



Article

The Effect of Occupancy and Environmental Physical Variables on Classrooms' Natural Ventilation: A Path Modeling Approach

Rogério Duarte ^{1,2,*} , António Moret Rodrigues ³ , Fernando Pimentel ¹ and Maria da Glória Gomes ³

¹ Department of Mechanical Engineering, Instituto Politécnico de Setúbal, ESTSetúbal, Campus do IPS, Estefanilha, 2914-508 Setúbal, Portugal; fernando.pimentel@estsetubal.ips.pt

² MARE—Marine and Environmental Sciences Centre, Campus do IPS, Estefanilha, 2914-508 Setúbal, Portugal

³ CERIS, Department of Civil Engineering, Architecture and Environment, Instituto Superior Técnico, Universidade de Lisboa, Av. Rovisco Pais, 1, 1049-001 Lisboa, Portugal; moret.rodrigues@tecnico.ulisboa.pt (A.M.R.); maria.gloria.gomes@tecnico.ulisboa.pt (M.d.G.G.)

* Correspondence: rogerio.duarte@estsetubal.ips.pt

Abstract: In this paper, we use a path model to study natural ventilation in classrooms and research the link between air change rate, occupancy, and both outdoor and indoor physical variables. In general, the path model is derived from the building physics and occupant behavioral considerations via structural equation modeling (SEM), and allows for the use of continuous observable and unobservable factors. The latter are often employed in behavioral and social sciences to represent personal and group attributes. The path model is validated with data gathered during two consecutive academic years from four classrooms of a Portuguese school. The results confirm indoor and outdoor air temperature as major drivers of classroom ventilation, with standardized total path coefficients of approximately 0.55. Solar energy, precipitation, and occupancy are also significant drivers of classroom ventilation, with standardized total path coefficients of 0.24, -0.18 , and 0.17 , respectively. These results contribute to our understanding of the relative importance of occupancy as well as to identifying the most relevant environmental determinants of natural classroom ventilation. In spite of the statistical significance of the path model as a whole and its detailed causal relationships (direct, indirect, and feedback), only 58% of classroom ventilation variance is explained by the selected input variables. Because naturally ventilated classrooms depend significantly on occupants' interactions with the built environment, i.e., opening/closing windows and blinds, extending path modeling to include additional personal and context-related drivers of occupants' behavior would allow for further insights into the complex multi-domain topic of natural classroom ventilation.

Keywords: path model; natural ventilation; school classrooms; structural equation modeling; human behavior; window opening/closing



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1. Introduction

The number of school buildings in Southern European countries is stable, with most schools having been built in the 1900s and classrooms frequently being naturally ventilated through manual window opening [1–5]. Together with adequate solar protection and the use of building mass, natural ventilation is part of a traditional passive cooling strategy that has been successful in reducing classroom overheating, allowing for indoor conditions with warm weather that are often preferred to those found in mechanically cooled classrooms [2,3,6–9]. Indeed, classroom windows are typically opened as outdoor temperatures increase, and both students and teachers welcome the fresh outdoor airflow into the classrooms. Natural ventilation provides benefits in terms of indoor air quality, as well as significant energy conservation by avoiding the need for mechanical cooling.

During wintertime, the combination of Southern Europe's mild climate and the use of passive solar heating allows acceptable indoor thermal environments to be maintained in naturally ventilated classrooms. However, this is possible only if air change rates are

kept to a minimum. During wintertime, the inflow of cold outdoor air causes drafts, and occupants' reaction is to leave classroom windows closed; as a result, the likelihood of poor indoor air quality increases. Poor indoor air quality during cold weather has been confirmed for schools located in Portugal and Greece [3,10–12], and is an obvious cause for concern considering the increase in health symptoms [13–16], a subject that moved to the center of designers' attention during the early 2020s due to the COVID-19 pandemic [17,18]. In this context, a number of studies have considered the undesirable effects on students' absenteeism [19] and academic performance [20–24].

Thus, traditional natural ventilation allows for important energy savings; however, risks around decreased academic performance and the spread of infectious diseases justify continued research on natural ventilation with manual window opening.

Although customary, the act of manually opening/closing a window entails complex perception and behavioral processes that depend on numerous factors [25], including physical (e.g., thermal, visual, acoustic, air quality), personal (physiological, psychological) and contextual (social, demographic) factors. The dependence on psychological and social factors, which according to several authors [26–31] can be as important as physical variables, justifies the gradual adoption of non-physical drivers in research on occupants' behavior in naturally ventilated rooms [25,31,32]. Moreover, to accommodate non-physical drivers and allow for multi-domain studies, instruments and modeling tools associated with the behavioral and social sciences are being adopted in the study of natural ventilation [30,33–39].

Structural Equation Modeling (SEM, [40,41]) is a tool adapted to multi-domain studies. SEM uses a collection of statistical procedures that include general linear modeling, path analysis and exploratory factor analysis [42]. Compared to multiple or logistic regression analysis, which are the most common tools used to model natural ventilation with manual window opening/closing [37,43], SEM and path modeling provide graphical representations of the causal relationships (or paths) relating input and output variables, and allow for the simultaneous use of observable variables and unobservable hypothetical constructs (factors). These latter constructs are often used in behavioral and social sciences to represent attributes of a person, group of persons, or geographical region [40,42].

SEM helps in the identification of false models (those with a poor fit to the sample data), and as such is useful in model generation and confirmatory model analysis. Compared to machine learning methods, which aim for an improved fit to sample data [35–38], the goal of SEM is to test the validity of a model's internal structure and the understanding of causal effects and factors driving the researched phenomenon. SEM has been previously used in studies related to built environment [39,44–56]; however, to the best of our knowledge, SEM and path modeling have never been used to confirm a model relating natural ventilation with continuous occupancy and environmental physical variables. Moreover, most experimental studies on natural ventilation with window airing have dealt with offices and residences [26,27,31,33–38,43,57–62], where the group dynamics and window opening/closing dynamics are quite different from those found in classrooms [28,63].

Using a two-year-long experimental dataset, this paper provides a path modeling approach to the study of classroom ventilation, relating occupancy and environmental physical variables with air change rate. A major objective of this paper is to use continuous occupancy and environmental data to assess the use of path modeling, and structural equation modeling more generally, for natural ventilation research. Another objective is to identify the relative importance of occupancy and the most relevant environmental (physical) determinants of natural ventilation for school buildings in Southern Europe.

The rest of this paper is structured as follows: the Materials section presents the details of the classrooms and monitoring approach, followed by a description of the data screening process; the Methods section introduces the path model and the implied causal relations between the variables; the Results and Discussion section discusses the path modeling results and the model's fit to the monitoring data; finally, the paper ends with our conclusions.

2. Materials

2.1. Studied Classrooms

Four classrooms in a school for approximately 1000 students located in a quiet residential neighborhood in Lisbon, Portugal were selected for this study. Figure 1 shows the plan view of the school's third floor on the right-hand side, while the left-hand side shows the detailed plan view and elevation of the main school building and east wing. The location of the three monitored classrooms is highlighted. An additional classroom at the second floor of the east wing was also monitored.

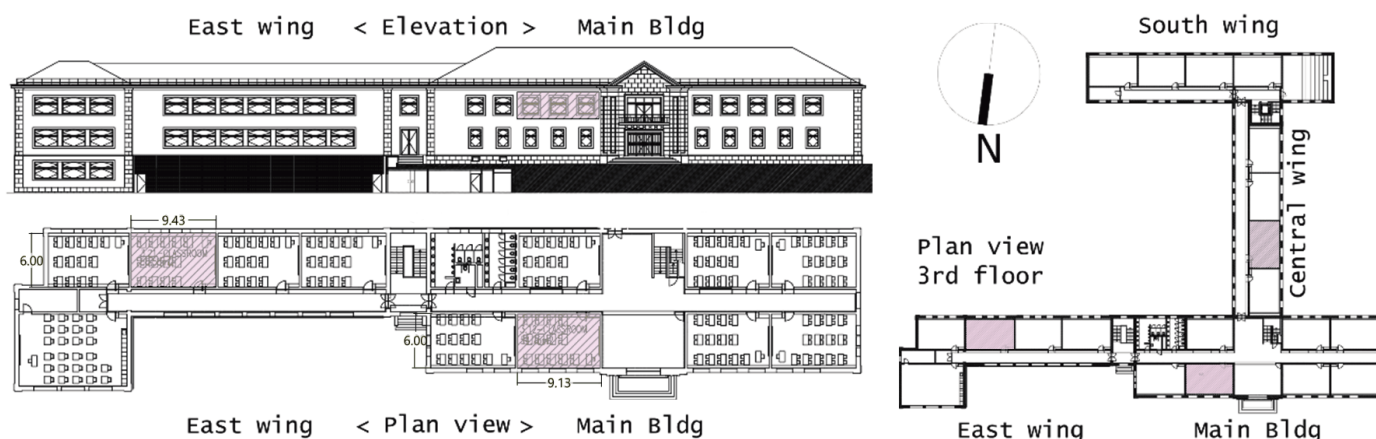


Figure 1. The studied school, with three of the monitored classrooms highlighted.

The school used in this study was built in the 1940s and retrofitted to contemporary standards in the early 2000s. A comprehensive characterization of Portuguese school building architecture and the standards used in retrofitting Portuguese school buildings is presented in [4,5].

Some relevant characteristics of the monitored classrooms are presented in Table 1.

Table 1. Characteristics of the monitored classrooms.

Geometry: Approximately 54 m ² floor area and 3 m headroom.
Usage: 5th to 12th grade classes with approximately 20 students per class and a 1:1 girls–boys ratio; casual dress code; classes (expository learning) taught from mid-September to mid-June, Monday to Friday, from 8.10 a.m. to 6.30 p.m. (excluding Bank, Christmas, February half-term (Carnival), and Easter holidays). Note: Term dates exclude the hot summer period from mid-June to mid-September.
Windows: Three manually operated windows per classroom; wood framing and double glazing; <i>very low air permeability</i> (class 3 or higher according to [64]); each window (1.4 × 1.9 m ²) divided into lower and upper pivoting parts.
Shading: Fixed vertical and horizontal shading along the perimeter of the window; horizontal shading between upper and lower window parts; movable roller blind (fabric) placed on the outside allowing <i>independent manual control of shading and window opening/closing</i> .
Lighting and equipment: Recessed luminaires using fluorescent tubular lamps (10 W/m ²); one video projector and one desktop computer.
Other: Massive (65 cm thick) stone masonry exterior walls; reinforced concrete slab floor with a cementitious covering; dropped ceiling made of perforated (sound absorbing) gypsum boards. <i>Classrooms are neither heated nor cooled.</i>

Figure 2 presents a photograph of a classroom taken on a warm day. The photograph shows the lower and upper window pivoting parts in the open position and the movable roller blinds (placed on the outside) covering different windows both partially and totally.



Figure 2. Photograph of a classroom.

Because using the blinds influences the windows' air permeability, the air change rates used in this study result from the combined effects of opening/closing both the windows and the blinds.

2.2. Monitoring

Data on the outdoor environmental conditions and the classrooms' indoor environmental conditions were monitored over a two-year period. Simultaneously, data on the number of students attending each class and the class grade being taught in the classroom were gathered in order to derive a measure of classroom occupancy. For the two-year study period, daily records for more than 20 different classes from 5th to 12th grade were analyzed, for a total of more than 500 students. Because the number of students per class remained fairly constant (approximately 20 students per class) regardless of grade, we used the metabolic CO₂ production as the measure of classroom occupancy to distinguish between classes of younger (5th grade) and older (12th grade) students.

Table 2 summarizes the sensor characteristics and the details of occupancy data gathering.

Table 2. Characteristics of the sensors and details of occupancy data gathering.

Outdoor Environment
<p>+Weather station [65]: Log duration: 2 years; Log frequency: 10 min.; Location: Outdoor, in an unobstructed area.</p> <p>.Air dry-bulb temperature (T_{out}): Resol.: 0.1 °C; Range: −40 to +65 °C; Accur.: 0.5 °C.</p> <p>.Air relative humidity (RH): Resol.: 1%; Range: 0 to 100%; Accur.: 3%.</p> <p>.Global radiation (on a horizontal plane, E_{sol}): Resol.: 1 W/m²; Range: 0 to 1800 W/m²; Accur.: 5%.</p> <p>.Precipitation (R): Resol.: 0.2 mm; Range: 0 to 6553 mm; Accur.: 4%.</p> <p>.Wind speed (10 m, WS): Resol.: 0.1 m/s; Range: 1 to 80 m/s; Accur.: 5%.</p> <p>+Atmospheric CO₂ concentration [66] (c_{atm}): Log details: 15 days periods in autumn, winter and spring; Resol.: 1 ppm; Range: 0 to 10,000 ppm; Accur.: ±30 ppm.</p>
Indoor environment [67]
<p>+Air temperature and CO₂ concentration: Log duration: 2 years; Log frequency: Sequence event recording implemented by the building management system; Location: Classrooms' interior walls, approx. 2.5 m above floor.</p> <p>.Dry-bulb temperature (T_{in}): Resol.: 0.1 °C; Range: −20 to +60 °C; Accur.: 0.4 °C.</p> <p>.CO₂ concentration (c): Resol.: 1 ppm; Range: 0 to 2000 ppm; Accur.: ±50 ppm.</p>
Classroom occupancy
<p>+Metabolic CO₂ production (S_c): Students' number and class grade were obtained from logs of lesson attendance for each class that took place in the monitored classrooms. Academic records were used to determine mean students' age and mean ratio of girls–boys per class. The rate of production of metabolic CO₂ was determined considering the average height and mass of male and female students at different ages [68–70] in the context of sedentary school work.</p>

Based on the gathered data, the upper plot in Figure 3 presents time series of the monitored indoor physical variables for one of the monitored classrooms: daily mean values of metabolic CO₂ production rate and indoor air temperature (\bar{S}_c and \bar{T}_{in} , respectively). Additionally, the daily mean values of outdoor air temperature and wind speed (\bar{T}_{out} and \bar{WS} , respectively) are presented in the upper plot. The time series for outdoor variables are continuous, while for the indoor variables we excluded weekends as well as Bank, Christmas, February half-term (Carnival), Easter, and summer holidays.

The lower plot in Figure 3 adds the monitored indoor physical variable, namely, the daily median CO₂ concentration (\bar{c}), along with the outdoor variables, namely, the daily mean outdoor relative humidity (\overline{RH}_{ma} ; note that to avoid clutter, the moving average (ma) of seven data points is presented for this variable) and daily sums for precipitation and total solar energy ($\sum R$ and $\sum E_{sol}$, respectively)

The outdoor temperatures in Figure 3 (upper plot) confirm Lisbon's temperate climate (Csa in Köppen scale [71]). The interquartile range of daily outdoor temperatures (outdoor relative humidity) varies between 13.0 and 20.5 °C (65 and 83%), with a median of 16.4 °C (74%). The median daily solar energy (daily total) equals 15.8 MJ/m². Daily precipitation is low, with the median daily total being 0.0 mm. The daily wind speed remains stable throughout the year, fluctuating around a median value of 2.2 m/s.

Confirming previous studies on naturally ventilated classrooms [2,3,10–12], Figure 3 (lower plot) shows that large daily classroom CO₂ concentrations (\bar{c} reaching 2000 ppm) are frequent during the wintertime when classrooms are in use. Given the fairly stable occupancy with stable values of the daily metabolic CO₂ production rate \bar{S}_c , and given the low air permeability of the window frames (see Table 1), the observed CO₂ concentration pattern is associated with the occupants' behavior, i.e., window (blind) opening/closing patterns. Indeed, in the absence of heating or cooling systems, window and blind opening/closing is how the indoor environment of these classrooms is controlled.

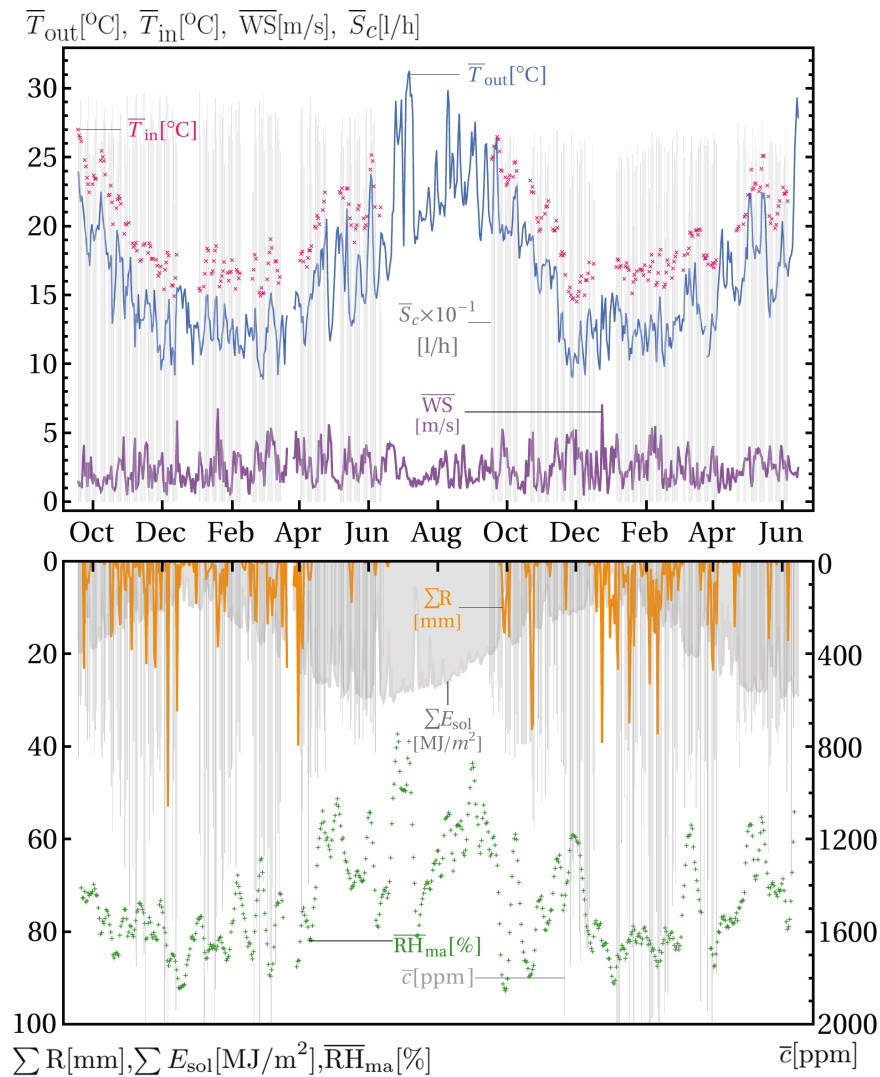


Figure 3. Data for two consecutive academic years, showing time series of the outdoor and of indoor variables for the monitored classroom on the second floor of the east wing. The time series for the outdoor variables are continuous, while those for the indoor variables exclude weekends as well as Bank, Christmas, February half-term (Carnival), Easter, and summer holidays.

3. Methods

3.1. Data Screening

Because monitoring records were gathered from different sources with different time-stamps, it was decided to work with daily statistics. For outdoor environmental variables, daily means or daily totals were determined depending on the most common format found in climatological reports. For indoor air temperature, the mean was also the selected statistic; however, because CO₂ sensor readings higher than 2000 ppm were truncated, as suggested in [72], the median was used as a measure of central tendency for indoor CO₂ concentration. When determining means and medians for indoor variables, because the study focuses on naturally ventilated classrooms with manual window (blinds) opening/closing, periods with no classes were removed. Missing records and univariate outliers present in the resulting dataset were dealt with considering listwise deletion [73]. The classrooms' daily air change rates were derived from class records of CO₂ concentration and of metabolic CO₂ production rate (c and S_c , respectively) using the solution of the decay equation [74–76].

To improve the efficacy of the path model analysis, values of the daily metabolic CO₂ production rate \bar{S}_c were scaled by 10^{-1} , reducing the variance range in the sample dataset. To ensure normal distribution of the studied variables, the daily total precipitation and daily air change rate required logarithmic transformation (see notes to Table 3 below).

Table 3. Pearson product moment correlations, means, standard deviations (SD), skew, and kurtosis of sample data.

Variable	\bar{T}_{out}	\overline{RH}	ΣE_{sol}	ΣR^*	\overline{WS}	\bar{S}_c^*	\bar{T}_{in}	\overline{acr}^*
Outdoor air temp., \bar{T}_{out} [°C] (daily mean)	1.0000	—	—	—	—	—	—	—
Outdoor air rel.hum., \overline{RH} [%] (daily mean)	−0.2522 **	1.0000	—	—	—	—	—	—
Solar energy, ΣE_{sol} [MJ/m ²] (daily total)	0.4237 **	−0.6649 **	1.0000	—	—	—	—	—
Precipitation, ΣR^* [ln(mm)] (daily total) ^a	−0.1708 **	0.6256 **	−0.5326 **	1.0000	—	—	—	—
Wind speed, \overline{WS} [m/s] (daily mean)	−0.1336 **	0.0462	−0.0545	0.3614 **	1.0000	—	—	—
Metab.CO ₂ prod.rate, \bar{S}_c^* [L/h] (daily mean) ^b	−0.0046	0.0191	−0.0074	0.0172	−0.0075	1.0000	—	—
Indoor air temp., \bar{T}_{in} [°C] (daily mean) ^c	0.8821 **	−0.2232 **	0.4255 **	−0.1500 **	−0.1400 **	0.0200	1.0000	—
Air change rate, \overline{acr}^* [ln(h ^{−1})] (daily mean) ^{c,d}	0.6626 **	−0.3682 **	0.5323 **	−0.3787 **	−0.1418 **	0.1626 **	0.6745 **	1.0000
Statistic	Mean	15.0276	75.1532	13.0961	0.7314	2.4513	20.5263	1.0824
	SD	3.5051	11.9659	7.7576	1.0321	1.1503	4.5551	0.6757
	Skew	0.611	−0.454	0.571	1.233	0.536	0.198	0.006
	Kurtosis	−0.247	−0.291	−0.724	0.308	−0.346	−0.231	−0.758

(a) $\Sigma R^* = \ln(1 + \Sigma R)$, with ΣR being the daily total precipitation; (b) $\bar{S}_c^* = \bar{S}_c \times 10^{-1}$; (c) classroom occupancy periods only; (d) $\overline{acr}^* = \ln(\overline{acr})$; (**) $p < 0.01$.

Table 3 presents statistics for the variables used in this paper, including the correlation, mean, standard deviation (SD), skewness, and kurtosis.

The values of skew and kurtosis did not exceed 1.25 and, with the exception of precipitation, $|skewness| < 1$ and $|kurtosis| < 1$, suggesting that the assumption of multivariate normality applies when using the maximum likelihood method to estimate a path model from sample data.

Regarding the correlations, Table 3 shows these are lower than 0.9 and that most are statistically significant considering $p < 0.01$. The correlations with $p > 0.01$ are those relating daily metabolic CO₂ production rate with daily outdoor and indoor environmental variables and those relating daily values of wind speed with relative humidity and solar energy. The fairly stable time series for daily values of metabolic CO₂ production rate (\bar{S}_c) and wind speed (\overline{WS}) presented in Figure 3 justify these nonsignificant correlations.

Despite being lower than 0.9, the strong correlation between daily outdoor and indoor air temperature (0.8821) must be noted; indeed, Figure 3 shows that despite differences in amplitude, the time series of daily outdoor and indoor air temperature (\bar{T}_{out} and \bar{T}_{in}) have similar trends, with both showing similar frequencies and no meaningful phase shift. This strong correlation between outdoor and indoor air temperatures has previously been reported by researchers studying room airing with window opening/closing [77,78].

Using the Variance Inflation Factor (VIF) to check sample data multivariate collinearity shows that the VIF values are lower than 5, suggesting the absence of multicollinearity problems [42].

Because our subsequent analysis always considers daily statistics, the term “daily” is omitted when referring to mean or total sample variables.

3.2. Conceptual Model

From building physics, it is known that classroom ventilation is driven by wind speed and temperature differences between the outdoor air and the classroom. Thus, a model for classroom ventilation requires causal links between the outdoor air and the classroom’s indoor physical variables. However, as classroom air temperature is driven by outdoor conditions such as outdoor air temperature and incident solar radiation [25], the classroom’s indoor variables are also linked to outdoor variables. The complex interrelation between the drivers of classroom ventilation is further extended by the realization that indoor conditions also depend on ventilation [78]. In the case of an increase in the indoor air temperature, there will be an increase in the difference between the indoor and outdoor temperature; if the outdoor temperature remains constant and lower than the indoor, natural ventilation will increase as well. However, because the outdoor air temperature is lower than the indoor air temperature, increasing the inflow of cold outdoor air decreases the indoor air temperature; therefore, ventilation and indoor air temperature are linked by causal relationships that implements a stable negative feedback loop [79].

Figure 4 presents a model depicting the internal structure of an unoccupied naturally ventilated classroom, where the solid arrows represent *passive* causal effects. This model links ventilation with both outdoor and indoor physical variables. Paths {1} and {2} represent the direct effect of outdoor physical variables on classroom ventilation and indoor physical variables, while paths {3} and {4} represent the feedback loop connecting classroom ventilation and classroom indoor physical variables.

In naturally ventilated rooms, the role played by occupants is paramount to the study of ventilation; indeed, students and teachers *actively* open/close windows depending on their perception of the classroom’s indoor physical environment [25,31,43,58,77,80]. This is the reason why path {3} in Figure 4 includes both a solid arrow, indicating a passive effect, and a dashed arrow indicating an active causal effect. The active effect represents occupants’ perception of the indoor physical variables and their behavior regarding classroom ventilation, i.e., window opening/closing.

Occupants’ personal (physiological, psychological) and contextual (social, demographic) factors are additional determinants of window opening/closing [25,78]. For this reason, Figure 4 includes path {5} linking these “other” factors to ventilation. Moreover, because the occupants exert both passive and active causal effects on indoor physical environment (passive metabolic production of heat and CO₂, active use of blinds/artificial lighting with consequent heat transfer/release), path {6} is included in Figure 4.

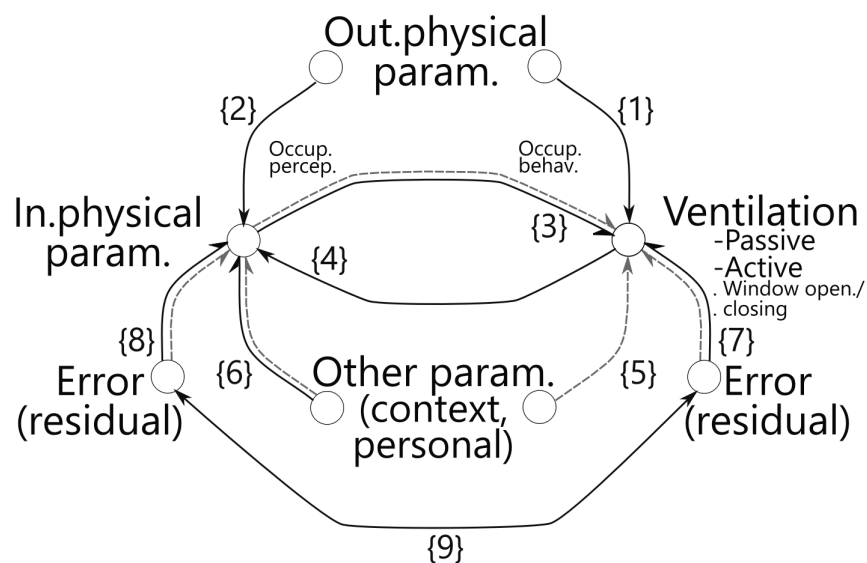


Figure 4. Conceptual model explaining ventilation variance in naturally ventilated spaces.

Because the conceptual model aims to understand classroom ventilation and its close link with the indoor physical environment, Figure 4 uses paths {7} and {8} to depict links between these model outputs and their respective errors or residues [42]. In the ideal case with all variables relevant to the study accounted for and with a known internal model structure, these residues represent measurement errors. In practice, because the model’s internal structure is object of research and given the large number of determinants of ventilation and the indoor environment, the residues reflect measurement errors, errors due to unaccounted variables, and errors due to inadequate model structure [42]. In order to model the possible covariance between residues in ventilation and in the indoor physical variables, Figure 4 also includes path {9}.

3.3. Path Model

Considering the available monitoring data and the causal relationships in Figure 4, the path model with the internal structure depicted in Figure 5 is used in this paper.

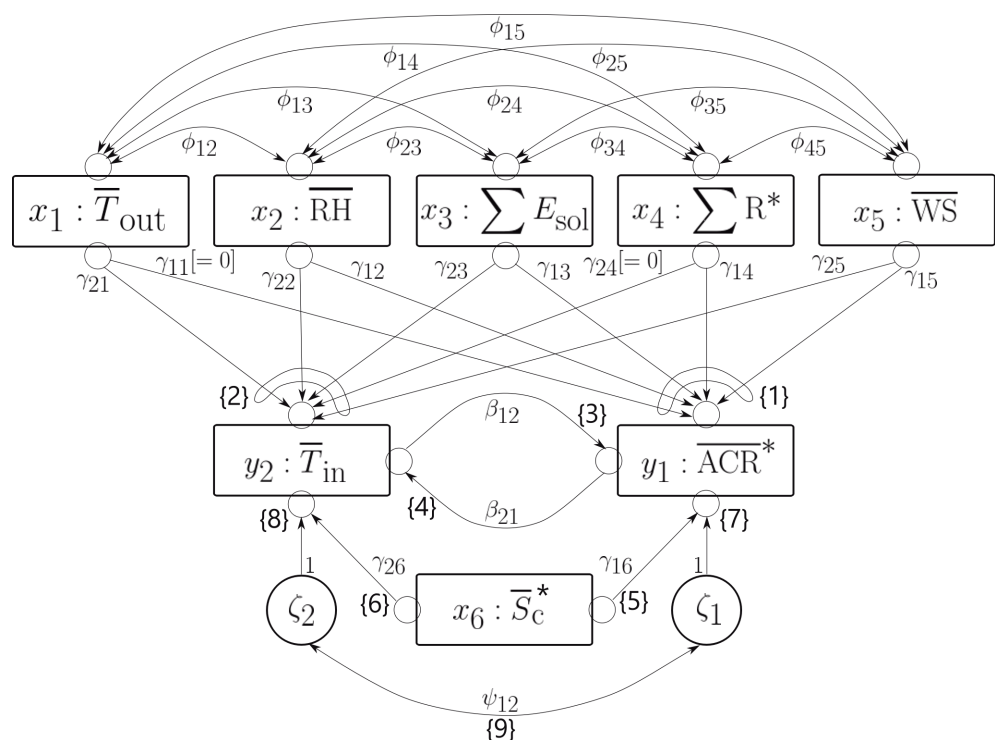


Figure 5. Path model explaining ventilation variance in naturally ventilated classrooms.

Figure 5 considers six exogenous variables (independent model inputs x_j with $j = 1, 2, \dots, 6$) and two endogenous variables (dependent model outputs y_i with $i = 1, 2$). The five inputs at the top (air temperature, air relative humidity, solar energy, precipitation, and wind speed) are used to characterize the outdoor physical environment, while the sixth input at the bottom (rate of metabolic CO₂ production) is the sole “non-physical” variable, as it does not characterize the outdoor or indoor thermal, visual, acoustic, or air quality environment. In the middle of Figure 5, the two dependent model outputs of air change rate and indoor air temperature characterize the classroom ventilation and indoor physical environment, respectively.

Paths {1}, {2}, {5}, and {6} in Figure 4 are represented by direct effects γ from input to output model variables. Paths {3} and {4} implementing the feedback loop in Figure 4 are represented by mediating effects β . The covariances ϕ between inputs x_1 to x_5 (outdoor physical variables) are also represented.

Paths {7}, {8}, and {9} in Figure 4 link the model outputs to their respective residues (ζ_1 and ζ_2) and represent the covariance ψ_{12} between the residues.

3.3.1. Model Validation and Estimation of Model Parameters

The goal of path modeling is to statistically validate the internal structure of a model such as the one depicted in Figure 5 through estimation of the model parameters γ and β and the variance of residues ζ_i .

To achieve this goal, the system of equations in Equation (1), translating the causal relationships between outputs, inputs, and residues depicted in Figure 5, is first established [40,42],

$$\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \begin{pmatrix} \gamma_{11} & \dots & \gamma_{16} \\ \gamma_{21} & \dots & \gamma_{26} \end{pmatrix} \begin{pmatrix} x_1 \\ \dots \\ x_6 \end{pmatrix} + \begin{pmatrix} 0 & \beta_{12} \\ \beta_{21} & 0 \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} + \begin{pmatrix} \zeta_1 \\ \zeta_2 \end{pmatrix} \quad (1)$$

$$\Leftrightarrow y = \Gamma x + B y + Z \quad (\text{in vector form}).$$

Next, expressions for the variances of the input and output variables and the covariances between them are derived, defining a system of equations in which the coefficients of the matrices Γ and B and the variances of the input variables $V(x)$ and residues $V(Z)$ are the model parameters requiring estimation. The solution of the system of equations uses the maximum likelihood procedure from [81], and the path model fit is assessed by comparing the resulting estimate and sample covariance matrices.

To assess the quality of the path model, the chi-square (χ^2) test is typically used under the null hypothesis that the model fits the data (in which case $\chi^2 = 0$). In this paper, the chi-square test was complemented with the Comparative Fit Index (CFI), Goodness of Fit Index (GFI), Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Squared Residual (SRMR), and Akaike Information Criterion (AIC). The standardized residual covariance matrix was also checked to confirm that coefficients were lower than 2 in absolute value.

Even if it is unsuitable for deterministic evaluation, a path models that fits the sample data is useful for confirming hypothesized model structures, validating cause–effect relationships, distinguishing relevant direct and indirect (mediated) effects, and identifying significant drivers, all of which can provide meaningful insights into a system’s structure and general behavior [82].

3.3.2. Modeling Assumptions, Constraints, and Unexplained Model Variance

Physical reasoning led to the exclusion of certain causal relations and modeling requirements, for example, ensuring matrix inversion [40,42], resulting in additional constraints on the structural equation problem. Table A1 in Appendix A presents the assumptions and constraints applied to the path model in Figure 5. This table details the reasoning justifying the assumptions and constraints and provides their expected contributions to output variables’ residues, i.e., to the unexplained model variance $V(\zeta_i)$.

4. Results and Discussion

4.1. Validation of the Model Structure

The path model in Figure 5 with the assumptions/constraints presented in Table A1 and covariance sample data from Table 3 converged to an admissible solution with chi-square close to one, which is statistically significant at the 0.05 level ($\chi^2(5) = 0.790$ with $p = 0.978$); hence, the exact fit hypothesis is not rejected. The relative fit of the model is a significant improvement over the baseline model fit with CFI = 1.00 (>0.95); according to the result of GFI = 1.00 (>0.95), the covariance matrix predicted by the model completely explains the variability in the sample covariance matrix. The RMSEA value of the model is 0.000 (<0.05 with 90% confidence interval 0.000–0.000) and the close fit hypothesis is not rejected ($p = 1.000$). The highest coefficient of the standardized residual covariance matrix is 0.651 (<2.00) and the model’s SRMR is 0.00 (<0.08). The Akaike Information Criterion (AIC) is 33,997.

Table 4 presents the unstandardized estimates (Unst.), corresponding standard errors (S.E.), and standardized estimates (St.) of the “full” path model parameters. The variances and covariances of the model variables (x and y) are equal to those determined from the standard deviations and correlation coefficients in Table 3.

In addition to the magnitude of the path coefficients, their statistical significance is also important. Several of the presented paths are not significant, such as the effects of wind speed (\overline{WS}) and relative humidity (\overline{RH}) on ventilation. The covariances between wind speed and relative humidity or solar radiation are also non-significant (not shown, but in accordance with Table 3). The covariance ψ_{12} between the residues of the output model variables is the least significant.

Table 4. Results of maximum likelihood estimation for the full and trimmed versions of the path model.

	Path Model				
	Full			Trimmed	
	Unst.	S.E.	St.	Unst.	St.
Direct effects, Γ					
$\gamma_{11} : \overline{T}_{out} \rightarrow \overline{acr}^*$	0.000 ^a	—	—	0.000 ^a	—
$\gamma_{21} : \overline{T}_{out} \rightarrow \overline{T}_{in}$	0.773 [‡]	0.049	0.967	0.751 [‡]	0.939
$\gamma_{12} : \overline{RH} \rightarrow \overline{acr}^*$	0.001	0.002	0.011	—	—
$\gamma_{22} : \overline{RH} \rightarrow \overline{T}_{in}$	0.012 [†]	0.005	0.049	0.012 [‡]	0.052
$\gamma_{13} : \Sigma E_{sol} \rightarrow \overline{acr}^*$	0.013 [‡]	0.003	0.147	0.013 [‡]	0.153
$\gamma_{23} : \Sigma E_{sol} \rightarrow \overline{T}_{in}$	0.060 [‡]	0.013	0.165	0.054 [‡]	0.148
$\gamma_{14} : \Sigma R^* \rightarrow \overline{acr}^*$	−0.149 [‡]	0.018	−0.227	−0.134 [‡]	−0.204
$\gamma_{24} : \Sigma R^* \rightarrow \overline{T}_{in}$	0.000 ^a	—	—	0.000 ^a	—
$\gamma_{15} : \overline{WS} \rightarrow \overline{acr}^*$	0.023	0.013	0.040	—	—
$\gamma_{25} : \overline{WS} \rightarrow \overline{T}_{in}$	−0.085 [†]	0.040	−0.035	—	—
$\gamma_{16} : \overline{S}_c^* \rightarrow \overline{acr}^*$	0.023 [‡]	0.003	0.155	0.023 [‡]	0.154
$\gamma_{26} : \overline{S}_c^* \rightarrow \overline{T}_{in}$	0.037 [†]	0.015	0.061	0.031 [‡]	0.050
Mediation effects, B					
$\beta_{12} : \overline{T}_{in} \rightarrow \overline{acr}^*$	0.156 [‡]	0.006	0.646	0.154 [‡]	0.637
$\beta_{21} : \overline{acr}^* \rightarrow \overline{T}_{in}$	−0.921 [†]	0.462	−0.222	−0.667 [‡]	−0.161
Disturbances’ variance, $V(Z)$					
$V(\zeta_1)$	0.194 [‡]	0.008	0.424	0.194 [‡]	0.425
$V(\zeta_2)$	2.11 [‡]	0.312	0.269	1.97 [‡]	0.251
Disturbances’ covariance, ψ_{12}					
$\zeta_1\zeta_2$	0.041	0.084	0.064	—	—

(a) Constrained parameter (see Table A1); (†) $p < 0.05$; (‡) $p < 0.01$.

After removing the statistically non-significant covariance ψ_{12} and trimming the resulting path coefficients to leave only those that were statistically significant to the $p < 0.01$ level, the “trimmed” path model was obtained, with unstandardized and standardized parameter estimates presented in the rightmost columns of Table 4.

For the trimmed-model, the chi-square statistic is $\chi^2(6) = 0.783$ ($p = 0.993$) and other fit statistics are CFI = 1.000, GFI = 1.000, RMSEA = 0.000 (0.000–0.000, $p = 1.000$), SRMR = 0.000, and AIC = 30,619. Except for the lower AIC, no significant difference is found between the goodness of fit statistics of the trimmed and full path models; moreover, both models have similar path coefficients.

These results confirm the validity of the internal structure proposed in Figure 5. As discussed in Section 3.2, both building physics and occupants’ adaptive behavior principles apply to the study of ventilation when using the path model approach, and should also apply to the case of structural equation modeling more generally. This is an important conclusion when considering that structural equation modeling allows for the simultaneous use of observable variables (included in this study) and unobservable constructs (not included) characterizing students’ and teachers’ group and personal attributes.

4.2. Estimates of Model Coefficients γ and β

The previous path analysis provides us with estimated magnitudes of the effects of the observable variables (see Table 4). Figure 6 provides a graphical interpretation of the trimmed model’s standardized estimates for the direct effects γ and mediation effects β .

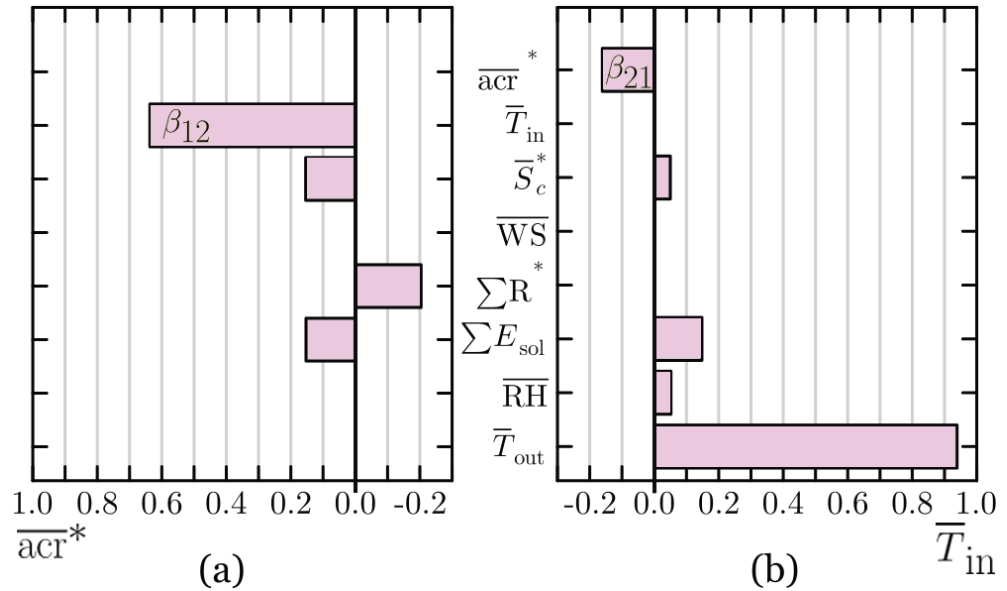


Figure 6. Bar charts with standardized coefficients β and γ for the trimmed path model from Table 4: (a) effects on air change rate and (b) effects on indoor air temperature. The bars represent the standard deviation change in \overline{acr}^* and \overline{T}_{in} per unit standard deviation change in the model parameters \overline{T}_{out} , \overline{RH} , ΣE_{sol} , ΣR^* , \overline{WS} , \overline{S}_c , \overline{T}_{in} , and \overline{acr}^* .

Starting with the path analysis of β between ventilation and the indoor thermal environment, it can be concluded that both are statistically significant and that their coefficients have opposite signs, confirming the negative feedback loop discussed in Section 3.2. From the magnitude of the standardized estimates, it can be concluded that the reciprocal causal effect is stronger in the direction from thermal environment to ventilation (0.637); in fact, the mediating effect of the indoor thermal environment β_{12} is the best determinant of classroom ventilation, and is much better than the direct effects γ_{1j} from classroom occupancy and outdoor physical variables. Because ventilation is determined by occupants’ behavior and is a function of the perceived environment, this result confirms indoor air temperature as the most important determinant of occupants’ behavior.

However, the proposed path model structure defines the coefficient β_{12} as a mediating effect, with indoor air temperature determined in turn by classroom occupancy and outdoor physical variables. Figure 6b shows that the outdoor air temperature has the largest effect by far on the indoor air temperature, with a standardized path coefficient of 0.939, i.e., one standard deviation change in the outdoor air temperature determines a 0.939 standard deviation change in the same direction in the indoor air temperature. Indeed, previous research is unanimous regarding the effect of indoor and outdoor air temperature on natural ventilation with window airing, concluding that both are very important drivers [34,78]. The internal structure used in this paper, with the indoor air temperature mediating the outdoor air temperature, allows for the use and association of both these variables in a single model, thereby circumventing the discussion of which temperature should be used [26,28,57,78]. In this approach, occupants perceive the direct effect of the indoor air temperature while retaining the indirect effect of the outdoor air temperature [43]; see Section 4.4.2 for a detailed description of the indirect effects.

To analyze the magnitude of the standardized effects γ_{1j} of occupancy and outdoor variables on ventilation, Figure 6a shows that the best predictors of ventilation are precipitation, metabolic CO₂ production rate (occupancy), and solar energy, with standardized coefficients -0.204 , 0.154 , and 0.153 , respectively. The negative sign for precipitation (also described in [83]) suggests a link between precipitation and window closing, and in turn with a reduction in the air change rate. The results for solar energy show that ventilation increases with increasing solar energy. Because solar energy contributes to the indoor thermal and visual environments, influencing opening/closing of both windows and blinds, these results testify to this combined effect.

Regarding classroom occupancy, the statistical significance of the direct effect on ventilation supports larger air change rates for larger class attendance levels, or for classes with older students considering similar attendance. It is interesting to point out the disproportion between the standardized coefficient relating occupancy and ventilation (0.154) as well as in the one relating occupancy and indoor air temperature (0.050). This result implies occupancy reduced effect on indoor air temperature (due to the use of artificial lighting and blinds and heat release associated with occupants' behavior and physiology) when compared to the effect of manual window opening/closing, associated with context-related drivers such as students' number and age [26,43] or students' and teachers' information about/awareness towards indoor air quality problems [84,85], among others.

Among the outdoor variables, those with the less relevant direct effects on classroom ventilation are relative humidity and wind speed. Results for the full-path model in Table 4 show that coefficients relating these variables with ventilation are statistically non-significant. For relative humidity, this result could be a consequence of the strong correlation (>0.6 , see Table 3) with solar energy and precipitation, with these variables better explaining ventilation variance. The non-significant effect of wind speed (also found in [28,62]) is understandable considering the low window permeability pointed out in Section 2.1. Indeed, with the exclusion of infiltrations, the agency role played by occupants modulates window opening/closing with the goal of reducing uncomfortable drafts, in this way unlinking the windspeed from classroom ventilation.

4.3. Path Model Equations

By replacing the trimmed path model's unstandardized direct and mediating coefficients γ and β in Equation (1), considering the system's mean structure [42], and using the variances of residues $V(\zeta_i)$, the following equations relate the estimated model (m) outputs $\overline{acr}^{*,m}$ and \overline{T}_{in}^m with the input variables x_j :

$$\begin{aligned} \overline{acr}^{*,m} &= \overline{acr}^{*,m0} + \sum_{j=1}^6 \gamma_{1j}x_j + \beta_{12}\overline{T}_{in}^m + W_1(V(\zeta_1)) \\ \overline{T}_{in}^m &= \overline{T}_{in}^{m0} + \sum_{j=1}^6 \gamma_{2j}x_j + \beta_{21}\overline{acr}^{*,m} + W_2(V(\zeta_2)) \end{aligned} \tag{2}$$

where $\overline{acr}^{*,m0}$ ($=7.494$) and \overline{T}_{in}^{m0} ($=-2.781$) stand for the path model intercepts [81] and $W_i(V(\zeta_i))$ defines the white noise for the output variables, with zero mean and constant variance equal to $V(\zeta_i)$.

By solving the system of equations in (2), the following path model equations for $\overline{acr}^{*,m}$ and \overline{T}_{in}^m are obtained:

$$\overline{acr}^{*,m} = -1.4754 + 0.1049\overline{T}_{out} + 0.0193\Sigma E_{sol} - 0.1215\Sigma R^* + 0.0252\overline{S}_c^* + 0.9068W_1(0.194) + 0.1396W_2(1.970) \tag{3a}$$

$$\overline{T}_{in}^m = 8.4781 + 0.6810\overline{T}_{out} + 0.0411\Sigma E_{sol} + 0.0810\Sigma R^* + 0.0142\overline{S}_c^* - 0.6049W_1(0.194) + 0.9068W_2(1.970). \tag{3b}$$

Figure 7 presents scatter plots comparing one year of sample monitoring data for the variables \overline{acr}^* (bottom graph, \circ) and \overline{T}_{in} (top graph, \circ) with the corresponding estimates $\overline{acr}^{*,m}$ and \overline{T}_{in}^m (denoted with $+$) determined using the path model Equations (3a) and (3b). Moving averages are also represented, with four points each for the sample data ($-$) and estimates ($*$).

Figure 7 confirms that the path model is unsuited for deterministic evaluation of classroom air change rate or classroom indoor air temperature. Nonetheless, the sample and estimate moving averages are fairly similar. Moreover, despite its simplicity, the constant-variance white noise used in Equations (3a) and (3b) estimates daily ranges of output variables that are not much different from those found in the sample, a sign that the system’s mean structure is correctly captured.

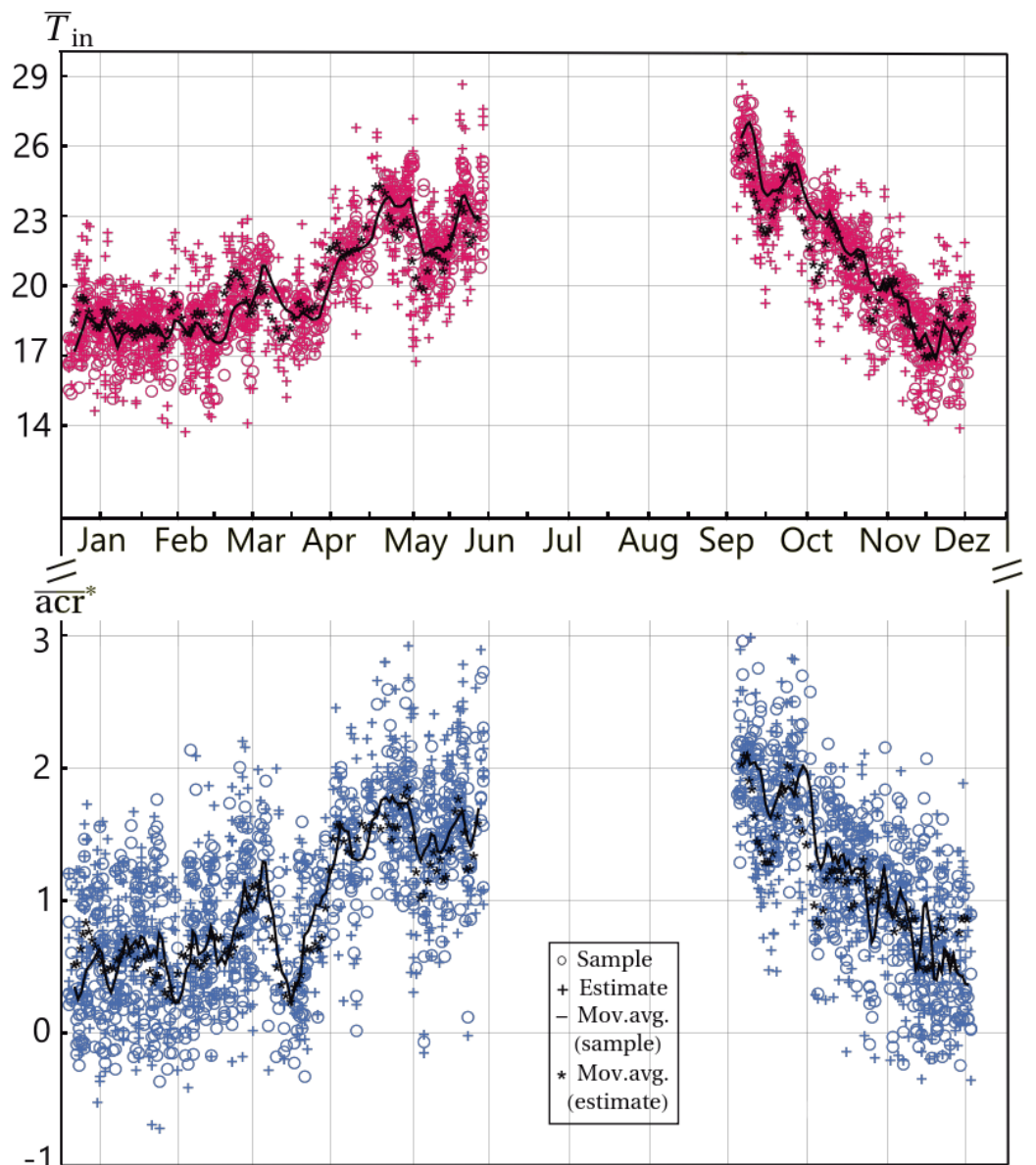


Figure 7. Scatter plot comparing one year of \overline{acr}^* and \overline{T}_{in} sample data with the corresponding estimates $\overline{acr}^{*,m}$ and \overline{T}_{in}^m determined with Equation (3). Moving averages (four points each for both sample data and estimates) are also shown.

Table 5 compares the sampled and estimated mean values of the output variables \overline{acr} and \overline{T}_{in} for different class intervals of the outdoor temperature. Table 5 confirms that the path model correctly captures the output variables’ mean structure as a function of the

outdoor air temperature, with errors not exceeding 6% and 1% for air change rate and indoor air temperature, respectively.

For behavioral and decision-making studies, knowledge of the mean air change rate per class interval with respect to the outdoor air temperature may be sufficient to characterize students’ and teachers’ behavior and support the adoption of an improved ventilation strategy. Moreover, the capability of path diagrams and of structural equation models more generally to represent and validate causal relationships between observable (physical) variables and unobservable (personal, context-related) factors may very well offset these tools’ lack of capacity for deterministic estimation.

Table 5. Comparison of sample and estimated mean structure of the output variables for different class intervals of outdoor temperature.

Mean or Variance	Data Used	Class Intervals of Outdoor Temperature				
		$\bar{T}_{out} < 13\text{ }^{\circ}\text{C}$	$13 \leq \bar{T}_{out} < 15\text{ }^{\circ}\text{C}$	$15 \leq \bar{T}_{out} < 17\text{ }^{\circ}\text{C}$	$17 \leq \bar{T}_{out} < 19\text{ }^{\circ}\text{C}$	$\bar{T}_{out} \geq 19\text{ }^{\circ}\text{C}$
$\overline{acr} [h^{-1}]^a$	Sample Estimate (Error [%])	1.88 1.83 (2.99)	2.27 2.34 (−3.15)	3.67 3.75 (−2.22)	4.91 4.69 (4.53)	6.18 6.51 (−5.45)
$\bar{T}_{in} [^{\circ}\text{C}]$	Sample Estimate (Error [%])	18.0 17.9 (0.573)	19.4 19.5 (−0.562)	21.3 21.1 (0.655)	22.9 22.7 (0.989)	24.7 24.7 (0.225)

(a) $\overline{acr} = \exp(\overline{acr}^*)$.

Comparison with a Simpler Regression Model

By using multiple linear regression [86] (lm function) and the same sample dataset to derive the path model, we obtained the following regression equation for the air change rate $\overline{acr}^{*,lm}$ ($F = 380$; $p < 0.001$; $R^2 = 0.566$):

$$\overline{acr}^{*,lm} = -1.3405 + 0.1050\bar{T}_{out} + 0.0181\Sigma E_{sol} - 0.1163\Sigma R^* + 0.0252\bar{S}_c^*, \tag{4}$$

with statistically significant ($p < 0.01$) intercept and regression coefficients.

Observing Equations (3a) and (4), the similarities between coefficients are obvious; moreover, the R^2 values for the regression and path models are also identical ($R^2 = 1 - V(\zeta_1) = 0.575$ for the path model). In [87], the authors also reported identical results obtained with the path model and multiple linear regression, which is understandable given that path modeling uses a collection of statistical techniques that include multiple regression [42].

In spite of the similarity between the regression and path model in terms of results, it is important to recall that the goal of the path model analysis presented in this paper is to assess the internal structure proposed in Figures 4 and 5, not to improve the fit between model estimates and sample data. Indeed, the analysis presented thus far has used continuous data on occupancy and environmental physical variables to extend the understanding of natural ventilation with window airing by validating and quantifying direct, mediation, and feedback effects taking place in the classrooms of a Portuguese school. Additional insights made available by the path model are described in the next section.

4.4. Additional Insights from the Path Model Analysis

4.4.1. Model Unexplained Variance

Figure 7 exposes the sample’s (o) large variability in terms of classroom air change rate and indoor air temperature. The path model estimates (+) and estimates moving average (*) depicted in Figure 7 visually represent the amount of unexplained variability in the air change rate and indoor air temperature. The standardized variances of the path model residuals ζ_1 and ζ_2 show that 42.5% and 25.1%, respectively, of the variance in total variability of these two model output variables remains unexplained, which translates into moderate and good prediction of the variability in ventilation and indoor air temperature

variance (R^2 equal to 0.575 and 0.749, respectively). This difference in the quality of the results for ventilation and indoor air temperature is highlighted by the path model, and deserves more detailed analysis. Despite the two-year experimental dataset ensuring high data variability, thereby reducing the relevance of individual students'/teachers' psychological or physiological traits, conditions specific to certain seasons, and classroom orientations, it is possible that personal and contextual factors not included in the model may have influenced occupants' behavior [25,43,78,88]. Because occupant behavior related to window opening/closing has a far more meaningful effect on classroom ventilation than any other effects on indoor air temperature due to occupant behavior, a reasonable explanation for the difference in unexplained variance between ventilation and indoor air temperature would be the model's lack of important personal and contextual determinants surrounding occupant behavior.

4.4.2. Direct and Indirect Effects

For outdoor physical variables and metabolic CO₂ production rate, the presence of mediation effects β implies the distinction between direct, indirect, and total effects on the output model variables y_i . The direct effects are those presented in Table 4, while the indirect effects consist of path combinations including at least one feedback loop path β , for example, $\bar{T}_{out} \rightarrow \bar{T}_{in} \rightarrow \overline{acr}^*$. Total effects are the sum of direct and indirect effects. For the air change rate, which has discernible indirect effects due to the larger β_{12} value linking indoor air temperature to air change rate, Figure 8 distinguishes standardized direct and indirect effects for the trimmed path model variables \bar{T}_{out} , ΣE_{sol} , ΣR^* , \bar{S}_c^* , \bar{T}_{in} , and \overline{acr}^* .

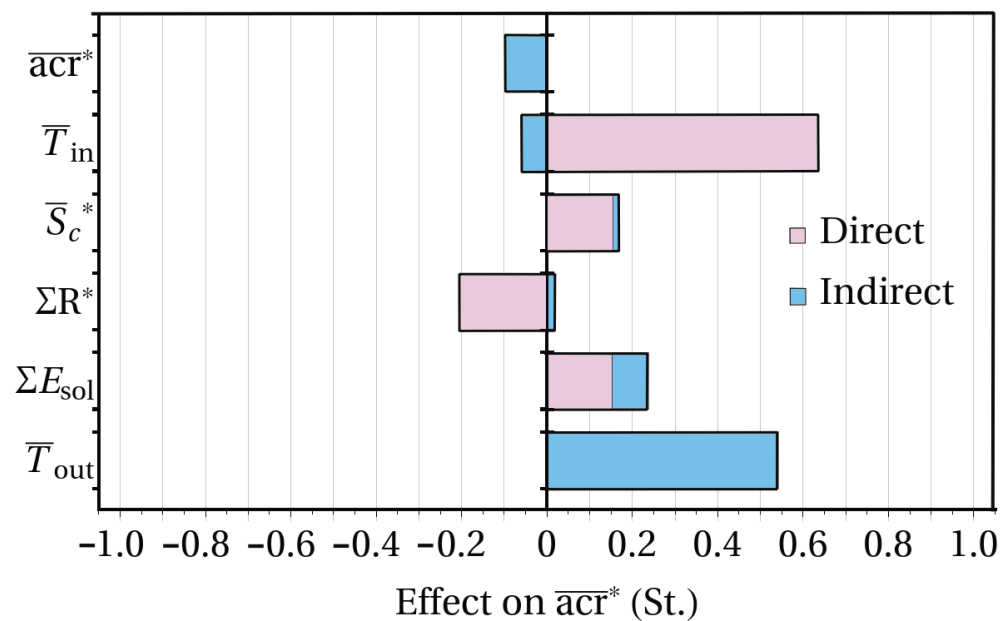


Figure 8. Standardized direct and indirect effects on air change rate for the trimmed path model. The presented indirect effects consider the sum of all possible paths, for example, the indirect effect of \bar{T}_{out} on \overline{acr}^* sums the standardized effect of path $\bar{T}_{out} \rightarrow \bar{T}_{in} \rightarrow \overline{acr}^*$ with path $\bar{T}_{out} \rightarrow \bar{T}_{in} \rightarrow \overline{acr}^* \rightarrow \bar{T}_{in} \rightarrow \overline{acr}^*$, and so on (i.e., a convergent series).

Figure 8 emphasizes the importance of the indirect effect of outdoor air temperature on classroom ventilation; at 0.542, it is almost as large as the direct effect of indoor air temperature (0.637; see Table 4). Other relevant indirect effects on ventilation are those associated with air change rate and solar energy (−0.093 and 0.085, respectively). The indirect effect of the air change rate on itself (by means of the negative feedback loop paths β) tends to reduce the air change rate, having a stabilizing effect that is opposed to disturbances in occupancy and outdoor environmental variables. For solar energy, both the indirect and direct effects contribute to increases in the air change rate, resulting in a total

effect of 0.238 ($=0.153 + 0.085$), which is the largest after air temperature. The indirect effects associated with indoor air temperature and precipitation are -0.059 and 0.019 , respectively. The metabolic CO_2 production rate has the lowest standardized indirect effect, at 0.015 .

Comparing the standardized direct effects on air change rate presented in Table 4 with the corresponding total effects derived from Figure 8, the effect of indoor air temperature decreases to ($0.637 - 0.059$) 0.578 , the effect of solar energy increases to ($0.153 + 0.085$) 0.238 , the effect of precipitation decreases to ($-0.204 + 0.019$) -0.185 , and the effect of occupancy increases to ($0.154 + 0.015$) 0.169 . These changes are small but meaningful, especially the 55% increase in the standardized effect of solar energy on the air change rate.

4.5. Limitations

Before concluding this article, it is important to mention some aspects that can influence the validity of the presented results.

First, it is fair to say that the research design ensured large data variability, thereby diminishing way the relevance of individual psychological or physiological traits as well as conditions specific to certain seasons and classroom orientations. Indeed, the extended monitoring period not only allowed for gathering two years of outdoor and indoor environmental data, but also led to the collection of lesson attendance data for more than 20 different classes from 5th to 12th grade, with a total of more than 500 students. The fact that the four classrooms had different orientations (south, west, north) and were located on different floors of the building (intermediate and top floors) also contributed to data variability. However, it is also true that environmental and lesson attendance data can be influenced, among other things, by school architecture, students' and teachers' cultural traits, and Lisbon's climate. Therefore, the external validity of the study is limited to architectonic, cultural and climatic conditions typical of Southern European countries.

Second, the research was designed to minimize unwanted residuals due to occupancy, especially those due to environmental variables. For this reason, great care was taken in the analysis of lesson attendance logs; in addition, a large number of outdoor environmental variables were included in the modeling, and we used sensors that were both accurate and precise. Nonetheless, it should be recognized that the measurement accuracy is lower for metabolic CO_2 production rate, and this variable (the only non-physical one) may be insufficient to characterize occupants' behavior.

Finally, although the developed path model takes into consideration both building physics and occupants' adaptive behavior, it is important to acknowledge that the excellent fit statistics of our trimmed model do not exclude alternative models which might produce similar or even better results [42].

4.6. Recommendations for Future Work

Considering the limitations presented in the previous section, further research into using SEM to research natural ventilation in classrooms would benefit from (i) the inclusion of additional personal and context-related drivers of occupants' behavior; (ii) extending the study to more schools in different locations; and (iii) alternatives to the proposed model's internal structure.

These research topics would confirm the importance of personal and contextual drivers of occupants' behavior and help to identify the most relevant ones; for classrooms, group dynamics and teachers' personal traits are both worthy of detailed investigation. It would also help to highlight cultural differences and the merit of specific architectural solutions, and could lead to a better understanding of the interplay between physical, personal, and contextual drivers of teacher and student behaviors.

In regard to the school studied in this paper, taking into consideration the classrooms' poor indoor air quality (especially during wintertime), more investment is needed to meet heating requirements and ventilation best practices. Applying the proposed path model to data gathered from a school where management, janitors, teachers, and students are empowered with information regarding the importance of window opening/closing should

result in far lower unexplained ventilation variance regardless of personal and cultural differences [89,90].

5. Conclusions

In this paper, we have used a path modeling approach to propose causal relationships relating classroom occupancy and outdoor environmental variables with classroom ventilation and air temperature. Sample data from a two-year experimental study of four naturally ventilated classrooms in a Portuguese school were used to validate the path model. Estimates of the magnitude of the causal effects were obtained, and the unexplained model variance was analyzed considering the selected input variables.

Concerning the path modeling results obtained for the studied classrooms, it can be concluded that:

- Indoor and outdoor air temperatures are paramount to classroom ventilation, with standardized total path coefficients of approximately 0.55.
- Other significant determinants of classroom ventilation include solar energy, precipitation, and occupancy (as expressed by metabolic CO₂ production rate), with standardized total path coefficients 0.24, −0.18, and 0.17, respectively.
- The model only explained 58% of the ventilation variance, whereas for the indoor air temperature it explained 75% of the variance. This difference is attributed to the absence of important personal and contextual factors regarded as determinants of occupants' behavior.

Regarding to the use of path modeling and SEM more generally to research natural ventilation, it can be concluded that:

- Causal relationships derived from building physics and principles of occupants' behavior resulted in a path model with an excellent fit to the sample covariance data gathered from naturally ventilated classrooms.
- Compared to the commonly used multiple and logistic regression methods, path modeling can expand the understanding of natural ventilation, providing detailed direct, mediation, and feedback effects as well as quantifying the unexplained variance associated with individual model output variables such as the air change rate and indoor air temperature.
- As a collection of statistical procedures that complements path analysis with exploratory factor analysis, SEM is well suited for multi-domain studies; thus, an extension of the present research to include additional personal and contextual determinants of occupants' behavior would allow for further insights.

Finally, practical advice to improve the studied classrooms' indoor air quality, especially during wintertime, would include raising the awareness of school management, janitors, teachers, and students regarding the importance of appropriate classroom heating and classroom ventilation (i.e., window opening/closing) best practices.

Author Contributions: Conceptualization, R.D.; methodology, R.D.; validation, A.M.R., M.d.G.G. and F.P.; formal analysis, R.D.; investigation, R.D.; resources, R.D. and F.P.; data curation, R.D. and F.P.; writing—original draft preparation, R.D.; writing—review and editing, R.D., A.M.R. and M.d.G.G.; visualization, R.D. and A.M.R.; project administration, M.d.G.G. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author due to privacy reasons.

Conflicts of Interest: The authors declare no conflicts of interest.

Nomenclature

acr	air change rate, h^{-1}
c	CO_2 concentration, ppm
E	solar energy density, W/m^2
R	precipitation, mm
RH	outdoor relative humidity, %
S_c	metabolic CO_2 production rate, l/h
T	air temperature, $^\circ\text{C}$
V	classroom volume, m^3
WS	windspeed, m/s

Subscripts

atm	denotes atmospheric
in	denotes indoor
ma	denotes moving average
out	denotes outdoor
sol	denotes solar

Superscripts and abbreviations

(\cdot)	denotes daily mean
$(\cdot)^*$	denotes logarithmic transformation or multiplication by 10^{-1}
m	denotes path model estimate
m0	denotes path model intercept
rm	denotes regression model estimate
SD	standard deviation
SEM	structural equation model/modeling

Appendix A

Table A1. Table with assumptions, constraints, and consequences regarding unexplained variances $V(Z)$.

Assumption i. Classroom ventilation is driven mainly by occupants' active behavior: Classrooms are neither heated nor cooled. Window frame low permeability class (see Table 1) implies low infiltration with closed windows. Since window (blinds) opening/closing is manual, classroom ventilation is driven mainly by occupants' active behavior.

Constraint: Not applicable.

Consequence: Occupants' behavior depends on numerous variables [25,43,88] classified as physical, personal, and context-related. The path model includes the most relevant physical variables and a single physiological/context factor, occupancy. Since physical variables are never enough to justify the variance in window opening/closing (Dutton and Shao [28], studying classrooms and using physical variables, report unexplained variance above 50%), it is concluded that a significant portion of unexplained ventilation variance could result from the model's incomplete characterization of personal and context factors. Because the *direct* impact (excluding window opening/closing) of occupants on classrooms' air temperature variance (i.e., physiological heat release, artificial fluorescent lighting turned on/off, blinds opening/closing) is small compared to the impact of manual window opening/closing on ventilation variance, indoor air temperature unexplained variance should be smaller than unexplained ventilation variance.

Assumption ii. The model includes the main indoor physical determinant of classroom ventilation: Indoor air temperature is the most important determinant of window opening/closing [26,30,78] and is included in the model. Indoor CO_2 concentration, associated with occupants' perception of indoor air quality, is also considered a determinant of window opening [28,30,62]. This variable is measured but is not included in the model given its strong correlation to classrooms' air change rate (see [3,75,76]). According to [25], a thorough bibliographic review found solar energy to be the main determinant of classroom lighting control and blinds opening/closing, with an effect stronger than that of indoor variables.

Constraint: Not applicable.

Consequence: The main indoor physical determinant of window opening/closing is included. Considering the strong inversely proportional relation visible in Figure 3 between indoor air temperature and CO_2 concentration and because metabolic CO_2 production rate is considered in the model, occupants' perception of indoor air quality is not excluded from the model. Still, some measure of unexplained variance could result from the incomplete thermal and visual characterization of the indoor physical environment.

Assumption iii. The model includes the main outdoor determinants of classroom ventilation: Outdoor air temperature, relative humidity, solar energy, precipitation are among the most commonly accepted outdoor determinants of window (and blinds) opening/closing [25–28] and are included in the model. Despite little researched [25], other outdoor variables can also determine window opening/closing, notably, noise and atmospheric pollution [3,59].

Constraint: Not applicable.

Consequence: The most commonly accepted outdoor determinants of window (and blinds) opening/closing are included in the model. The studied school is located in a residential area with almost no traffic and reduced commercial activity. Moreover, given its location on the Atlantic coast and steady wind speeds throughout the year, serious cases of poor atmospheric pollution are rare in Lisbon. The contribution of noise and atmospheric pollution to model unexplained variance should be small.

Table A1. Cont.

Assumption iv. Outdoor air temperature effect on ventilation is mediated by indoor air temperature: The large correlation between outdoor and indoor daily air temperature (see Table 3) limits the simultaneous use of these variables. Given the similar correlations coefficients between both these variables and air change rate (~ 0.67), a reasonable assumption is that outdoor temperature has a direct effect on indoor air temperature and that indoor air mediates the effect of outdoor air temperature on ventilation [58,77]. This condition is implemented by constraining the coefficient γ_{11} to zero.

Constraint: $\beta_{11} = 0$.

Consequence: The contribution of the missing direct effect of outdoor air temperature on air change rate unexplained variance should be small.

Assumption v. Precipitation effect on indoor air temperature is mediated by ventilation: Precipitation occurs during winter, when indoor air temperatures and air change rates are low and also during warmer months (e.g., June) when indoor air temperatures and air change rates are high. Still, Table 3 shows that the correlation coefficient between precipitation and indoor air temperature is only 2/5 of that between precipitation and air change rate (0.1500 versus 0.3787). This suggests a strong direct effect of precipitation on air change rate by means of window opening/closing patterns and a weaker mainly indirect effect on indoor air temperature. This condition is implemented by constraining the coefficient γ_{24} to zero.

Constraint: $\beta_{24} = 0$.

Consequence: The contribution of the missing direct effect of precipitation on indoor air temperature unexplained variance should be small.

Assumption vi. Metabolic CO₂ production rate and outdoor physical variables are independent (uncorrelated): Mandatory education up to the 12th grade justifies class attendance (with CO₂ release) regardless of outdoor environmental conditions. Table 3 very low and non-significant correlations between metabolic CO₂ production rate and outdoor physical variables attests to this assumption; implemented by constraining coefficients ϕ_{6j} to zero.

Constraint: $\Phi_{6j} = 0$.

Consequence: The contribution of the missing covariances on model unexplained variance should be small.

Assumption vii. Regarding measurement errors and model's internal structure: Sensor accuracy was confirmed and class attendance logs were carefully analyzed to reduce inconsistencies. Path model internal structure was derived from building physics principles as well as occupant adaptive behavior considerations.

Constraint: Not applicable.

Consequence: Despite the effort to ensure the quality of the sample dataset and that the model included the most relevant causal relationships, some measure of unexplained model variance should result from measurement errors and modeling simplifications.

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