\); \(D\) denotes the dilution ratio. In this study, both the infector and susceptible wear masks with a penetration factor of 0.25.

\[ D(t) = \frac{C_{infector}(t)}{C_{susceptible}(t)} \]  

Where \(t\) is the exposure time, \(s\). In this study, the exposure time is 3600s.

2.2. Three-step correlation analysis

A ventilation index with a linear relationship to airborne infection risk can effectively indicate the airborne infection risk control performance of air distribution. A three-step correlation analysis (Fig. 1) is conducted for the investigated ventilation indices to decide the most effective ventilation index for evaluating the airborne infection risk control performance of air distribution.

The first step is to evaluate the monotonic relationship between the ventilation index and airborne infection risk with Spearman’s rank correlation coefficient \[26\]. A monotonic relationship with the airborne infection risk is the most basic requirement for an indicator to evaluate the airborne infection risk control performance \[20\]. The value of Spearman’s rank correlation coefficient indicates the direction and strength of the monotonic relationship. A positive value of Spearman’s rank correlation coefficient means a positive correlation, and a negative value means a negative correlation. The absolute value of Spearman’s rank correlation coefficient closer to unity indicates a better monotonic relationship. The results with a p-value \(p < 0.05\) are considered statistically significant \[27\].

The second step is to evaluate the linearity between the ventilation index and airborne infection risk using the Pearson correlation coefficient \[28\]. Once the monotonic relationship between the ventilation index and airborne infection risk has been confirmed, the linearity of the correlation is concerned. Because if an indicator has high linearity to the airborne infection risk, the improvement of the airborne infection risk control performance can be quantified by the value change of the indicator. A Pearson correlation coefficient closer to the Spearman’s rank correlation coefficient indicates the relationship between the ventilation index and airborne infection risk is explained more by the linear relationship. Otherwise, the non-linear relationship dominates. The absolute value of the Pearson correlation coefficient closer to unity indicates better linearity. A positive value of the Pearson correlation coefficient means a positive correlation, and a negative value means a negative correlation. A p-value \(p < 0.05\) is statistically significant for the Pearson correlation coefficient analysis.

The third step uses the goodness of fit (Eq. (8)) \[29,30\] to further validate the linear relationship indicated by the Pearson correlation coefficient. The goodness of fit is between 0 and 1, and larger goodness of fit is preferred \[31,32\].

\[ G = 1 - \frac{s}{\sigma} \]  

Where \(s\) is the square mean error of the fitted value and reference value of the airborne infection risk, \(\sigma\) is the standard deviation of the reference values of the airborne infection risk. A better fitting correlation has a higher value of goodness of fit.

2.3. Min-max normalization-based error analysis

The errors of the ventilation indices in evaluating the airborne infection risk control performance are quantitatively evaluated based on a normalization analysis. Because the scales and units for CDI, AUE, CRE, ACE, AoA, and airborne infection risk are different, the ventilation indices and airborne infection risk are rescaled to be between 0 and 1 by the min-max normalization \[33-35\], so they can be equally compared. The min-max normalization has been widely used to normalize parameters of different scales and units for fair and reasonable comparisons \[33-35\]. Eq. (9) shows the min-max normalization formula.

\[ A' = \frac{A_i - A_{\text{min}}}{A_{\text{optimal}} - A_{\text{virulent}}} \]
Fig. 1. Three-step correlation analysis.

Fig. 2. (a) Plan view of two-bed ward (mm) and (b) schematic of two-bed ward with different air distributions.

S1 - S4 are at the level of 1500 mm above the floor.
S8 - S13 and E1 - E4 are at the level of 300 mm above the floor.
S5 - S7, S14, and S15 are at the ceiling.
Where \( A \) is the index to be normalized, \( A^* \) is the normalized index, \( A^* \in [0,1] \). \( A_{\text{optimal}} \) is the optimal \( A \). \( A_{\text{worst}} \) is the worst \( A \). By the data normalization as Eq. (9), a higher normalized index indicates a better performance. The higher values for \( AUE \), \( CRE \), and \( ACE \) indicate a better ventilation performance, so the optimal values are the maximum values, and the worst values are the minimum values. For \( CDI \), \( AoA \), and airborne infection risk, the higher values indicate a worse performance, therefore, the optimal values are the minimum values, and the worst values are the maximum values.

As shown in Eq. (10), the mean absolute error (MAE) of the normalized ventilation index to the normalized airborne infection risk is used to quantify the accuracy. The ventilation index with a lower MAE has better accuracy in indicating the airborne infection risk.

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} |P_i - A_i^*| \tag{10}
\]

Where \( P_i \) is the normalized airborne infection risk and \( A_i^* \) is the normalized ventilation index (Eq. (9)).

2.4. CFD model

The relationships between air distribution indices and airborne infection risk control performance are analyzed for a typical two-bed ward with four air distributions. As shown in Fig. 2, there are two patients in the ward with the dimension of \( 5.5 \times 3.0 \times 2.4 \) m\(^3\). The patient at the right of Fig. 2 is the infector. The \( CO_2 \) exhaled by the infector is used as a biomarker to evaluate the airborne infection risk. The dimension of the mouth is \( 0.02 \times 0.02 \) m\(^2\) [36]. The exhalation flow rate is \( 0.49 \) m\(^3\)/h with the \( CO_2 \) mass fraction of 0.04 and the temperature of 34 °C [37]. The heat sources are two patients and two ceiling lamps. They are set as walls with the heat flux of 45 W/m\(^2\) and 150 W/m\(^2\). The other walls are adiabatic. P1–P7 are sampling points monitoring the concentration of \( CO_2 \) exhaled by the infector. P1–P6 are possible locations for health workers. P7 is 50 mm above the mouth of the patient to monitor the \( CO_2 \) concentration of the inhaled air of the patient. Table 2 shows the coordinates of the sampling points.

Four air distributions are investigated. Mixing ventilation (MV) is the most common air distribution. In this study, the four-way ceiling diffuser with the discharge angle of 20° [38] is used to provide fully mixed air distribution. The air exhaust inlets are located at the lower wall near the head of the infector to decrease the exposure risk [39]. Displacement ventilation (DV) has high ventilation effectiveness [40] but is not recommended for wards because the thermal stratification locks the exhaled contaminant in the breathing zone and increases personal exposure risk [41–43]. However, increasing the supply airflow rate can elevate the height of the stratification layer of DV [40,44,45]. Stratum ventilation (SV) improves indoor air quality by supplying fresh air directly to the breathing zone. Studies have shown that SV reduces the risk of exposure to the exhaled droplets and aerosols by diluting their concentrations in the breathing zone of the susceptibles [46–49]. Downward ventilation (DVW) [41,50] is recommended for isolation wards. It supplies air from ceiling to push down the exhaled contaminants and exhausts the air from the floor level. With the different supply airflow rate, the supply air temperature is adjusted to maintain thermal comfort. Table 3 shows the layout of the supply and exhaust inlets and the boundary condition settings for different air distributions.

The CFD simulation is solved by Fluent software. The air temperature and velocity fields are solved by Reynolds-averaged Navier-Stokes equations. The RNG \( k-\varepsilon \) model is used for turbulence modeling [51], and the \( CO_2 \) dispersion is solved by the species transport model [19]. The pressure-velocity coupling applies the SIMPLE algorithm [52]. The discretization of the gradient is Green-Gauss cell based. The pressure interpolation applies the body force weighted scheme. The other variables are discretized by the second-order upwind scheme. Three grids of the two-bed ward model with the maximum grid size of 25, 50 and 100 mm are compared to test the grid independency. The fine, medium and coarse grids are composed of 2.7, 0.33, and 0.05 million cells. Fig. 5a compares the mean airflow velocity, temperature, and tracer gas concentration for different grids at planes of different heights. The medium grid shows good accuracy compared with the fine grid, with the difference in airflow velocity, temperature, and \( CO_2 \) concentration less than 6.1%, 0.18%, and 4.9%, respectively [19]. The steady-state simulation is conducted to obtain stable air velocity and temperature fields.

Then an unsteady-state simulation of 3600s with the time step of 0.5 s is conducted to simulate the \( CO_2 \) transmission in the ward. Fig. 3b shows the air velocity, air temperature and contaminant concentration (indicated by the tracer gas \( SF_6 \) predicted by the CFD model) are close to the measurements with the mean absolute errors of 0.04 m/s, 0.49 °C and 0.66 ppm respectively. More details about the validation of the CFD model refer to the previous study [19].

3. Results

3.1. Simulation results

The distributions of \( CO_2 \) exhaled by the infector at 3600s are shown in Fig. 4. The \( CO_2 \) concentration decreases with the increased distance to the infector. Compared with DV, SV, and DWV, the \( CO_2 \) distribution under MV is more uniform. Compared with DV and DWV, the \( CO_2 \) distribution under SV shows less concentration difference on the horizontal plane because the fresh air is directly supplied to the middle height of the room. The horizontal \( CO_2 \) concentration difference under DWV is less than that under DV because the airflow velocity is higher, and the \( CO_2 \) is more dispersed.

Fig. 5 shows the airborne infection risks at P1–P7 under SV, DV, MV, and airflow. The results show that the airborne infection risk is lower under MV because the fresh air is directly supplied to the middle height of the room.
The airborne infection risks are calculated with a large quantum generation rate of 515 h$^{-1}$, indicating a high infectivity intensity [14, 53]. The airborne infection risk is non-uniformly distributed, even under MV, indicating the need to spatially investigate the airborne infection risk. Table 4 shows the mean and maximum airborne infection risk and the investigated ventilation indices. The mean airborne infection risk is calculated by the average inhaled quanta at P1–P7. The AoA at P1–P7 is calculated by the CFD user-defined scalar [23]. The AoAave is the average value of AoA at P1–P7. The ACEave is calculated with the AoAave (Eq. (4)). The contaminant concentration in the breathing zone for AUEave and CREave are calculated with the average CO$_2$ concentration at P1–P7 (Eqs. (1) and (5)). The average values of AoA, ACE, AUE and CRE are used to indicate the mean airborne infection risk. The maximum airborne infection risk is the maximum airborne infection risk among P1–P7. The sampling points for CDI are P1–P7. The $\text{AUE}_{\text{min}}$, $\text{AoA}_{\text{max}}$, $\text{ACE}_{\text{min}}$, and $\text{CRE}_{\text{min}}$ are the minimum AUE, maximum AoA, minimum ACE, and minimum CRE among P1–P7. The minimum values of AUE, ACE and CRE and the maximum AoA are used to indicate the maximum airborne infection risk.

Fig. 3. Comparisons of (a) air velocity, temperature, and tracer gas concentration for different grid sizes and (b) measured and simulated air velocity, temperature, and tracer gas concentration.
3.2. Ventilation indices for overall airborne infection risk

Fig. 6a and b show that the mean airborne infection risk (indicating the overall airborne infection risk [19]) is negatively related to the AUEave and CREave, indicating that the higher the air utilization effectiveness and contaminant removal effectiveness, the better the mean airborne infection risk control performance of air distribution. As shown in Table 5, AUEave shows linearity to the mean airborne infection risk with Spearman’s rank correlation coefficient and Pearson’s correlation coefficient of −0.90 (p < 0.05) and −0.87 (p < 0.05) respectively. The Pearson’s correlation coefficient closing to Spearman’s rank correlation coefficient indicates that the linearity mainly explains the correlation between the AUEave and the mean airborne infection risk. The correlation has a goodness of fit of 0.50. CREave correlates with mean airborne infection risk with Spearman’s rank correlation coefficient and Pearson’s correlation coefficient of −0.90 (p < 0.05) and −0.74 (p < 0.05) respectively. The correlation has a goodness of fit of 0.33. The Pearson’s correlation coefficient smaller than the Spearman’s rank correlation coefficient indicates that the correlation between the CREave and the mean airborne infection risk is partially non-linear, supported by the relatively small goodness of fit value. The reciprocal of the mean airborne infection risk is linearly related to the CREave [19]. As shown in Fig. 6c and d, the ACEave and AoAave show poor correlations to the mean airborne infection risk, supported by the correlation analysis of ACEave and AoAave with p-values over 0.05. Therefore, the AUEave has the strongest linear relationship with the mean airborne infection risk.

Table 5 shows the MAE of the normalized ventilation index to the normalized mean airborne infection risk. The normalized AUEave has the
The error analysis shows that compared with the commonly used ventilation indices of CRE, ACE, and AoA, the AUE for the mean airborne infection risk improves the accuracy by 47%–61%. From the qualitative and quantitative analyses, the AUE is recommended to evaluate the overall airborne infection risk control performance of air distribution.

### 3.3. Ventilation indices for local airborne infection risk

As shown in Fig. 7a, the maximum airborne infection risk (indicating the local airborne infection risk [19]) is positively related to the CDI, indicating that with a higher contaminant dispersion index, the local infection risk control performance of air distribution is worse. As shown in Table 6, CDI has strong linearity to the maximum airborne infection risk with Spearman’s rank correlation coefficient and Pearson’s correlation coefficient of 0.99 (p < 0.05) respectively. The correlation has a goodness of fit of 0.85. Fig. 7b shows that the maximum airborne infection risk is negatively related to the AUE min, indicating that the local high infection risk control performance of air distribution is better with the higher the minimum air utilization effectiveness. It shows linearity to the maximum airborne infection risk with Spearman’s rank correlation coefficient and Pearson’s correlation coefficient of −0.96 (p < 0.05) and −0.97 (p < 0.05) respectively. The correlation has a goodness of fit of 0.74. Because the local contaminant concentration is not linearly related to the supply airflow rate, the AUE min is defective when comparing different supply airflow rates. Fig. 7c shows an exponential correlation between the maximum airborne infection risk and the CRE min, indicating a high absolute value of Spearman’s rank correlation coefficient over 0.9 but a low Pearson’s correlation coefficient value. Therefore, CRE min has a monotonic but not linear relationship with maximum airborne infection risk. As shown in Fig. 7d and e, the ACE min and AoA max have poor correlations to the maximum airborne infection risk, supported by the correlation analysis of ACE min and AoA max with p-values over 0.05.

Table 6 shows the MAE of the normalized ventilation index to the normalized maximum airborne infection risk. The normalized CDI has the lowest MAE to the normalized maximum airborne infection risk of 0.04. The error analysis shows that compared with the commonly used ventilation indices of CRE, ACE, and AoA, the CDI for the maximum airborne infection risk improves the accuracy by 27%. Compared with the commonly used ventilation indices of CRE, ACE, and AoA, the CDI for the maximum airborne infection risk improves the accuracy by 87%–92%. Therefore, the quantum generation rate is 515 h⁻¹.

### Table 4
Mean and maximum airborne infection risk and ventilation indices indicating mean airborne infection risk in hospital (Fig. 2).

| Air distribution | Mean airborne infection risk | AUE ave | AoA ave | ACE ave | CRE ave | Maximum airborne infection risk | CDI x 10⁴ | AUE min | AoA max | ACE max | CRE max |
|------------------|----------------------------|---------|---------|---------|---------|-------------------------------|-----------|---------|---------|---------|---------|
| SV:6ACH          | 3.97%                      | 0.27    | 604     | 0.50    | 1.38    | 6.35%                         | 5.85      | −0.09   | 956     | 0.31    | 0.92    |
| SV:9ACH          | 1.61%                      | 0.61    | 336     | 0.60    | 2.53    | 2.79%                         | 2.84      | 0.31    | 463     | 0.43    | 1.46    |
| SV:12ACH         | 0.78%                      | 0.76    | 246     | 0.61    | 4.14    | 1.55%                         | 1.68      | 0.51    | 322     | 0.47    | 2.04    |
| DV:6ACH          | 8.09%                      | −0.35   | 449     | 0.67    | 0.74    | 33.19%                        | 43.5      | −5.01   | 622     | 0.48    | 0.17    |
| DV:9ACH          | 5.41%                      | −0.15   | 312     | 0.64    | 0.87    | 18.02%                        | 18.1      | −2.66   | 438     | 0.46    | 0.27    |
| DV:12ACH         | 2.64%                      | 0.20    | 223     | 0.67    | 1.26    | 9.21%                         | 10.1      | −1.79   | 277     | 0.54    | 0.36    |
| MV:6ACH          | 4.77%                      | 0.01    | 889     | 0.34    | 1.01    | 6.55%                         | 5.01      | −0.39   | 931     | 0.32    | 0.72    |
| MV:9ACH          | 2.83%                      | 0.27    | 579     | 0.35    | 1.38    | 4.38%                         | 2.98      | −0.01   | 629     | 0.32    | 0.99    |
| MV:12ACH         | 2.99%                      | 0.05    | 430     | 0.35    | 1.05    | 5.84%                         | 4.82      | −0.82   | 488     | 0.31    | 0.55    |
| DWV:6ACH         | 6.95%                      | −0.22   | 634     | 0.47    | 0.82    | 14.90%                        | 20.7      | −1.61   | 763     | 0.39    | 0.38    |
| DWV:9ACH         | 5.82%                      | −0.44   | 447     | 0.45    | 0.70    | 12.58%                        | 15.9      | −2.11   | 546     | 0.37    | 0.32    |
| DWV:12ACH        | 4.07%                      | −0.29   | 331     | 0.45    | 0.78    | 6.83%                         | 7.65      | −1.12   | 378     | 0.40    | 0.47    |

Note: The quantum generation rate is 515 h⁻¹.

![Fig. 6](image_url) Variation of mean airborne infection risk with (a) average air utilization effectiveness (AUE ave); (b) average contaminant removal effectiveness (CRE ave); (c) average air change effectiveness (ACE ave); and (d) average age of air (AoA ave).

![Table 5](table_url) Qualitative and quantitative analyses of ventilation indices indicating mean airborne infection risk in hospital (Fig. 2).

| Ventilation index | Spearman’s rank correlation coefficient (p-value) | Pearson’s correlation coefficient (p-value) | Goodness of fit | MAE to normalized mean airborne infection risk |
|-------------------|--------------------------------------------------|-------------------------------------------|-----------------|---------------------------------------------|
| AUE ave           | −0.90 (<0.01)                                    | −0.87 (<0.01)                             | 0.50            | 0.14                                        |
| CRE ave           | −0.90 (<0.01)                                    | −0.74 (<0.01)                             | 0.33            | 0.34                                        |
| ACE ave           | −0.07 (0.83)                                     | 0.03 (0.93)                               | 0.00            | 0.37                                        |
| AoA ave           | 0.50 (0.19)                                      | 0.39 (0.22)                               | 0.07            | 0.27                                        |
3.4. Integrated index of AUE and CDI

From the correlation analysis of the ventilation indices and airborne infection risk, $AUE_{\text{ave}}$ is recommended to evaluate the mean airborne infection risk, and $CDI$ is recommended to evaluate the maximum airborne infection risk. Compared with the linearity between $CDI$ and the maximum airborne infection risk, the linearity between $AUE_{\text{ave}}$ and the mean airborne infection risk is slightly weaker, supported by lower Spearman’s rank correlation coefficient, Pearson correlation coefficient, and goodness of fit. Air distribution controls the airborne infection risk from two aspects, e.g., removing the contaminant from the breathing zone by supplying clean air to the breathing zone and decreasing the locally high concentration by dispersing the contaminant. Both the contaminant removal and dispersion influence the mean airborne infection risk, while the maximum airborne infection risk is mainly determined by the contaminant dispersion because it focuses on the local area [19]. The air utilization effectiveness only characterizes the contaminant removal by utilizing the fresh air. Hence, the $CDI$, which indicates the dispersion performance of the air distribution, is integrated with the air utilization effectiveness as a new index (Fig. 8). The integrated index of $AUE_{\text{ave}}$ and $CDI$ shows linearity with mean airborne infection risk with Spearman’s rank correlation coefficient and Pearson correlation coefficient of 0.95 ($p < 0.05$) and 0.94 ($p < 0.05$) respectively, and the correlation has the goodness of fit of 0.67, which outperforms only using $AUE_{\text{ave}}$. The normalized integrated index of $AUE_{\text{ave}}$ and $CDI$ shows the lowest MAE to the normalized mean airborne infection risk of 0.07. Compared with the $AUE_{\text{ave}}$, the integrated index for the mean airborne infection risk further improves the accuracy by 48%. Compared with the commonly used ventilation indices of $CRE$, $ACE$, and $AoA$, the integrated index for the mean airborne infection risk improves the accuracy by 73%–80%. From the qualitative and quantitative analyses of ventilation indices indicating maximum airborne infection risk in hospital (Fig. 2).

![Fig. 7. Variation of maximum airborne infection risk with (a) contaminant dispersion index (CDI); (b) minimum air utilization effectiveness ($AUE_{\text{min}}$); (c) minimum contaminant removal effectiveness ($CRE_{\text{min}}$); (d) minimum air change effectiveness ($ACE_{\text{min}}$); and (e) maximum age of air ($AoA_{\text{max}}$).](image)

### Table 6

Qualitative and quantitative analyses of ventilation indices indicating maximum airborne infection risk in hospital (Fig. 2).

| Ventilation index | Spearman’s rank correlation coefficient (p-value) | Pearson’s correlation coefficient (p-value) | Goodness of fit | MAE to normalized maximum airborne infection risk |
|-------------------|-----------------------------------------------|------------------------------------------|-----------------|-----------------------------------------------|
| CDI               | 0.99 (<0.01)                                  | 0.99 (<0.01)                             | 0.85            | 0.04                                          |
| $AUE_{\text{min}}$ | -0.96 (<0.01)                                | -0.97 (<0.01)                            | 0.74            | 0.06                                          |
| $CRE_{\text{min}}$ | -0.96 (<0.01)                                | -0.67 (0.02)                             | 0.26            | 0.43                                          |
| $ACE_{\text{min}}$ | 0.33 (0.30)                                   | 0.38 (0.23)                              | 0.07            | 0.52                                          |
| $AoA_{\text{max}}$ | 0.10 (0.77)                                   | 0.10 (0.76)                              | 0.00            | 0.33                                          |

Note: The quantum generation rate is 515 h$^{-1}$.

$CDI$ is recommended to evaluate the local airborne infection risk control performance of air distribution.

### 3.4. Integrated index of AUE and CDI

From the correlation analysis of the ventilation indices and airborne infection risk, $AUE_{\text{ave}}$ is recommended to evaluate the mean airborne infection risk, and $CDI$ is recommended to evaluate the maximum airborne infection risk. Compared with the linearity between $CDI$ and the maximum airborne infection risk, the linearity between $AUE_{\text{ave}}$ and the mean airborne infection risk is slightly weaker, supported by lower Spearman’s rank correlation coefficient, Pearson correlation coefficient, and goodness of fit. Air distribution controls the airborne infection risk from two aspects, e.g., removing the contaminant from the breathing zone by supplying clean air to the breathing zone and decreasing the locally high concentration by dispersing the contaminant. Both the contaminant removal and dispersion influence the mean airborne infection risk, while the maximum airborne infection risk is mainly determined by the contaminant dispersion because it focuses on the local area [19]. The air utilization effectiveness only characterizes the contaminant removal by utilizing the fresh air. Hence, the $CDI$, which indicates the dispersion performance of the air distribution, is integrated with the air utilization effectiveness as a new index (Fig. 8). The integrated index of $AUE_{\text{ave}}$ and $CDI$ shows linearity with mean airborne infection risk with Spearman’s rank correlation coefficient and Pearson correlation coefficient of 0.95 ($p < 0.05$) and 0.94 ($p < 0.05$) respectively, and the correlation has the goodness of fit of 0.67, which outperforms only using $AUE_{\text{ave}}$. The normalized integrated index of $AUE_{\text{ave}}$ and $CDI$ shows the lowest MAE to the normalized mean airborne infection risk of 0.07. Compared with the $AUE_{\text{ave}}$, the integrated index for the mean airborne infection risk further improves the accuracy by 48%. Compared with the commonly used ventilation indices of $CRE$, $ACE$, and $AoA$, the integrated index for the mean airborne infection risk improves the accuracy by 73%–80%. From the qualitative and quantitative analyses of ventilation indices indicating maximum airborne infection risk in hospital (Fig. 2).
analyses, the integrated index outperforms only using \( AUE_{\text{ave}} \) to evaluate the overall airborne infection risk control performance of air distribution.

4. Discussion

4.1. Validity for different infectivity intensities of airborne infection diseases

The results show that CDI and the integrated index of AUE and CDI have good linearity with the airborne infection risk under different air distributions and supply airflow rates, supported by the high absolute values of Spearman’s rank correlation coefficient, Pearson correlation coefficient, and goodness of fit. The analysis is conducted with an airborne infectious disease of high infectivity intensity (\( q = 515 \text{ h}^{-1} \)).

The validity of these ventilation indices with medium and low infectivity airborne infection diseases (e.g., \( q = 100 \) and \( 1 \text{ h}^{-1} \)) [12] are further investigated. As shown in Tables 7 and 8, the results of the qualitative and quantitative analysis hold with the quantum generation rate decreases to \( 100 \text{ h}^{-1} \) and \( 1 \text{ h}^{-1} \). Therefore, the recommended ventilation indices (integrated index and CDI) are also effective in evaluating the airborne infection risk of disease with medium and low infectivity.

4.2. Validity for different room configurations with different occupant distributions

Both the qualitative and quantitative results show that CDI and the integrated index of AUE and CDI have good eligibility to indicate the airborne infection risk for hospital wards (Sections 3 and 4.1). The validity of these ventilation indices with different room configurations and occupant distributions is further investigated. The configuration of the classroom is adopted from Ref. [54], which is different from the studied hospital in Sections 3 and 4.1 with the dimensions of \( 8.8 \times 6.1 \times 2.4 \text{ m}^3 \) (Fig. 9). The occupant distribution of the classroom is also different from the studied hospital in Sections 3 and 4.1 with a larger occupant density (i.e., 16 occupants). The heat sources are the 16 occupants (1600 W), ceiling lamps (1176 W), and one workstation (300W) [55]. Four air distributions, MV, DV, SV, and DWV, are investigated. The infector is sitting in the first row, and the exhalation flow rate is 0.49 \( \text{m}^3/\text{h} \) with the CO\(_2\) mass fraction of 0.04 and the temperature of 34°C. The quantum generation rate is \( 515 \text{ h}^{-1} \). The sampling points are 0.05 m in front of the other 15 susceptibles at the breathing level of 1.1 m above the floor. Eight scenarios, i.e., the four air distributions with two different supply airflow rates of 7 ACH and 10 ACH, are investigated.

As shown in Table 9, the integrated index shows linearity to the mean airborne infection risk with Spearman’s rank correlation coefficient and Pearson’s correlation coefficient of \(-0.93 (p < 0.05)\) and \(-0.95 (p < 0.05)\) respectively. The Pearson’s correlation coefficient closing to Spearman’s rank correlation coefficient indicates that the linearity mainly explains the correlation between the integrated index and the mean airborne infection risk. The correlation has a goodness of fit of 0.70. The normalized integrated index shows the lowest MAE to the normalized mean airborne infection risk of 0.08. Compared with the AUE, the integrated index for the mean airborne infection risk further improves the accuracy by 19%. Compared with the commonly used ventilation indices of CRE, ACE, and AoA, the integrated index for the mean airborne infection risk improves the accuracy by 52%–63%.

As shown in Table 10, CDI shows linearity to the maximum airborne infection risk with Spearman’s rank correlation coefficient and Pearson’s correlation coefficient of \(1.00 (p < 0.05)\) and \(1.00 (p < 0.05)\) respectively, and the correlation has a goodness of fit of 0.90. The normalized CDI shows the lowest MAE to the normalized maximum airborne infection risk of 0.03. Compared with the AUE, the CDI for the maximum airborne infection risk further improves the accuracy by 29%. Compared with the commonly used ventilation indices of CRE, ACE, and AoA, the CDI for the maximum airborne infection risk improves the accuracy by 91%–93%. From the qualitative and quantitative analyses, the recommended integrated index and CDI are also effective in evaluating the overall and local airborne infection risk respectively for different room configurations with different occupant distributions.

5. Conclusion

This study investigates the proper ventilation indices for evaluating the airborne infection risk control performance of air distribution by testing the linear relationships between the ventilation indices and airborne infection risk. The linear relationship test is conducted using a three-step correlation analysis based on validated CFD simulations in a hospital ward under mixing ventilation, displacement ventilation, stratified ventilation and downward ventilation. Two ventilation indices, e.g., the air utilization effectiveness (AUE) and contaminant dispersion index (CDI), are introduced, and the common ventilation indices, i.e., the age of air (AoA), air change effectiveness (ACE), and contaminant removal effectiveness (CRE), are also tested. Furthermore, the errors of the ventilation indices in evaluating the airborne infection risk control performance are evaluated based on the min-max normalization analysis.

The main findings are as follows:

- The integrated index of AUE and CDI is recommended to indicate the overall airborne infection risk control performance of air
distribution, which improves the accuracy by 52%–80% compared with the commonly used ventilation indices of CRE, ACE, and AoA.

- CDI is recommended to indicate the local airborne infection risk control performance of air distribution, which improves the accuracy by 87%–93% compared with the commonly used ventilation indices of CRE, ACE, and AoA.

- The recommended ventilation indices can robustly indicate the overall and local airborne infection risk control performance of air distribution regardless of the effects of air distribution, supply airflow rate, infectivity intensity, room configuration and occupant distribution.

CRediT authorship contribution statement

Yalin Lu: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation. Dun Niu: Visualization, Writing – review & editing. Sheng Zhang: Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. Han Chang: Visualization, Writing – review & editing. Zhang Lin: Writing – review & editing, Software, Resources, Project administration, Funding acquisition, Formal analysis.

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.
Data availability

Data will be made available on request.

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