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A Multi-Criteria decision analysis framework to determine the optimal combination of energy efficiency and indoor air quality schemes for English school classrooms

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ABSTRACT

Maintaining good Indoor Environmental Quality (IEQ) in English schools in terms of overheating and air quality is important for the health and educational performance of children. Improving energy efficiency in school buildings is also a key part of UK's carbon emissions reduction strategy. To address the trade-offs between energy efficiency and IEQ, a Multi–Criteria Decision Analysis (MCDA) framework based on an English classroom stock model was used. The aim was to determine robust optimal school building interventions across a set of criteria (including child health, educational attainment and building energy consumption) and settings (comprising different climate scenarios, construction eras, geographical regions and school geographical orientations). Each intervention was made up of the pairwise combination of an energy efficiency retrofit scheme and an IEQ improvement scheme. The MCDA framework was applied to the school building stock in England. This study shows that the framework represents a transparent approach to support decision making in determining the optimal school building intervention from different perspectives. The optimal interventions included measures that improved IEQ and resulting indoor learning environments, such as external shading, or increased albedo and internal blinds, for the particular set of interventions, criteria and stakeholders in this study. The results of the MCDA analysis were sensitive to the preferences elicited from stakeholders on the relative importance of the criteria and to the range of interventions and criteria selected for evaluation.

1. Introduction

The English school building stock plays a critical educational role to school-age children, who spend 30 % of their waking hours within classrooms until the age of 16[1]. Health and educational attainment can be linked to the provision of Indoor Environment Quality (IEQ) within school buildings [2]. IEQ comprises many factors, including acoustic, lighting and air quality of the environment, and its impact on schoolchildren and staff, as well as their thermal comfort, health and wellbeing. In this study we have considered only overheating and indoor air contaminant concentrations as we evaluate IEQ. Additionally, as non–domestic buildings are responsible for 18 % of the wider UK's energy demand [3], school buildings are also subject to the UK's drive to reach net zero greenhouse gas emissions by 2050 [4]. Building fabric characteristics and the operation of heating, cooling and ventilation systems can, therefore, influence both indoor temperatures and contaminant concentrations, leading to variations in educational attainment, health and energy performance [5]. These variations can occur both longitudinally, as changes are made to external conditions, retrofit status and operation of the building [6], and across the school building stock, dependent on different constructions and geographical regions [7]. Building simulation models can be used to determine relative changes in performance indicators of energy demand, health and educational attainment associated with changes in building fabric characteristics and the operation of heating, cooling and ventilation systems. However, these performance indicators are often conflicting, for example improving energy performance through increasing insulation and air–tightness could worsen susceptibility to overheating, in

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the absence of further IEQ improvement measures [5]. Furthermore, different stakeholder groups could have different and competing priorities or targets. There is need for additional analysis to demonstrate which changes could be favourable to school building stock performance across several criteria.

There is an increasing interest from policymakers in the use of simulation models to support their decision-making [8,9]. Policymakers addressing climate change mitigation and adaptation in the built environment are often faced with several feasible interventions to choose from such as different retrofit strategies. For models to be used effectively in decision support, they should be placed within a decision-analytical framework.

Policymakers make their decisions based on several criteria; in the case of English schools, this includes health, educational attainment, energy consumption and cost. Because some of the criteria are conflicting and an intervention can be beneficial to one criterion and detrimental to another, appropriate methods are required to solve such decision problems. There is a plethora of methods that can be used for this purpose that fall under the umbrella of Multi–Criteria Decision Analysis (MCDA). The aim of this study was to develop a model–based decision–analytical MCDA framework to support policymakers in determining robust optimal combinations of energy efficiency and IEQ improvement strategies in school buildings in England and Wales, taking into consideration multiple criteria.

2. Background

Several recent studies have used MCDA to evaluate energy efficiency interventions for residential and school buildings. The studies used various MCDA methods of different orders of complexity. These varied from operations research type methods, such as multi-objective optimization methods to decision-analytical methods. Romani et al. [10] developed an MCDA tool to determine the optimal intervention for sustainable and passive residential buildings. They constructed a *meta*-model to predict energy needs based on building simulation models and combined them with life cycle assessment methods to measure the impacts on a set of environmental indicators, financial analysis to measure key economic impacts and a thermal comfort calculator. They employed a multi-objective optimization method to optimise simultaneously all the metrics. Their method entailed transforming the multiple objectives to a single objective by weighting each objective according to user (owner) preferences. They applied their MCDA method as a decision support tool to a social housing case study in France. Ongpeng et al. [11] developed an MCDA framework for sustainable energy retrofit in residential buildings. To determine the optimal retrofit intervention, they used a suite of models to measure the impacts of the interventions on six specified criteria: damage to human health, damage to ecosystem, depletion of natural resources, investment cost, energy potential and payback period. They elicited stakeholders' preferences using the Analytic Hierarchy Process (AHP) to calculate the relative weight of each criterion and finally employed the VIKTOR MCDA method to rank the interventions in terms of their performance. They applied their framework to a case study in the Philippines.

In relation to school buildings, Bernardo et al. [12] used the ELECTRE TRI MCDA method to assess the energy performance of school buildings across six criteria: energy consumption, greenhouse gas emissions, operations and maintenance cost, indoor air quality, thermal comfort and maintenance accomplishment. The latter is defined as implementation of preventive maintenance measures which adhere to legal standards for school buildings. They applied their method to a few case studies in Portugal. Abidin et al. [13] developed a scoring tool to evaluate retrofit energy reduction options in higher educational institutions based on various criteria, including occupants' comfort, economic, environmental and buildings factors. They applied their tool (called McREEB) to case studies in Malaysia. Moazzen et al. [14] used a pragmatic multi-criteria system-based approach based on the revised European Performance of Buildings Directive (EPBD recast) to determine affordable energy-efficient retrofit interventions of primary school buildings. They applied their approach to case studies in Turkey. Neither McREEB nor the Moazzen et al. [14] approach is based on MCDA methodology. The abovementioned studies demonstrate how MCDA can be used to support decision making for energy efficient retrofits in residential and school buildings. However, their applications were focused on case studies and localized in space and time. By contrast, policymakers often need to perform national-level evaluations over decades into the future.

The model-based MCDA approach proposed in this study differs significantly from the above studies in four ways:

i. The first difference is the nature of the indoor environment model. It is a comprehensive model that simulates thermal comfort and air contaminant concentrations in the indoor environment of classrooms in England and Wales across 60 settings consisting of school archetypes of different combinations of construction eras, class orientations, regions and climates.
ii. The second difference is that this study used a transparent and user-friendly MCDA approach, which captures the decision problem succinctly and which can be communicated easily to stakeholders.
iii. Thirdly, although this study elicited preferences from stakeholders as in the case of a few of the above studies, we studied the variability of the preferences across different stakeholder groups and their impact on the robustness of the optimal intervention.
iv. Last, this study included criteria associated with children's health and learning capability.

3. Decision problem

The aim of this study is to determine the robust optimal school

Table 1
Energy efficiency retrofit schemes.

Index of Energy Retrofit Scheme	Abbreviation	Brief description
$i = 1$	NoRetrofit	Status quo (baseline)
$i = 2$	BuildRegs	Compliance to Building Regulations 2021, Part L (England)
$i = 3$	IntRetrofit	Intermediate energy retrofit package, based on (Grassie et al. 2022a)
$i = 4$	EnerPHIt	Compliance to EnerPHIt standard (Passive House Institute, 2016)

Table 2
IEQ management schemes.

Index of IEQ Scheme	Abbreviation	Description
$j = 1$	BaseOp	Status quo (baseline)
$j = 2$	Albedo&Blinds	Increasing external surface albedo and using internal blinds
$j = 3$	ExtShading	External shading and using overhangs above windows
$j = 4$	ThermalMass	Increasing the thermal mass of the structure without changes to ventilation regime
$j = 5$	PassiveVent	Passive ventilation provision during weekdays only when building unoccupied at night-time
$j = 6$	CombineOps	All the above four

Table 3
Modelled settings (climate, orientation, geographical region and construction era) considered for the MCDA.

Index of Setting	Climate (2 settings)	Orientation (2)	Geographical region (3)	Construction era (5)
$k = 1$	2020 s	South-facing	London	Pre-1918
$k = 2$				Inter-war
$k = 3$				1945–1967
$k = 4$				1967–1976
$k = 5$				Post-1976
$k = 6$			Birmingham	Pre-1918
$k = 7:10$				etc. …
$k = 11$			Leeds	Pre-1918
$k = 12:15$				etc. …
$k = 16$		North-facing	London	Pre-1918
$k = 17:30$			etc. …	etc. …
$k = 31$	2050 s	South-facing	London	Pre-1918
$k = 32:60$		etc. …	etc. …	etc. …

building intervention across geographical, climatic, orientation and construction-era settings. Each intervention is defined as a pairwise combination of an energy efficiency retrofit scheme and an operational IEQ scheme applied to the school building stock in England and Wales. Details of the interventions and their rationale are provided in Grassie et al. [5].

Briefly, Tables 1 and 2 list, respectively, the energy efficiency retrofit standards applied, and the operational IEQ management schemes. These were applied to all four orientations within each model, even though effectiveness of shading would decrease for West- and East-facing orientations at particular times of the day, and not be relevant for North-facing orientations.

Table 3 lists all the settings which have been considered for the MCDA.

The *decision problem* can be defined as follows. Denote:

- The settings by $s_k, k = 1 \cdots 60$ (2 * 2 * 3 *5 different combinations)
- The set of interventions by $I_{ij}, i = 1 \cdots 4, j = 1 \cdots 6$, where each intervention corresponds to retrofit scheme i and IEQ management scheme j;
- The optimal intervention for setting s_k across all the selected criteria by $I^*_{ij}(s_k)$

The decision problem to be solved by the MCDA framework is to determine the robust optimal intervention $\widetilde{I}^*_{ij}$ which is defined as the intervention which performs best across the highest number of settings.

4. Methods

4.1. English school classroom stock model

The English school classroom stock model used to generate results is described in detail in Grassie et al. [5], based on an archetype models of school [7]. We provide a brief summary of its salient features below:

- The original model of a typical school classroom geometry was created in the dynamic building performance software EnergyPlus v9.5 (US Department of Energy 2015). It consisted of four non-connecting cuboid classrooms with floorspace of 8 × 6.5 m each. Each classroom had a single surface available for air and heat flow with the surroundings through external wall infiltration and ventilation using windows and trickle vents. The classrooms were oriented in North, South, East and West directions, as shown in Fig. 1. Only single-sided ventilation has been analysed for this study, although in many school blocks, windows on opposing walls facilitates cross-ventilation.
- Stock-wide variation in building properties was then accounted for by generating archetypes of different settings, based on combinations of 5 construction eras (impacting wall U-values and floor to ceiling heights, window glazing ratios and U–values) and 3 geographical regions (impacting the choice of external annual weather file used for the simulation) shown in Table 3. For the MCDA, this study modelled only naturally ventilated primary school classrooms, accounting for 72.5 % of the floorspace of the English primary and secondary school building stock [6], of which mechanically ventilated schools account for 5 %. Archetypes incorporating additional features such as type of heating system and length of school day could be incorporated into the modelling. However, knowledge of how prevalent these features are across the English stock is limited by the available data from the Property Data Survey Programme on which the archetype model is based.
- A complete set of interventions was applied to the models and settings as detailed in Tables 1 and 2. A summary of the technical details used within the models and settings is provided in Tables A.1 and A.2 of Supplementary Material A.
- Building performance was simulated under a range of climate change scenarios using weather files for the 2020 s, 2050 s and 2080 s, which are available based on 2009 UK Climate Projections (UKCP09) [15]. More recent UKCP18 files were not yet available to use in the EnergyPlus simulations. Medium emissions, 50th percentile climate change scenarios were selected for the 2050 s and 2080 s, and High emissions, 50th percentile climate change scenario for the 2020 s.
- Heating and ventilation were simulated year-round based on heating and cooling setpoints of 18 and 23 °C, respectively, applied during weekdays throughout the year from 9.00 to 16.00, based on Building Bulletin 101 guidelines (BB101, Education and Skills Funding Agency, 2018). The cooling setpoint of 23 °C was derived from the National Calculation Methodology (NCM) [16]. This is a set of rules

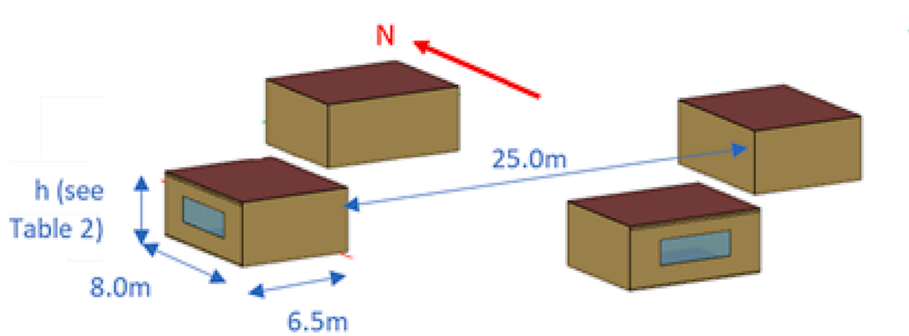

Fig. 1. Geometric representation of classroom models.

Fig. 2. A MCDA matrix representing the inputs (ratings and weightings) and the outputs (scores).

which must be used in models which demonstrate compliance of new school building design with overheating calculations. Weather files from the CIBSE Test Reference Year (TRY) and the Design Summer Year (DSY1) were combined to utilise:

o The TRY data, indicative of a typical year, for calculating heating demand from October 1st to April 30th.

o The DSY1 data, indicative of a moderately warm summer, for calculating overheating from May 1st to September 30th.

- The following criteria were generated from post-processing of the hourly EnergyPlus output data:

o Annual energy costs (£/m^2) and CO_2 emissions (kgCO_2/m^2): Summing hourly heating demand and dividing by an efficiency factor based on the retrofit scenario. The efficiency factors are 80 % for the lowest set of interventions, 85 % and 90 % for subsequent sets. The highest level of interventions involves converting boilers to heat pumps so uses a coefficient of performance of 350 %.

o Annual internal CO_2 concentration: Averaging hourly CO_2 concentration over the entire year while the building was occupied.

o Internal NO_2 and $PM_{2.5}$ concentrations: These were calculated hourly by multiplying the indoor-outdoor ratio (I/O) of contaminants based on ventilation and infiltration by external hourly NO_2 and $PM_{2.5}$ data from each geographical region. The data were then averaged during periods when the building was occupied only.

o Overheating [17] and educational attainment [18] criteria were generated from hourly internal temperature and ventilation rate data, based on existing definitions and established relationships, respectively. For the overheating criterion, the total hours of exceedance (Criterion 1 from BB101 [17] was calculated, representing the number of hours between May 1st and September 30th, when an adaptive thermal comfort temperature was exceeded.

4.2. MCDA

The MCDA method used in this study is known as the Simple Multi-Attribute Rating Technique (SMART) or weighted-sum method [19]. This method has been used to evaluate environmental health interventions in the UK, including risk prioritisation of environmental hazards [20], comparative evaluation of air quality policies [21] and energy efficiency interventions in residential buildings [22].

The method consists of four elements: a set of interventions to evaluate, a set of criteria to compare the interventions, models to evaluate the impact of each intervention on each criterion (as described above) and a set of weights to assign the relative importance of each criterion. In addition, the method consists of four procedures:

1. The first procedure elicits rankings of the criteria from stakeholders who were asked via an online survey to rank a set of criteria in importance order. While it was intended to obtain these through in-person workshops, the Covid-19 pandemic prevented these being carried out in July 2021, when the online survey was conducted instead.

2. The second procedure converts the survey rankings into a set of weights (numerical values between zero and 1), which add up to unity to give the relative importance of the criteria.

3 The third procedure normalizes the impacts to be between zero and unity so that all impacts are dimensionless.

4. The fourth procedure combines the normalized impacts and the weights to score the interventions for their performance across all criteria. All impacts are presented for convenience as gains (i.e. increases relative to baseline) and so the intervention which scores the highest is deemed to be the optimal intervention.

For the purpose of transparency and ease of replication, the method is described in Supplementary Material B to E. S-B tabulates mathematically the interventions, criteria and the modelled impacts. S-C describes the method for normalizing the impacts. S-D describes how to convert stakeholder survey rankings to aggregate weights for the criteria and finally S–E outlines the scoring of the interventions across the criteria.

Fig. 2 below shows schematically an illustration of the MCDA process. It uses the SMART MCDA software *Annalisa* template. Annalisa (©Maldaba Ltd, Maldaba 2021) [23]. This template has been used for communicating MCDA results of various environmental health interventions [20–22]. In this illustration, for simplicity of visualization and exposition of the SMART method, we assume we are comparing 24 interventions across 6 criteria.

The figure is comprised of three rows. Starting with the second row (Step 1, "Weightings"), this gives the aggregate weights of Criterion 1 to 6 (processed from stakeholder survey rankings, see below). They add up to unity. The third row (Step 2, "Ratings") consists of a 24×6 matrix where the rows are the interventions and the columns are the criteria. The (nth, mth) element of the matrix is the normalized impact of Intervention n on Criterion m. In this illustrative example, the normalized impact of Intervention 2 on Criterion 4 is 0.250 and the normalized impact of Intervention 24 on Criterion 6 is 0.570. The first row (Step 3, "Scores") gives the performance score of each intervention across all criteria. Intervention 1 here scored the highest (0.686) and is therefore the optimal intervention. The ratio of its score relative to other interventions represents how much better it performed relatively. For

Table 4
Criteria used for comparative evaluation of interventions.

Criterion	Criterion identifier	Objective
Educational attainment	C1	Maximise
Indoor overheating	C2	Minimise
Indoor air stuffiness	C3	Minimise
Hospital (National Health Service, NHS) cost	C4	Minimise
Building energy cost	C5	Minimise
Greenhouse gas emissions	C6	Minimise

example, Intervention 1 outperformed Intervention 2 by 0.686/0.273 ~ 2.5 times.

4.3. Criteria

The selection of the criteria was informed by seeking the advice of members of the ASPIRE Project Advisory Group consisting of construction industry practitioners, educational and public health government officials and academics. Table 4 lists the criteria in the survey (all are assessed annually).

For a detailed description of the criteria and how they are assessed refer to Grassie et al. [5] for all the criteria except the National Health Service (NHS) costs. The criteria are briefly described below:

- Educational attainment: This is based on an empirical model consisting of two factors: indoor air temperature and ventilation rate, which reduces relative cognitive performance from 100 % when the temperature increases above 20 °C or the ventilation rate falls below 7.35 l/s/person [24]. In many cases 3 l/s/person and 8 l/s/person have been provided as minimum and optimum standards, with respect to CO_2 removal for example in BB101 [17].
- Indoor overheating: This is the number of hours of exceedance above an indoor temperature threshold specified by BB101 [17] Criterion 1.
- Indoor air stuffiness: This characterises air freshness and is measured by the indoor CO_2 concentration.
- Building energy cost: This is the cost of total annual energy used for space heating normalized by floorspace.
- Hospital (National Health Service, NHS) cost: This represents the hospital costs incurred by treating children with asthma associated with indoor NO_2 pollution.
- Greenhouse gas emissions: This measures the CO_2 equivalent emissions associated with annual heating energy use.

Further details of the criteria developed through Grassie et al. [5] can be found in Table A.3 in the Supplementary Material. Both the building energy cost and greenhouse gas emissions utilise energy cost and carbon intensity parameters which have also been given in the Supplementary Material.

For NHS costs, first, impacts on childhood asthma incidence due to nitrogen dioxide (NO_2) exposure were estimated using a standard comparative risk assessment approach with incidence data from the Global Burden of Disease (GBD) study and the exposure–response relationship from Khreis et al. [25]. Then, we assumed an equivalent proportional change in asthma incidence and childhood asthma-related hospital admission costs based on standard NHS reference costs [26].

4.4. Elicitation of stakeholder preferences

To elicit school sector stakeholder preferences, 210 respondents were recruited from 11th June to 26th July 2021 through engagement with industry and education bodies, and utilising local and national government contacts and colleagues of the research team. Snowball sampling was used, most notably through local government contacts, who were encouraged to send out the survey to schools within their authority area. The online survey was generated using the *Microsoft Forms* tool [27]. Each stakeholder was invited to rank the above set of six criteria from 1 to 6 with rank 1 representing the most important criterion. Of the 210 responses, 115 were accepted, with most rejected due to failing to rank the criteria sequentially (i.e. duplicate scores being recorded for 2 or more criteria).

In order to perform sub-group analysis, the survey asked each respondent to select their profession as one of the following: “National and local government”, “Construction industry practitioners”, “Education professional associations”, “School teaching staff”, “Other school staff”, “Parent” and “Other” (those who selected this option were allowed to enter a free text description). Section D in Supplementary Material shows how to convert stakeholder survey rankings to aggregate weights between 0 and 1 which add up to unity.

Table 5
Number of survey respondents per stakeholder group.

Group	Group identifier	Number of respondents
National and local government	Group 1	17
Construction industry practitioners	Group 2	11
Teaching school staff and education professionals	Group 3	54
Non-teaching staff	Group 4	23
All (including 10 Other/Parents)	Group 5	115

5. Results

5.1. Stakeholder survey

Table 5 gives the number of respondents to the online survey per group. Three of the groups (1, 2 and 4) have sample sizes around 50 % and 25 % of Group 3 and 5 sample sizes, respectively, thus differences from these groups are less likely to be statistically significant.

Fig. 3 shows the aggregate weights for each criterion by stakeholder group. In each group, the ratio of the weights of two criteria gives how important the respondents considered one criterion relative to the other. All groups considered educational attainment as the most important criterion and most groups considered reducing the building’s carbon footprint as the least important criterion. For example, Group 5 (all respondents) rated educational attainment to be 2.4 times more important than reduction in school building carbon footprint and 2.6 times more important than energy costs. There was some variation between groups on the lower priorities. For instance, Group 2 (construction industry practitioners) had a higher preference for reducing greenhouse gas emissions than hospital or building energy costs. It is important to emphasise that this survey represents a single snapshot in time and priorities for IEQ and energy costs derived in mid-2021 may not have persisted post-pandemic.

5.2. Optimal interventions per setting

The scores of each of the 24 interventions per setting were calculated; Fig. 4 shows the scores of the intervention for the first three settings in Table 3 selected for illustration. The figure compares the scores of each intervention across three construction eras: pre-1918, inter-war and 1945–1967 for south-facing classrooms (S) in London and simulation time slice 2020 s. In each setting, the intervention with the highest score is the optimal intervention for that setting. The ratio of the scores in each setting quantifies the extent to which an intervention outperforms another. In Fig. 4a, the scores were calculated using the aggregate weights elicited from the stakeholders. It shows that all these interventions score highest in pre-1918 schools and are nearly comparable for Inter-war and 1945–1967 schools except for a few interventions. As a comparator, Fig. 4b shows the scores of the intervention for the same three construction eras (pre-1918, inter-war and 1945–1967) but the scores were calculated using equal weighting across criteria, rather than those given in Fig. 4a.

Fig. 4b shows that different optimum interventions apply for different construction eras, thus indicating that, among the combinations of interventions tested, there is no one-size-fits-all solution with regard to retrofit and IEQ management schemes across the school building stock. It also illustrates how sensitive the scores are to the aggregate weights. When equal weightings are applied to the criteria, the scores of the interventions across inter-war and 1945–1967 era schools are not comparable as previously.

Criteria	Group 1 (National and local government)	Group 2 (Construction industry practitioners)	Group 3 (Teaching school staff & education professionals)	Group 4 (Non-teaching school staff)	Group 5 (All)
Educational attainment	0.272	0.277	0.272	0.273	0.273
Indoor overheating	0.188	0.182	0.206	0.230	0.204
Indoor air stuffiness	0.182	0.221	0.195	0.184	0.192
Hospital (NHS) cost	0.118	0.082	0.101	0.085	0.098
Building energy cost	0.126	0.078	0.114	0.139	0.118
Greenhouse gas emissions	0.115	0.160	0.112	0.089	0.115

Fig. 3. Aggregate weights per stakeholder group.

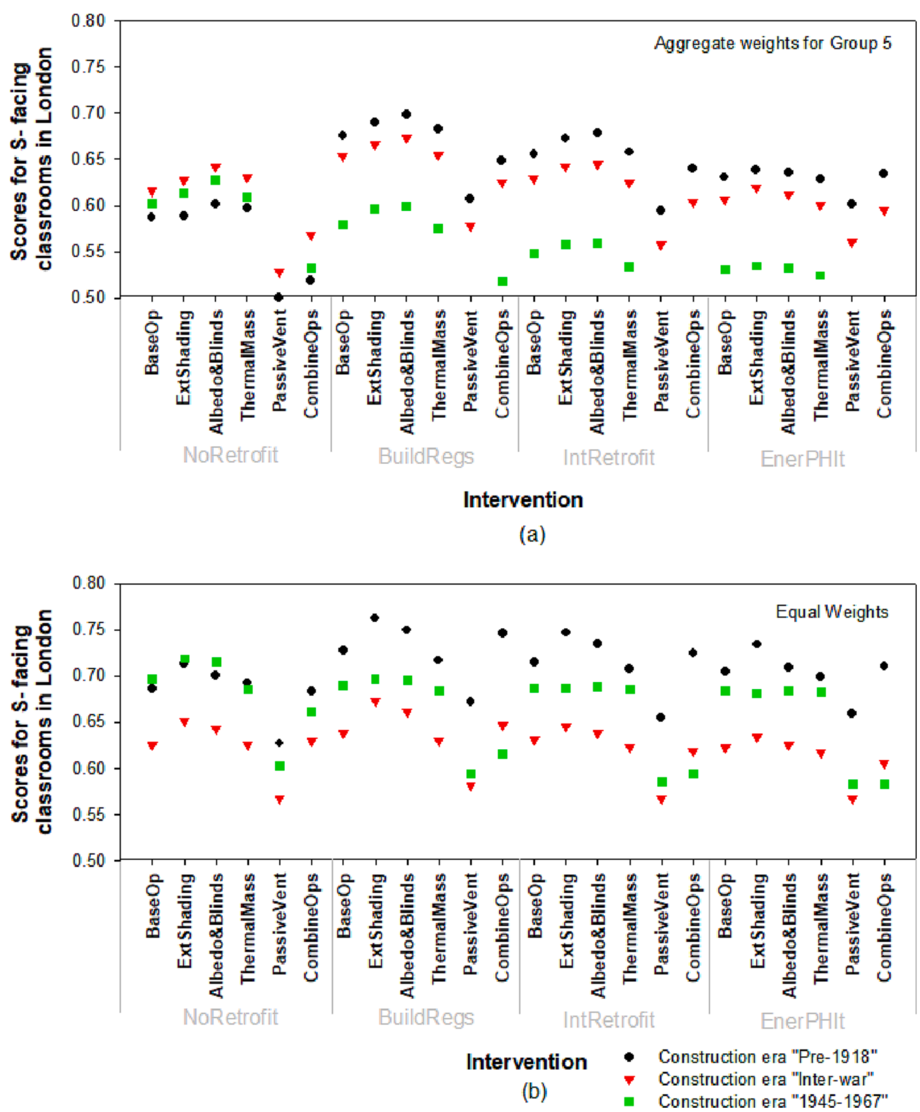

Fig. 4. Intervention scores for three settings using (a) the aggregate weights of all stakeholders (Group 5) and (b) equal weights for each criterion.

5.3. Robustness of optimal intervention

The optimal intervention was calculated for each setting (60 settings in total). Then, the robust optimum interventions were calculated to determine the intervention which has the highest probability of being optimal. Fig. 5a displays the probability that each intervention is optimal given by the number of times an intervention scored the highest by the total number of settings. Fig. 5b displays the counterpart result when equal weights are used.

Fig. 5a shows that four pairwise combinations of energy retrofit and IEQ improvement schemes are the robust optimal choices based on the weighted stakeholder criteria over all 60 modelled settings (including the climate change scenario, geographical region, building orientation, and construction era combinations summarised in Table 3). These four optimal choices consist of no-retrofit and retrofit with minimal building regulation compliance, combined with external shading, and increased

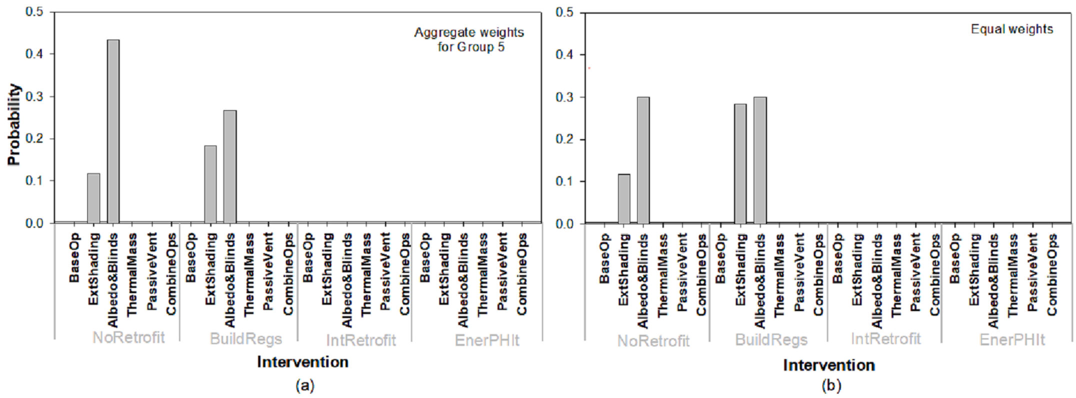

Fig. 5. The probability that each intervention is optimal over all settings using (a) the aggregate weights of the stakeholders (Group 5) and (b) equal weights for the criteria.

albedo and internal blinds for IEQ improvement. Note that the weights in this case are based on the preferences of all stakeholders. However, Fig. 5b clearly shows that under equal weighting the intervention identified as optimal loses some of its prominence relative to the other three interventions. Supplementary Material F includes more outcomes of the MCDA framework to interpret the highest probability of being optimal for different stakeholder groups and in accordance with different climate (2020 and 2050) and regions (London, Birmingham and Leeds).

6. Discussion

6.1. Main findings

The impact of school energy efficiency retrofit and IEQ improvement schemes was evaluated using MCDA to determine optimal combined interventions across multiple criteria. For the stakeholder group containing all survey respondents, four pairwise interventions were identified as optimal under different scenarios. These interventions incorporate all possible combinations of no-retrofit or Building Regulations compliant minimal retrofit coupled with external shading, or increased albedo and internals blinds. These results suggest that there are trade-offs between building fabric efficiency and IEQ, under the specific modelling assumptions made in this study. These trade-offs will need to be considered carefully given the imperative (and legal requirement) for the UK to meet its climate change objectives by improving the energy efficiency of school buildings. The aim of this paper was to showcase the MCDA approach as a mean of facilitating decision making for school retrofit and operation but only a limited number of retrofit interventions was tested. Future modelling work will examine additional interventions and technological systems (e.g. heat pumps), so as to identify win–win options that meet both IEQ and net zero targets.

It was shown that the SMART MCDA method provides a transparent way for integrating the modelled impacts with the weights of the criteria to assess the performance of the interventions across several criteria. Preceding work by the authors [5] demonstrated that the performance of pairwise energy and IEQ improvement interventions varies widely across multiple criteria of school building performance. This means that in order to differentiate the effectiveness of results more clearly across conflicting energy and IEQ performance criteria, it would make sense to use MCDA. MCDA assigns weights to the criteria through an elicitation process and combines them with the impacts of the interventions on the criteria in order to ascertain which intervention is (mathematically) optimal across all criteria.

6.2. Sensitivity of MCDA results to the weights assigned to criteria

The results of the MCDA were found to be sensitive to the elicited weights. We compared the MCDA results using aggregate weights of the criteria (based on stakeholders' preferences) with those using equal weights. Fig. 4 showed that the weights of the criteria influence which classroom construction eras are "best performing" under each set of interventions. For example, the MCDA scores indicated that the performance of the pre-1918 construction is deemed to be better than that of 1945–1967 construction for the classrooms without retrofitting when the stakeholder weighting is applied (Fig. 4a), but not when equal weighting is applied (Fig. 4b). This means that, since educational attainment is relatively more highly valued by these stakeholders, and energy costs and emissions are not as much valued in survey-derived weightings, older, leakier Victorian buildings which are more challenging to heat, perform better compared to overheating post-war buildings with low ceilings. Such a conclusion may seem counterintuitive. This may also suggest that in future it will be necessary to increase ventilation effectiveness year-round while utilising smart modern means of heating and circulating air to reduce energy costs in winter. These results from our proof-of-concept, model-based decision-analytical approach suggest that future use of the MCDA tool should take into consideration the sensitivity of the results to criteria weightings. Sensitivity analyses were provided in the Supplementary Material (F) where we evaluated the sensitivity of the MCDA results to the weights.

Additionally, although the stakeholder survey carried out in this study provides a scientific and evidential basis to the weighting described in Fig. 3, the survey represents only a snapshot in time from a select group of stakeholders. Other stakeholder groups may have provided different weights and stakeholders' preferences may evolve over time, for instance due to global events, such as the Covid-19 pandemic or rapid increases in UK consumer energy costs throughout 2022 [28].

Additional analysis such as stochastic multi-criteria acceptability analysis could have been carried out to investigate how the results of the MCDA are influenced by the weights [29]. This entails determining the theoretical relationships between the weights of the criteria that would make each intervention robust optimal. This could be important because it provides insights on how the weights affect the ranking of the interventions in terms of performance for a fixed set of normalized impacts. This mathematical analysis is, however, beyond the scope of this study.

6.3. Limitations of research

The results of the MCDA can also be sensitive to the normalization process used to make the metrics of the criteria commensurate. Ideally, the sensitivity of the results could be evaluated in terms of the normalization constants. This was not carried out because it would

Fig. 6. One dimensional array of criteria. C1 = "Educational attainment", C2 = "Overheating", C3 = "Stuffiness", C4 = "Hospital (NHS) cost", C5 = "Energy cost", and C6 = "Greenhouse gas emissions".

dilute the interpretation of the results as there will be many permutations of normalizing constants to consider. We chose the minimum and maximum bounds of each criteria based on many simulations to ensure that they represent the true bounds of the values of the criteria. In the case of equal weights, the normalized impacts can be used to explain to some extent why some interventions have high probability of being optimal while others do not by exploring the impact space (Supplementary Material G).

In this work, in terms of relative positioning of criteria, it was assumed that the criteria were on the same level with no hierarchy (Fig. 6).

The criteria however could have been considered to be hierarchical, which could have led to different categorisations, based on how underperformance impacts the school, rather than the underperforming criteria alone. For example, a new criterion (C7) could have been created to represent "costs" and then divided in turn into two sub-criteria, "NHS costs" (C4) and "Energy cost" (Fig. 7).

There are several MCDA methods which can handle hierarchy in criteria. These include the Analytic Hierarchy Process (AHP) [30,31], Multi-Attribute Value Theory (MAVT) and outranking methods [30–33]. Although introducing hierarchy into the set of criteria enriches the MCDA, it introduces complexity particularly in relation to eliciting the weights for the criteria as it can be demanding on stakeholders.

We did not take into consideration the uncertainty in the modelled impacts and how this affects the performance scores of the interventions. The modelled impacts are based on building physics outputs from building stock models which are subject to parametric and structural uncertainties. To determine the uncertainties in the modelled impacts requires the propagation of the uncertainties between the models generating the impacts on the various criteria (Fig. 8). The propagation of uncertainty between a series of models requires careful scrutiny which is beyond the scope of this study [34].

Finally, we emphasise a well-known fact that for a fixed set of interventions the results of any MCDA depend to a great extent on the criteria selected for the comparative evaluation of the interventions. For example, the health impacts were not defined explicitly as a criterion but were included indirectly as part of the healthcare costs. Although the costs are linearly related to health burdens, it is expected that survey respondents would assign significantly more weight to the health of schoolchildren than to the associated healthcare costs. Introducing health instead of healthcare costs as a criterion could have therefore changed the ranking of the interventions in terms of their performance. One possible solution to the sensitivity of the MCDA to the selected set criteria is to include all possible criteria and then formulate them in a logical hierarchy as described above. In this example, health and healthcare costs would enter as separate criterion. The drawback of this approach however is that the use of hierarchical criteria adds more complexity to the weight elicitation process.

7. Conclusions

A model-based MCDA framework was developed and applied to evaluate school energy efficiency and IEQ management schemes in English classrooms across several criteria of relevance to children's educational attainment and their health as well as energy efficiency

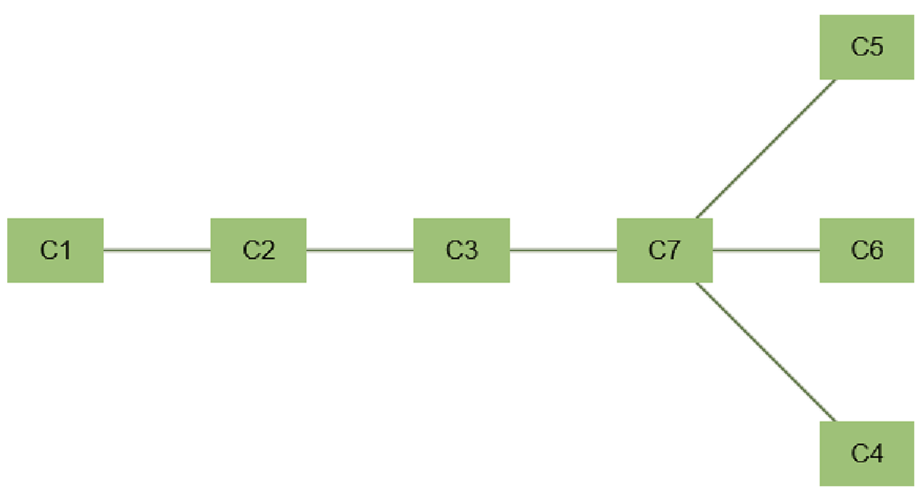

Fig. 7. Hierarchical set of criteria. A new criterion "cost" is created which is subdivided into NHS costs (C4) and energy cost (C5). C1 = "Educational attainment", C2 = "Overheating", C3 = "Stuffiness", C7 = "Costs" and C6 = "Greenhouse gas emissions". C4 ("Hospital (NHS) cost") and C5 ("Energy cost") are at a different level from the other criteria.

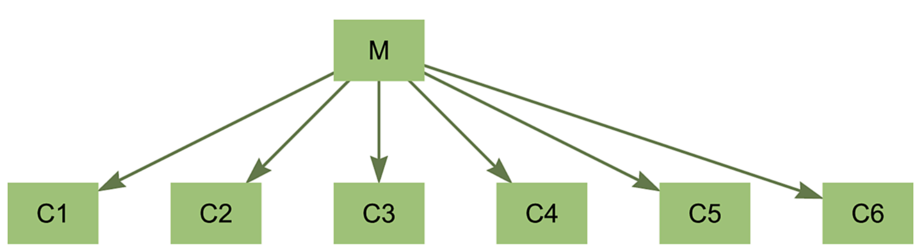

Fig. 8. To quantify the uncertainty in the modelled impacts, the uncertainty in the building physics and building stock models (M) should be propagated to the models generating the impacts on the criteria (C1 to C6).

performance and costs. The relative importance of the criteria was elicited from a wide range of stakeholders from national and local government, the construction industry, school teaching staff and education professionals, non-teaching staff and others including parents. The model–based MCDA calculations were carried out on 60 settings comprising different climate scenarios, school building orientation (north-facing and south-facing), geographical region and school building construction era, to determine the intervention which has the highest probability of being optimal. For the particular set of interventions, criteria and stakeholders in this study, the optimal interventions entailed low/intermediate energy efficiency interventions coupled with external shading, or increased albedo and internal blinds. The results were sensitive to the preference weights assigned to the criteria and to the selected intervention for evaluations. This study demonstrated the principle of using MCDA to support decision-making in relation to selecting energy retrofit and IEQ schemes which address multiple criteria. It also highlighted that the results are dependent on which interventions and criteria are selected and whose preferences are elicited to assign the relative importance of the criteria.

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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