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School building energy efficiency and NO_2 related risk of childhood asthma in England and Wales: Modelling study

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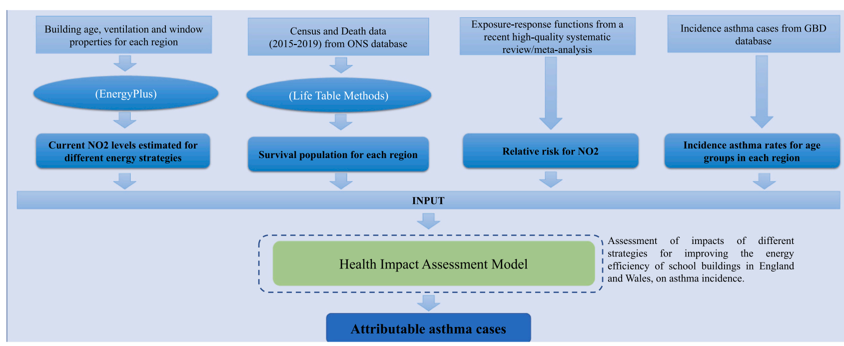
HIGHLIGHTS

- We compared the effects of school energy efficiency measures on indoor NO_2 exposure.
- We modelled the impact on childhood asthma incidence and hospitalization costs.
- Scenarios without operational measures increased NO_2, asthma and hospital costs.
- Asthma reduced with operational strategies to improve indoor environmental quality.
- Appropriate school building operational strategies are critical for child health.

GRAPHICAL ABSTRACT



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ABSTRACT

Background: Climate change legislation will require dramatic increases in the energy efficiency of school buildings across the UK by 2050, which has the potential to affect air quality in schools. We assessed how different strategies for improving the energy efficiency of school buildings in England and Wales may affect asthma incidence and associated healthcare utilization costs in the future.

Methods: Indoor concentrations of traffic-related NO_2 were modelled inside school buildings representing 13 climate regions in England and Wales using a building physics school stock model. We used a health impact assessment model to quantify the resulting burden of childhood asthma incidence by combining regional health and population data with exposure-response functions from a recent high-quality systematic review/meta-analysis. We compared the effects of four energy efficiency interventions consisting of combinations of retrofit and operational strategies aiming to improve indoor air quality and thermal comfort on asthma incidence and associated hospitalization costs.

Results: The highest childhood asthma incidence was found in the Thames Valley region (including London), in particular in older school buildings, while the lowest concentrations and health burdens were in the newest schools in Wales. Interventions consisting of only operational improvements or combinations of retrofit and operational strategies resulted in reductions in childhood asthma incidence (547 and 676 per annum regional average, respectively) and hospital utilization costs (£52,050 and £64,310 per annum regional average,

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respectively. Interventions that improved energy efficiency without operational measures resulted in higher childhood asthma incidence and hospital costs.

Conclusion: The effect of school energy efficiency retrofit on NO_2 exposure and asthma incidence in schoolchildren depends critically on the use of appropriate building operation strategies. The findings from this study make several contributions to fill the knowledge gap about the impact of retrofitting schools on exposure to air pollutants and their effects on children's health.

1. Introduction

The UK's non-domestic building sector has a substantial role to play in the transition to a low carbon economy since it is responsible for 18 % of the UK's carbon emissions (Carbon Trust, 2009). The UK has set targets through the 2008 Climate Change Act to reduce greenhouse gas emissions by 2050 (CCA, 2008), and this legislation will require dramatic increases in the energy efficiency of buildings across the UK by 2050. Schools are a part of the non-domestic sector and may be important locations of exposure to air pollution, since they are where children spend 30 % of their waking hours (Csobod et al., 2014). It is essential to ensure that future retrofits do not compromise indoor air quality and children's health and learning.

Particulate matter (e.g. $PM_{2.5}$), nitrogen dioxide (NO_2), ozone (O_3), and carbon monoxide (CO) are examples of traffic-related air pollutants that have been associated with higher rates of asthma occurrence. Children are more vulnerable to airborne pollutants than adults as their developing lungs breathe in more air relative to the size of their bodies and their ability to cope with pollutants is underdeveloped (Chatzidiakou et al., 2014). The UK has among the highest prevalence, emergency admissions and death rates for childhood asthma in Europe, with children and young people in the most deprived areas experiencing worse outcomes (NHS, 2021a). Increasing the energy efficiency of buildings through retrofitting, e.g. improving building fabric thermal insulation, can potentially increase temperatures inside the building, if poorly designed, i.e. not combined with appropriate ventilation/cooling means (Fosas et al., 2018). Creating a more airtight building envelope, as part of energy retrofit, can provide protection to those indoors from pollutants in the outside air, which may have positive impacts on physical and mental health (Thomson et al., 2013); however, it can also affect levels of pollutants generated inside the building (Davies et al., 2004). Both thermal comfort levels and indoor air quality have a crucial role to play in producing an environment that supports optimal educational and health outcomes.

Several studies (Hamilton et al., 2015; Khreis et al., 2018; Milner et al., 2014; Tieskens et al., 2021) have evaluated the impacts of energy efficiency retrofit strategies in residential buildings on human health, but there has been less focus on schools. Tieskens et al. (2021) developed a discrete event model for paediatric asthma exacerbation to assess the effects of different types of energy retrofits in homes. Hamilton et al. (2015) assessed the potential health impacts of changes to indoor air quality and temperature due to energy efficiency retrofits in English dwellings. They applied three scenarios including different levels of airtightness and ventilation systems. We are aware of no previous studies on the impacts of energy efficiency retrofit strategies on the health of children in school buildings. To address this gap, this work aimed to illustrate the potential impact of hypothetical but realistic energy efficiency retrofits, including with operational measures to improve indoor environmental quality (IEQ), on childhood asthma across schools in England and Wales. We quantified the number of childhood asthma cases and associated health service costs, attributable to exposure to NO_2 from outdoor sources in schools, and compared the hypothetical impacts for four interventions consisting of combinations of building fabric retrofit and operational strategies.

2. Methods

2.1. Location

In this study, we estimated the impact of energy efficiency retrofits on changes in NO_2 exposures in schools on the burden of childhood asthma incidence for 13 climate regions of England and Wales based on CIBSE degree day regions (CIBSE, 2008): Thames Valley, South Eastern, Southern, South Western, Severn Valley, Midland, West Pennines, North Western, Borders, North Eastern, East Pennines, East Anglia, and Wales (Fig. S1, Supplementary Material). The results were quantified for England and Wales as a whole and also separately for each of the 13 regions.

2.2. Framework

Our conceptual framework for assessing the impacts of indoor air pollution and childhood asthma is shown in Fig. 1. We used a life table-based health impact assessment (HIA) model to estimate (i) current (baseline) asthma incident cases attributable to NO_2 and (ii) averted asthma incident cases under three energy efficiency interventions to compare with baseline outcomes. The life table method was used to estimate the surviving population over time to provide a baseline population for the asthma calculations. The overall modelling approach is given in Section 2.3 with the life table approach used to adjust the future population size detailed in Section 2.2.1. In the second part of this study, the model results were also evaluated for a cohort of children over a period of 11 years, to analyse and compare the change in asthma cases for children over the ages of 5–16 years, including periods of primary and secondary school education.

The HIA model requires four inputs:

(1) A dynamic population of school-aged children
(2) NO_2 exposures in schools at baseline and under energy efficiency interventions
(3) Baseline asthma incidence rates
(4) Relative risk for NO_2-related asthma

The details of each are given below:

2.2.1. Population of school-aged children

A dynamic population of children aged 5–16 years in England and Wales was produced using the life table model, IOMLIFET (Miller and Hurley, 2003). Life tables were set up using 2019 age-specific population and mortality data (i.e. death from all causes) for each county in England and Wales using data from the Office for National Statistics (ONS), with separate life tables set up for males and females to reflect different mortality rates and life expectancy (ONS, 2010). The ONS data are provided for government office regions (Table S1) which do not exactly match the 13 (CIBSE-based) climate regions used in our study. Therefore, the counties in both cases were matched in order to find and group the counties in the climate regions. For this purpose, firstly, the boundaries of government office and climate regions were compared. Then, the counties were allocated to the relevant climate region (Table S2).

We generated mortality rates for each region using the average of five years' population and mortality data, after subtracting neonatal data. We applied and compared Piecewise Cubic Hermite Interpolating Polynomials (Pchip) and cubic spline interpolation methods in MATLAB R2010 (MathWorks Inc., Natick, MA, US) to calculate the age specific population size to be used in the life table (Miller and Hurley, 2003). We obtained better fit with the Pchip method, and therefore used it to perform the calculations. Survival populations obtained by the life table method in 2020 provided a dynamic baseline population for the asthma calculations.

2.2.2. Internal NO_2 concentrations

Indoor NO_2 concentrations in UK schools were modelled using a school building stock indoor environment model, which uses the building physics model EnergyPlus version 9.5 (US Department of Energy, 2021) as its core calculation engine to predict energy demand and IEQ across the school building stock. We used the model to simulate indoor NO_2 exposures for different scenarios consisting of combinations of pair-wise energy retrofit and operational strategies and accounting for the glazing ratio and prevailing climatic conditions of different building age and geographical region archetypes across the UK. Hourly external NO_2 concentrations were acquired for 2019 from UK-wide monitoring sites (DEFRA, 2021) for each of the 13 geographical regions and annual profiles for each site were then plotted by region. For each region, the individual monitoring site which provided the most representative profile relative to the median values across the entire year was then selected and used to provide the profile of external NO_2 concentration. In the model, the external hourly data was multiplied at each time step by the Indoor/Outdoor ratio to give internal concentrations. The model is described in detail in Grassie et al. (2023).

To provide credence to the results of the modelling, it was critical to validate both the method and calculated results. The use of airflow network modelling within EnergyPlus has previously been validated against measured data of other contaminants (Dutton et al., 2008), measured data from air conditioning equipment (Gu, 2007) and other types of contaminant modelling (Dutton et al., 2008). While the classroom models represent a hypothetical case, it has been possible to verify the range of NO_2 concentrations against measured data in real classrooms. A range of 4.3 to 29.7 ppb (Gaffin et al., 2018) with median of 10.4 ppb and mean of 11.1 ppb has been measured across 218 classrooms in 37 US schools. From a wider study (Salonen et al., 2019) of 47 publications, this range in classrooms across the world increases to 6 to 68.5 ppb, with a median of 26.1 ppb and mean of 30.1 ppb. This compares well to the annual exposure range we have calculated across all settings of 1.6 ppb (Wales) to 29.6 ppb (London). While this provides a reasonable setting for the baseline of modelling, differences in NO_2 exposures across settings are the main focus of our study.

In this work, we considered current NO_2 concentrations related to 10,201 naturally-ventilated primary and secondary schools across the 13 geographical regions. We also calculated the weighted average exposures for five construction eras (Pre-1918, Inter-war, 1945–1967, 1967–1976 and Post-1976), four orientations (north, south, east and west) to use in the HIA model. Average values of the raw data across all regions are given in Table S3 in the supplementary material.

We quantified changes in indoor NO_2 exposures under four scenarios to estimate the resulting asthma impacts:

1. Baseline: current exposures in the existing school building stock of England and Wales;
2. Retrofit scenario: incorporating retrofit strategies in compliance with the EnerPHIt (Institute, 2016) energy efficiency standard. The use of mechanical ventilation with heat recovery (MVHR), specified in the EnerPHIt standard, was not modelled;
3. Operational scenario: consisting of only operational strategies to control heat flows. These included the use of albedo, external shading, thermal mass, internal blinds and passive night-time ventilation.
4. Combined scenario: including a pair-wise combination of the above retrofit and operational strategies.

For each scenario, EnergyPlus was also used to estimate the number of overheating hours per year, the annual average indoor concentration of carbon dioxide (CO_2) generated by the schoolchildren and the annual greenhouse gas (GHG) emissions in kg/m^2 from space heating.

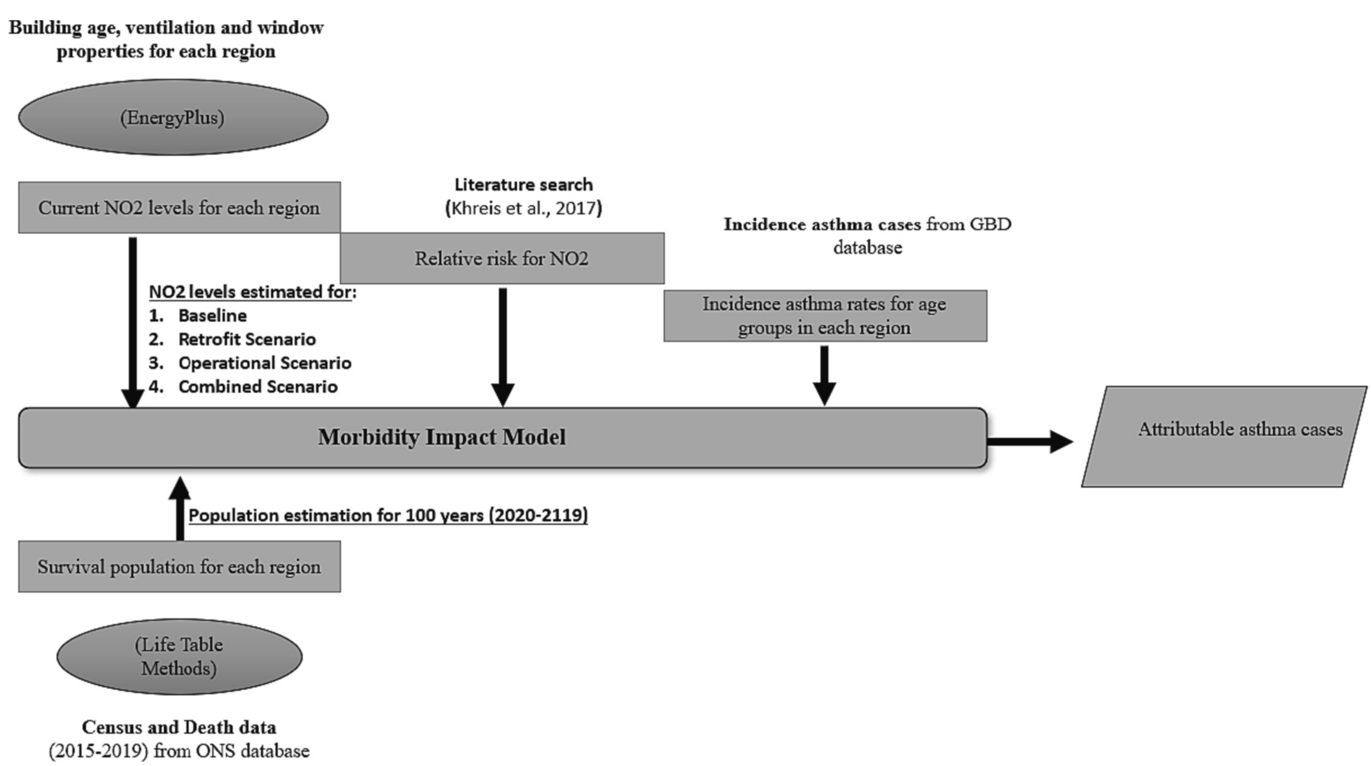

Fig. 1. Health impact assessment: conceptual framework.

Further details on all scenarios can be found in Table S4 in the supplementary material.

2.2.3. Baseline asthma incidence

Data on incident cases of asthma in children aged 1–4, 5–9, 10–14 and 14–19 years old were obtained from the Global Burden of Disease (GBD) study database (GBD, 2023). The GBD incidence cases were extracted at the county level for 2019 (before the Covid-19 pandemic), the most recent data at the time of this analysis. As the counties of Bath and North East Somerset, City of Bristol, Gloucestershire, North Somerset, Plymouth, Somerset and South Gloucestershire did not match the boundaries of the climate regions, we assumed the equivalent asthma incidence cases for these counties with their population ratios in Wales and Severn Valley. The incidence rate of a region was estimated by dividing the total number of incidence cases by the total population of the counties in that region. The asthma incidence rates are given in Table S3 in the supplementary material.

2.2.4. NO_2 exposure-response function

The exposure-response function reported by Khreis et al. (2017) (1.26 increase in risk per 10 ppb increase in NO_2) was used to estimate relative risks of NO_2-related asthma incidence under each scenario. We assumed a counterfactual concentration of 0.8 ppb, as used previously in the literature (Fabian et al., 2012; Oftedal et al., 2009). This means that long-term exposure to NO_2 <0.8 ppb does not pose a risk of asthma incidence in children.

2.3. Quantification of asthma incidence

The calculation steps to estimate the attributable number of childhood asthma cases, based on the inputs described above, are given in Table 1. We calculated population attributable fractions (PAF) (Hanley, 2001) for each scenario and applied these to the baseline incidence estimates to calculate attributable incident cases under each scenario. We assumed that children spend 8 h per weekday at school, equivalent to 24 % of their time ((8 h × 5 days) / (24 h × 7 days) = 0.24). Thus, we multiplied our final results by the factor of 0.24 to account for the proportion of time children spend at school.

We then estimated the change in the burden of asthma incidence for each of the three interventions by subtracting their results from the baseline results. The outcomes were expressed in the unit of averted cases per 100,000 children per year and the unit of annum average over 13 regions for attributable cases. The averted asthma cases were also compared for the cohort of children entering school education aged 5 years in the year 2019.

Table 1
Steps of estimation of population attributable fraction and attributable number of cases.

Steps	Equations
1	$RR_{exposure_{difference}} = e^{\left(\left(\frac{Ln(RR)}{E_{RRunit}}\right) \times E_{exDoneposure\_difference}\right)}$
2	$PAF = \frac{\sum_{i=1}^{n} P \times RR_{exposure_{difference}} - 1)}{\sum_{i=1}^{n} P \times RR_{exposure_{difference}} - 1) + 1}$
3	Total asthma cases (due to all risk factors) = population * baseline asthma incidence rate
4	Attributable asthma cases = PAF*expected asthma cases

where: RR: the relative risk obtained from the exposure-response function for NO_2; PAF: Population attributable fractions; $RR_{exposure\_difference}$: the RR that corresponds to the difference in exposure level between the counterfactual (no exposure and reference (current exposure) scenario; E_{RRunit}: the exposure unit that corresponds to the RR obtained from the exposure-response function; n: the number of exposure levels; P: the proportion of the exposed population.

2.4. Healthcare utilization costs

We estimated the resulting annual costs of asthma hospitalization in school age children across England and Wales for the three interventions (relative to the Baseline scenario). Firstly, the proportion of the burden averted under each intervention was calculated for each region by dividing each by the total asthma incident cases for that region. The proportion was then multiplied by the population of that region and the rate of hospital admissions to estimate the change in asthma hospitalization. Emergency hospital admissions for asthma per 100,000 children and young people aged 0 to 18 years were 174 in 2017/2018 and 148 in 2018/2019 for England (RCPCH, 2020). In our study, the rate of hospital admissions was therefore assumed to be 160/100,000.

The change in the annual cost of asthma hospitalization was then quantified by multiplying the proportions by the unit cost per admission. The unit cost per admission was estimated by the ratio of 2019/20 NHS reference costs for childhood asthma to baseline hospital admissions per year for childhood asthma (NHS, 2021b). The calculations and NHS reference values can be found in Table S5 in the supplementary document.

2.5. Data output and statistical analyses

The model outputs include estimation of (i) attributable asthma incident cases for each scenario (ii) averted asthma incident cases under the three intervention scenarios compared with the baseline scenario, and (iii) changes in asthma hospitalization costs under the three intervention scenarios. The averted asthma incident cases were also estimated for the cohort of children aged 5 years in 2019 until the age of 16 years. All results are quantified for each region and for England and Wales as a whole.

2.6. Probabilistic sensitivity analysis to determine the most influential model parameters

A sensitivity analysis was performed to identify how key health model parameters influenced the output. We examined the sensitivity of our modelling to four parameters (internal NO_2 concentration, asthma exposure-response coefficient, asthma rate and population) to understand which parameters affected the outcomes of the model the most. The ranges of parameters defined in Table S3 were used separately. Then, uncertainty analysis was conducted to define the confidence intervals on the output results, and to evaluate the potential effect of the sensitive parameters on the model outputs. The distributions of parameters were assumed to be uniform, lognormal and/or normal distributions (Table S7) based on the literature (Table S3). Accordingly, population follows a log-normal distribution (Parr and Suzuki, 1973) with a confidence interval of plus or minus 0.2 %, based on estimation of the population of the UK in mid-2020 (ONS, 2021). The regional NO_2 concentrations were assumed to follow log-normal distributions (Tieskens et al., 2021) with means ranging from 23.73 to 2.3 and variation ranging from 4.73 to 0.06, calculated by averaging the results of twenty-four scenarios simulated by EnergyPlus (Grassie et al., 2023). Uniform distributions were assumed for the other parameters as default. Thus, the asthma exposure-response coefficient varied from 1.1 to 1.37 (Khreis et al., 2017). Regional asthma rates for children aged 1–4, 5–9, 10–14, and 14–19 years old ranged between 0.009 and 0.020, 0.004 and 0.014, 0.005 and 0.019, and 0.005 and 0.012, respectively, for females. For males, the rates ranged between 0.013 and 0.026, 0.006 and 0.021, 0.005 and 0.015, and 0.003 and 0.006, respectively. By incorporating the uncertainty and variability of the above input parameters, the model was run 1000 times using Monte Carlo (MC) simulations in MATLAB R2010.

3. Results

3.1. Attributable asthma cases under energy efficiency scenarios

Table 2 presents the results of the HIA model of asthma incidence, calculated by averaging the results of 13 regions in England and Wales. As well as asthma incidence and indoor NO_2, the table also presents the average results for GHG emissions from heating systems, overheating, and indoor CO_2. The lowest NO_2 is seen in the Operational scenario, due to the additional capability of ventilating the building during the night-time for cooling, when there is less traffic. This leads to a lower requirement for ventilation and hence less ingress of NO_2 from the outdoors when traffic peaks in the morning (resulting in the lowest attributable asthma cases and hospitalization costs). Aside from a 10-min purge period at the start of each occupied hour, ventilation is entirely driven by the need to cool classrooms to below 23 °C. In terms of operational strategies, external shading minimises the penetration of solar radiation through windows, high albedo limits the absorption of solar radiation by opaque building surfaces and thermal mass delays the re-release of heat indoors. These effects lower internal temperature and reduce the demand for cooled air. Passive ventilation facilitates the ingress of outdoor air during cooler night-time periods, which is beneficial since this is when NO_2 levels are lowest.

By contrast, the Retrofit scenario, while improving considerably the energy performance through reducing heat losses through building fabric, leads to higher internal temperatures during the day, requiring intermittent ventilation at busier times of the school day. This draws in NO_2 from the outdoor air, leading to a greater number of asthma incident cases and higher hospitalization costs. The Combined scenario represents a balance between the Retrofit and Operational scenarios, with a slight overall decrease in asthma cases and hospitalization costs. These patterns are observed for England and Wales as a whole and each of the 13 regions. The results of the HIA model for each region are provided, along with results for indoor NO_2, GHG emissions from heating systems, overheating, and indoor CO_2, in Table S9 in the supplementary materials.

A typical illustrative example of the differences between ventilative practices for a week during spring across different scenarios is shown in Fig. 2. For the Baseline scenario, the building leaks a considerable amount of heat at night-time when it is unoccupied, so there are some days when ventilation is not required fully for cooling until the afternoon. After upgrading the fabric under the Retrofit scenario, ventilation is required for cooling for the entirety of every school-day, since the night-time leaking of heat has been reduced and the school day typically starts with temperatures already above the window-opening setpoint of 23 °C. However, adding night-time ventilation operation for the Combined scenario allows the ventilation period to be extended in the evening and morning flexibly. This leads to temperatures at the start of the day which are lowered and gives additional potential in the future for lowering this setpoint even lower to reduce reliance on ventilation in the day, which drives the ingress of NO_2 when cars are present outside.

Table 2
Model results for 13 climate regions in England and Wales.

	Baseline mean (sd)	Retrofit scenario mean (sd)	Operational scenario mean (sd)	Combined scenario mean (sd)
Attributable asthma cases	697 (826)	775 (907)	**547(664)**	676 (796)
Hospitalization cost (GBP/y)	£66,326 (£76,932)	£73,767 (£84,489)	**£52,050 (£61,824)**	£64,310 (£74,148)
NO_2 (ppb)	14.48 (6.24)	16.47 (7.08)	**11.00 (4.71)**	14.06 (6.05)
Indoor CO_2 (ppm)	1135.30 (35.96)	**935.34 (17.33)**	1767.72 (60.4)	1435.56 (23.73)
Overheating (h)	354.28 (102.47)	610.94 (84.32)	**99.62 (66.77)**	342.39 (109.23)
GHG emissions (kg/m^2)	2.36 (0.62)	0.28 (0.11)	1.52 (0.45)	**0.00042 (0.0004)**

Mean(standard deviation), the lowest mean indicated in bold.

Fig. 3 shows the hospital cost reductions and averted asthma cases under the scenarios for the 13 regions. Positive values represent benefits for asthma (i.e. reductions in cases) while negative results are additional health burdens. A similar trend is seen for each region in terms of asthma cases, NO_2 levels and hospitalization cost (Fig. 3). The Operational and Combined scenarios result in positive effects on childhood asthma incidence and hospital utilization. The highest childhood asthma incidence is in the Thames Valley region (including London), in particular in older school buildings, while the lowest concentrations and health burdens are in the newest schools in Wales. This reflects differences in external NO_2 concentrations in each geographical region, as well as the thermal properties of schools built in different era, and their subsequent ventilation requirements.

Fig. S3 in the supplementary materials shows averted asthma cases per 100,000 population plotted against the change in GHG emissions (relative to the baseline) for the three scenarios. This demonstrates the relationship between GHG emissions abatement through improved energy efficiency and asthma cases averted through reduced NO_2 exposure. The graph illustrates that there is an inverse relationship between health (asthma) and GHG reduction. The change in GHG emissions is lowest (<1 kg/m^2) in the Operational scenario where the lowest burden of asthma occurs. However, the reduction in GHG emissions is greater (between 1 kg/m^2 and 3.5 kg/m^2) under both the Retrofit and Combined scenarios. Regions where significant differences between the Operational and Combined scenarios were found for both outcomes include North Western; the change in GHG emissions there is from 3.5 kg/m^2 to 1 kg/m^2 while the change in asthma is from 0 to 40 cases per 100,000 population (Fig. S4). Similarly, the reduction in internal CO_2 is greater under both the Retrofit and Combined scenarios in this region (Fig. S5).

3.2. Cohort results

Fig. 4 illustrates the averted asthma cases (per 100,000 population) for England and Wales under each scenario for a cohort of children starting school at age 5, and changes in costs from hospital utilization. Both health outcomes and healthcare cost savings were estimated relative to baseline for 3 scenarios by subtracting the scenario outcomes from the baseline outcomes. Thus, positive values represent reductions and negative values show additional health burdens and costs.

As seen from the figure, there are large differences in the number of cases between the scenarios, reflecting the patterns described above, and the model demonstrates changes in asthma incidence with age. Asthma incidence decreases with age, with primary school children nearly twice as likely to develop asthma as secondary school children. The trend of asthma incidence decreasing with age is observed across each region (Fig. S6). In terms of differences between scenarios, the inclusion of operational IEQ measures leads to an improvement relative to the Retrofit scenario. Similarly, cost savings are obtained in operational and combined scenarios (approximately £16,000 and £2000 annual reductions in hospital utilization, respectively).

3.3. Sensitivity analysis

Table S6 gives the percentage changes in incident cases from the baseline after examining the sensitivity of our results to the internal NO_2 concentration, asthma exposure-response coefficient, asthma rate and population. The health outcomes in the 13 regions were most sensitive to changes in three parameters: NO_2 concentration (max 33 %), asthma coefficient (max 68 %) and asthma rate (max 68 %). Uncertainty in the population data resulted in no significant changes in health outcomes. As such, NO_2 concentration, asthma coefficient and asthma rate were considered in the uncertainty analysis. The distribution of outcomes related to each region and between 2020 and 2031 is presented in

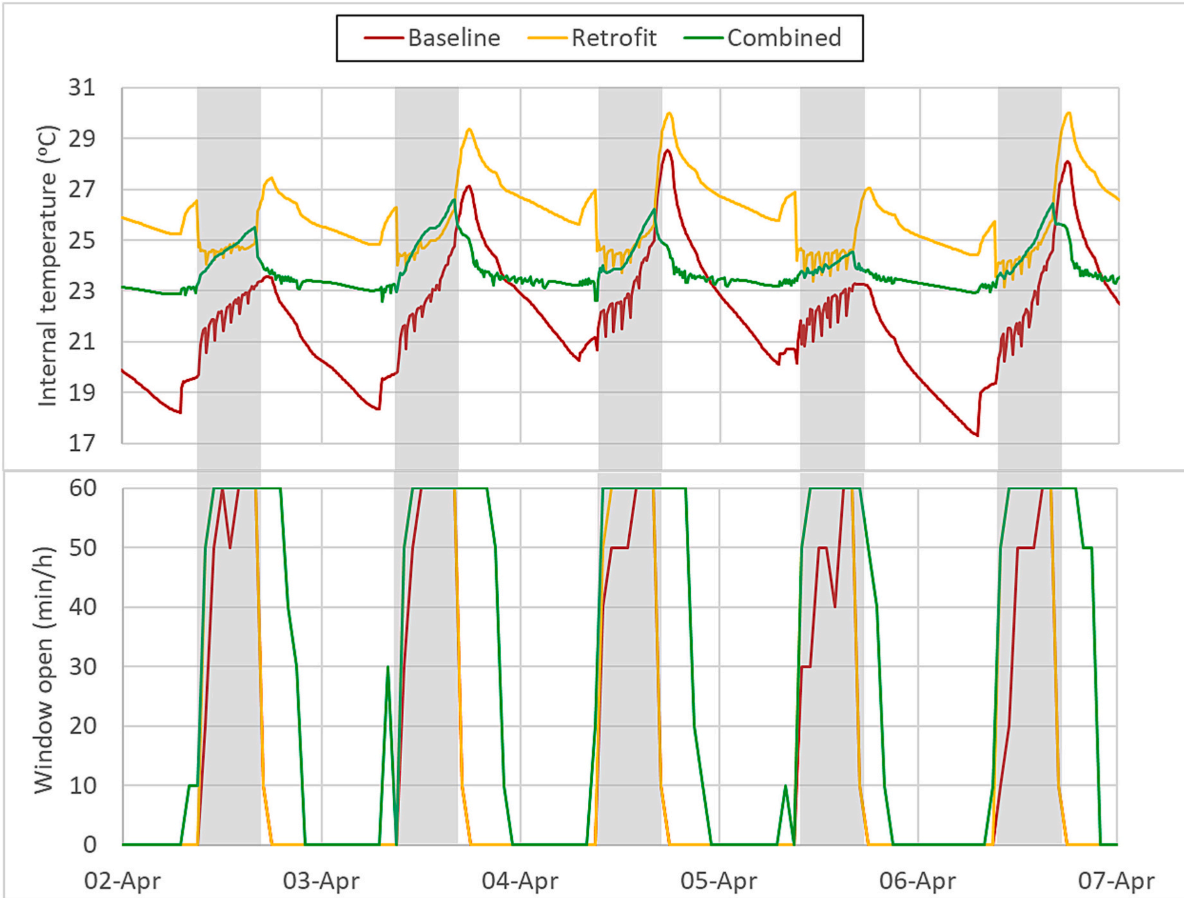

Fig. 2. Illustrative example of difference in window opening across different scenarios.

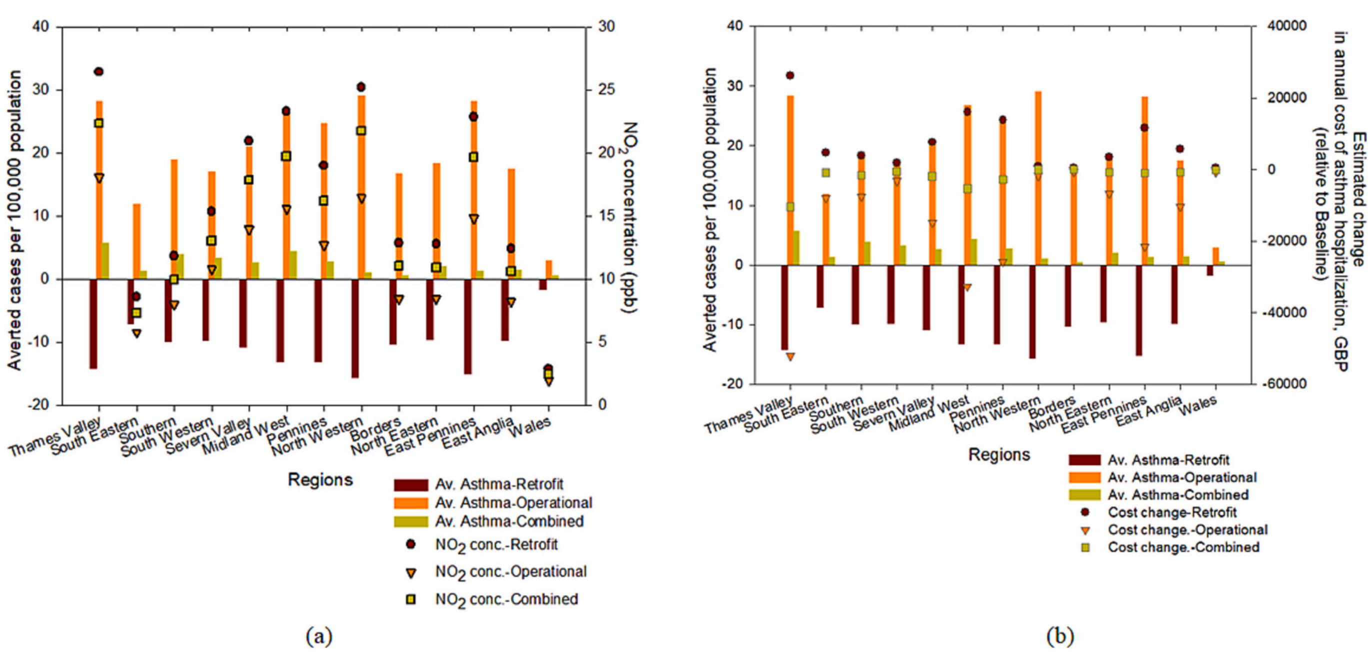

Fig. 3. Averted asthma cases in one year (per 100,000 population) with (a) indoor NO_2 concentration and (b) reduction in hospital utilization.

Fig. S2 in the supplementary material. The uncertainty analysis indicated that the relative standard deviation (RSD) of output ranges from 28 % to 32 %. The regions which have high external NO_2 concentrations (London) are less sensitive than regions with low external concentration (Wales) to change in NO_2, possibly due to starting from a lower point and the percentage changes therefore being relatively greater.

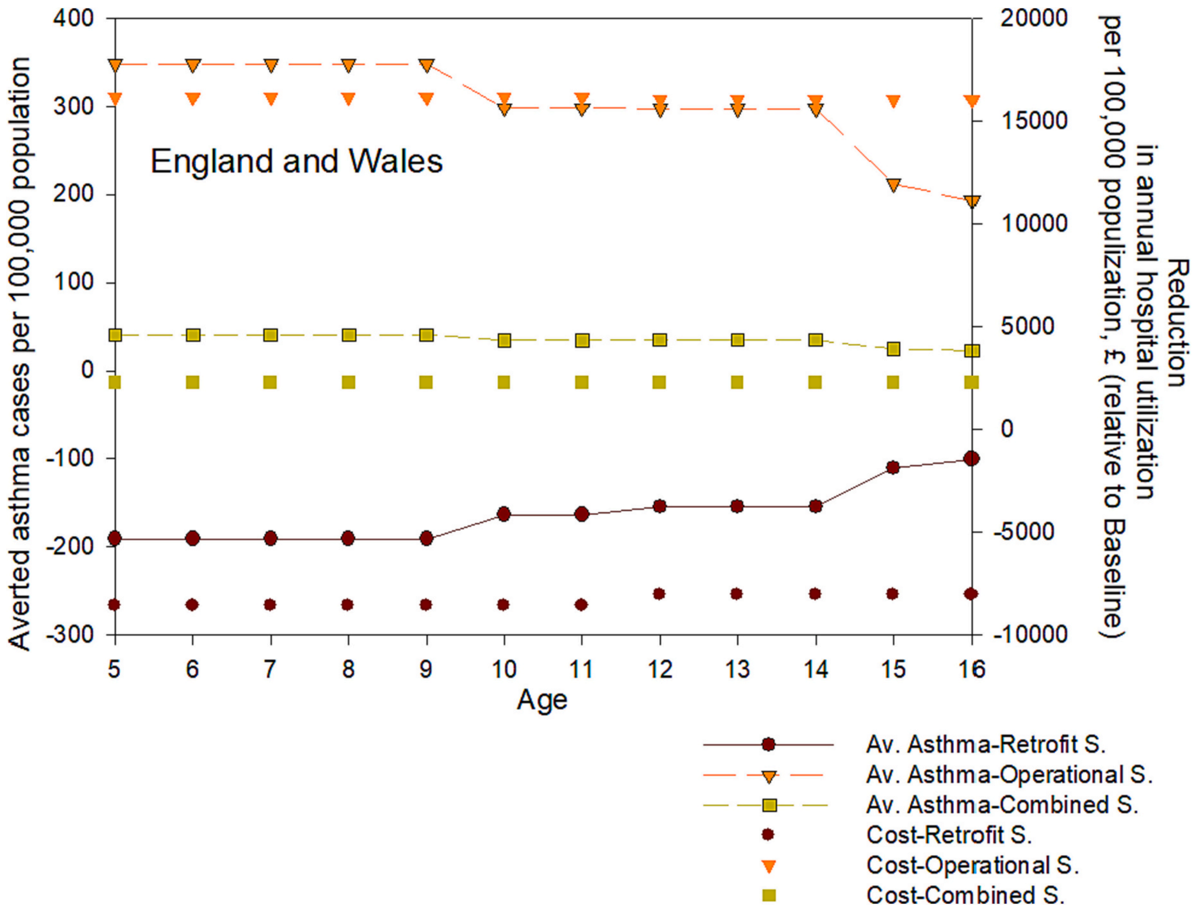

Fig. 4. Cohort study for England and Wales (sum of each region).

4. Discussion

4.1. Key findings

Our study primarily focused on NO_2-related asthma, which served as an example to illustrate the potential scale of impacts and to highlight important trade-offs. Specifically, we aimed to examine the potential effects of retrofits on reducing NO_2 levels and the resulting health consequences, particularly focusing on asthma. Our results demonstrate that improving the energy efficiency of schools in England and Wales, when combined with measures to improve indoor environmental conditions such as ventilation and shading, would provide reductions in asthma incidence and associated healthcare costs from exposure to NO_2 in schoolchildren, relative to the present-day baseline. However, increasing the energy efficiency of school buildings without such IEQ measures would result in increases in both incidence and hospitalization costs. This happens because energy efficiency improvement acts to make buildings more airtight, which initially reduces the ingress of air pollution (NO_2) from the outdoors. However, it also makes buildings warmer leading to increased overheating during warmer times of the years, and so increased ventilation (e.g. window opening) is needed to cool the building down when children are present during the day. Overall, this leads to increased exposure to NO_2 for children within schools and therefore an increase in asthma and asthma-related hospitalization.

Retrofitting school buildings will be important to help achieve targeted reductions in GHG emissions. However, our results suggest that improving the energy efficiency of school buildings in England and Wales has the potential to lead to adverse effects on asthma in school children unless these buildings are suitably ventilated during times when traffic levels are lower (primarily during the night). While some previous studies have shown positive effects of retrofitting buildings on health, other studies found worse or less clear positive effects for more energy efficient buildings (Tieskens et al., 2021). The different findings may be related to the specific details of these studies, such as the exact nature of the interventions, the local climate, and the behaviour of occupants (Sharpe et al., 2019; Tieskens et al., 2021; Vardoulakis et al., 2015). Therefore, it is difficult to compare the results of other studies with ours directly. In our case, the Retrofit scenario resulted in increased asthma incidence as internal NO_2 (from outdoors) increases, although night-time opening of windows was not implemented and defined in the scenario (Table 2). However, as more ventilation is needed during the day due to air tightness, the occupants (students) may need to open the window more. Hamilton et al. (2015) showed previously that naturally ventilated buildings can result in high exposures to internally-generated pollutants due to airtightness of the dwelling and the practices of the occupants (although internally-produced pollutants were not included in our modelling). As explained above, one of the important factors for this result may be the impacts of individual behaviours which results in variation in the need to open windows (Tieskens et al., 2021). On the other hand, our Operational scenario with measures to improve IEQ provided a reduction in asthma incidence and associated healthcare costs (Fig. 3), decreasing overheating and indoor exposure NO_2 from outside sources. This scenario increases internal CO_2 within schools due to night ventilation, and with only modest decrease in GHG emissions from space heating. School buildings are a key part of the UK's carbon emissions reduction strategy. It is necessary to take into account retrofit strategies and changes in the operation of the building by mitigating against overheating in order to reduce carbon emissions and health burdens.

The Combined scenario represents a balance between the Retrofit and Operational scenarios, demonstrating the need for appropriate management of IEQ to accompany energy efficiency improvements. In this scenario, as daytime ventilation is slightly reduced and it is not necessary to open windows as often, there is a slight decrease in overheating and decreases in internal CO_2 and NO_2 exposure. This demonstrates the important point that retrofitting in itself does not lead to increases in asthma rates, showing that operational practices should be adopted to manage internal temperatures in order to prevent the ingress of contaminated air for cooling at times of the day when traffic is heaviest (and school buildings are occupied).

The findings of the cohort study suggest that asthma incidence tends to decrease with age. This is in line with the findings of Hu et al. (2022), who also found that the highest number of new asthma cases can be attributed to exposure to NO2 among the youngest age group (<6 years old). They also found that areas with higher population density tend to have a greater burden of new asthma cases. This finding aligns with the results of our study, which found the highest incidence of childhood asthma in the Thames Valley region. Overall, these findings indicate that NO_2 exposure is a significant factor contributing to the development of asthma, particularly in young children.

4.2. Strengths and limitations

To our knowledge, this is the first study assessing the impacts of energy efficiency retrofit strategies on the health of school children in the UK. We believe that such assessment is important for policy decision making as it can inform and develop effective policies, in particular helping to guide efforts to reduce GHG emissions from school buildings. Furthermore, the applied framework is generic and therefore has the ability to serve as a valuable point of reference for researchers worldwide. The main strength of this study has been the capability of examining the health impacts of energy efficiency strategies coupled with IEQ measures by using an advanced validated building physics model. Another strength is the analysis of the uncertainties coming from health model input parameters (NO_2 concentrations, population, and asthma incidence rates). Although it was not possible to assess uncertainties in the upstream (i.e. building physics) models, the uncertainty analysis indicated that changes in the values of parameters regarding the assumed distributions did not create high variations in HIA model outputs (Table S8). The distributions of the parameters were guided using evidence from the literature, therefore increasing the reliability of our results.

Among the limitations of this study are the application of only a limited number of energy efficiency/operational interventions. We simulated only four interventions, including one scenario for each strategy (retrofit and IEQ improvement). However, we applied an energy retrofit scenario (Grassie et al., 2023) which is the most energy retrofitted option to Building Simulation Regulation. For the IEQ improvement scenario, we included the combination of four individual IEQ improvement measures (i.e. ventilation and thermal control, shading). Therefore, our results are likely to give minimum and maximum asthma incidence and hospitalization costs for the UK with these interventions. When individual IEQ improvement measures with the most and least energy retrofit options are performed, the health outcomes and costs can be improved progressively. By this way, the optimum options can be decided from the range of interventions. There is also relatively high uncertainty in the exposure-response function we applied to estimate the relative risk for asthma development. We relied on the coefficient extracted from the global systematic review and meta-analyses reported in Khreis et al. (2017). This coefficient may not be directly applicable to the setting modelling in this work. However, Khreis et al. (2017) did include studies from cities in the UK in their study. We focused specifically on the incidence of asthma in relation to chronic NO_2 exposure, drawing upon existing evidence and modelling approaches utilized in previous studies of childhood asthma. However, we recognize that there is also strong evidence relating asthma exacerbation in both children and adults to fluctuations in short-term exposure to NO_2 and other air pollutants (e.g., Orellano et al. (2017)). Modelling these short-term effects would require a distinct approach that was beyond the scope of our current study.

We assumed that children spend 8 h per weekday at school, which provides a representation of the maximum exposure levels and health risks for children. However, the duration of a school day can vary depending on the age group and educational system in different regions. In particular, 5–6 h per weekday might be more appropriate for primary school children. Therefore, as an additional sensitivity analysis, we estimated asthma cases for the 4 scenarios assuming a 6-h/weekday duration (Table S10). Compared to the 8-h/weekday duration, the attributable asthma estimates for a 6-h/weekday period in each region are 25 % ((0.18–0.24)*100/0.24 = −25 %) lower.

The relationship between asthma incidence and severity is complex and relies on many factors. In our study, we assumed that the change in asthma incidence would lead to a proportionally equivalent change in asthma-related hospitalization, assuming no change in the distribution of asthma severity. Our modelling also considered only changes in indoor exposure to ambient (external) NO_2, primarily representing emissions from traffic. Most school buildings would not have many internal sources of NO_2, but this could be a limitation in some settings. Finally, although we estimated changes in asthma-related hospital utilization costs, a full economic appraisal of the scenarios was not performed. Future work should consider the complete range of economic costs and benefits of improving school building energy efficiency, including the wider societal impacts.

5. Conclusions and policy implications

Our study indicates that the net effect of school energy efficiency retrofit on NO_2 and asthma incidence in schoolchildren depends critically on the effectiveness of ventilation systems and the building operation strategy. Therefore, a balance should be found between these strategies. Overall, the findings suggest that, in general, NO_2 levels can be lowered by improving the energy efficiency of schools in England and Wales and thus a proportion of incident childhood asthma cases could be prevented, as long as appropriate means for indoor environmental control are present. The findings from this study make several contributions to fill the knowledge gap about the impact of retrofitting schools on air pollutant exposure and their effects on children's health. Our findings contribute in several ways to our understanding of energy efficiency and operational interventions for school buildings in terms of health assessment, as well as providing a basis for policymakers to identify solutions that reduce GHG emissions while improving children's health in school buildings.

CRediT authorship contribution statement

Filiz Karakas: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Duncan Grassie:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – review & editing. **Yair Schwartz:** Validation, Investigation, Writing – review & editing. **Jie Dong:** Validation, Formal analysis. **Zaid Chalabi:** Validation, Formal analysis, Investigation, Data curation, Writing – review & editing, Visualization, Supervision. **Dejan Mumovic:** Funding acquisition, Project administration, Supervision, Writing – review & editing. **Anna Mavrogianni:** Validation, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition. **James Milner:** Validation, Writing – review & editing, Supervision, Project administration, Funding acquisition.

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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Appendix A. Supplementary data

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