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Large-scale school building infrastructure improvement: The case of the city of Cali, Colombia

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ABSTRACT

Quality education is influenced by various factors, including infrastructure, curricula, and educators. Among these factors, school infrastructure significantly impacts the learning process. However, managing and improving existing school infrastructure in low- and middle-income countries presents complex challenges due to limited resources, inadequate regulations, and poor maintenance practices. To effectively prioritize limited funds and balance short-term needs with long-term sustainability, decision-making processes must consider simultaneously functionality and safety aspects. This paper introduces an extended decision-making framework for enhancing school buildings, by determining optimal investment levels and prioritizing interventions in the building portfolio. The framework comprises multiple analytic models that are interconnected. The methodology starts with the identification of building typologies using a clustering algorithm; then, through a multi-criteria utility function with parametrized decision-maker profiles, it considers the trade-offs between safety and functionality; last, an optimization model prioritizes the buildings' interventions. The framework is adapted to a regional context in the city of Cali (Colombia). The outcome of this implementation provides analytics to decision-makers at an early stage in the formulation of school building improvement programs. This helps unveiling the extent of the project by defining the needs of improvement and the budget required to implement a large-scale intervention program.

1. Introduction

The United Nations Sustainable Development Goals (SDG) serve as a pressing global mandate for collective action towards achieving peace and prosperity for all individuals. These goals are designed to eradicate poverty, diminish inequalities, foster economic growth, preserve the environment, and enhance health and education. Of particular relevance is the fourth goal, which emphasizes the need for inclusive and equitable access to quality education for all [1]. This laudable objective is also in line with Article 26 of the Universal Declaration of Human Rights, which asserts that everyone has the right to education [2]. However, there are various factors that impact the quality of education, including accessibility, inclusivity, teacher qualifications, use of technology, and school infrastructure. Particularly, ageing infrastructure and limited maintenance budgets increase the current problems of school infrastructure [3]. Thus, improving school infrastructure, can positively impact the quality of education [4]. Understanding how this infrastructure can be improved is the main topic of this paper.

A recent example of decision-making framework to prioritize interventions and improve infrastructure in school facilities has been proposed by the authors [5]. The decision-making framework prioritizes school buildings' investment within limited budgets, using an unsupervised learning (clustering) procedure, an *a-priori* multi-criteria utility function, and an optimization model. This framework requires key input from decision makers and technical experts. Its purpose is to obtain a prioritized set of interventions, given a particular decision-maker set of preferences and a fixed budget. The original framework has been illustrated with an application to the public school system infrastructure in Dominican Republic [5].

Considering the difficulties of involving several decision-makers at the early stages of a large-scale improvement project, the objective of the present study is to switch the framework towards an *a-posteriori*

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articulation of preferences. This is done by extending the existing framework to accommodate multiple decision-maker preference profiles. By doing so, the results can support decisions such as the distribution of investments by type (functional or safety interventions) and help identifying the most efficient level of investment to improve the quality of a particular school building portfolio. In this extended framework, the purpose is to give valuable information to a set of decision makers to define, based on this information, the investment needs and the priorities for improvement. Therefore, the framework can be used as an exploratory preliminary step when decisions are not yet fixed, and the problem is still at the feasibility stage. In this paper we illustrate this extended method through an application to the public-school infrastructure of the city of Cali in Colombia. Also, this case study shows the applicability of the framework at the city level.

This paper is organized as follows. Section 2 presents the literature review; Section 3 explains the methodology; Section 4 illustrates the methodology in a case study; Section 5 analyzes the results from the decision-maker perspective, showing how to inform policy development; and finally, Section 6 concludes and outlines future work.

2. Literature review

School facilities have a significant impact on the learning process. As established by Barrett et al. [6], school building design affects the health, safety, and learning processes of students. A relatively substantial literature exists on this topic. For instance, Cuesta, Glewwe & Krause [7] analyzed whether school infrastructure has a causal impact on student enrollment and learning. The results showed that several factors, such as the Water and Sanitation Hygiene (WASH) conditions, relate to learning and enrollment in Latin America. Another study conducted in the region based on 3000 school facilities in 15 countries showed that the availability of basic infrastructure and services influences the performance in mathematics and language at primary education level [8]. A more country-specific case study in Peru, assessed the impact of investments in school infrastructure on school attendance, showing a positive effect in the intervened schools [9]. Similar studies have been developed using Data Envelopment Analysis (DEA), where the authors identified the impact of school infrastructure on school performance in India [10], in Brazil [11], and Ecuador [12]. In these three studies, the authors agreed on the relevance of infrastructure, and particularly the impact of infrastructure investments on improving education quality. The Organization for Economic Co-operation and Development (OECD) analyzed how infrastructure conditions relate to the well-being of students. The findings show higher average grades for students who reported experiencing a good quality of school infrastructure, in contrast to those reporting having infrastructure of poor quality [13]. Similarly, Fisher [14] studied how students in refurbished or new buildings performed around 5%–10% better than students in older buildings.

It is also important to understand all the elements of a school facility and their specific functions in educational services. The OCDE studied the quality of infrastructure in South Africa, developing the School Infrastructure Performance Indicator System (SIPIS). This indicator includes several components of the school infrastructure and was designed to be used in the decision-making process of infrastructure investment, for both new and existing buildings [15]. The indicator includes elements of safety, efficiency, and operational costs, as well as density and comfort. Another relevant factor is the information technology (IT) infrastructure in schools, which is a necessary condition for teaching Information and Communications Technology (ICT) skills as well as other subjects [16]. School safety is also a relevant aspect of infrastructure quality since it can be threatened by natural hazards, such as cyclones or earthquakes. For instance, in 2015, the Gorkha earthquake in Nepal showed the high vulnerability of schools after several buildings collapsed, putting children and teaching staff at risk [17].

However, managing school infrastructure improvement programs is often complex, costly, and time-consuming. Several stakeholders participate in this process such as students, parents, school administration, teachers, governments (national and local), private sector, and international organizations [18]. The roles in managing infrastructure at national and local governments are country specific. The efficiency of any improvement program implementation is also conditioned by contextual factors such as decentralization, socio-economic conditions, political tendencies, corruption, development, democratization programs, civil society, and sustainability concerns [18]. For instance, in Nigeria the combination of an inadequate government intervention, lack of maintenance, lack of community involvement, and no sense of commitment by other stakeholders have turned into a deplorable educational public infrastructure [19].

To tackle these problems in the implementation of school improvement programs, international agencies have promoted public and private sector partnerships. Multi-stakeholder partnerships for education (MSPE) have been widely studied, showing, among other findings, how different aims, constituencies, and ways of working should be synchronized in cooperation agreements [20]. Examples of applications are reported in India, to expand the educational network with the involvement of state and non-state education providers [21]; in Ghana, leading to the failure of the Ghana Education Trust Fund (GETFund) which objective was to provide and maintain educational infrastructure [22], and in China, where the need of a collective institutional agreement with public and private schools providing education was brought to the fore [23]. Mayerle et al. [24] developed a decision support methodology to increase public school efficiency by allocating efficiently the students in the existing infrastructure. Similarly, Dhansinghani et al. analyzed the surrounding walking infrastructure near schools to prioritize interventions and investments [25]. However, in these studies the effect of quality of infrastructure and particularly its safety was not part of the scope. The examples above show the need for a better understanding of the role and the impact of each stakeholder's preferences on the implementation of improvement programs in education.

The situation is rather different for other types of infrastructure. Indeed, Kabir, Sadiq & Tesfamariam [26] reviewed about 300 papers where multi-criteria decision-making methods were used to include technical values and stakeholders' preferences in infrastructure projects. In this study, more than 80% of the papers refer to water resource systems, wastewater, bridges, and transportation, management. For instance, in wastewater infrastructure, a study developed by Lienert, Duygan & Zheng [27] explored the possible differences in the outcomes of an environmental decision when different stakeholder preferences were considered. Similarly, Lima et al. [28] developed a multi-voiced multi-criteria analysis to integrate the preferences of researchers and decision-makers in the prioritization of groundwater management instruments in watersheds. Related to transportation, several authors have studied the life cycle management of civil infrastructure considering service life and probability of failure in bridges [29]. Also, for bridges, Valkonen & Glisic [30] studied the impact on decision makers' preferences and the influence on structural health monitoring. Another similar analysis for new building offices considered decision maker preferences related to costs, potential damages, casualties, and CO2 emissions [31]. Last, but not least, decision-maker preferences are also relevant in the insurance of infrastructure exposed to low-probability high--consequence events [32].

Approaches such as the ones presented above have been extended to develop decision-making frameworks to prioritize investments in different types of infrastructure systems [33–36]. However, these efforts usually lack a systematic approach for improving safety and functionality of existing school infrastructure at an early stage of large-scale intervention programs [37–39]. This research paper aims to fill this gap.

3. Methodology

The proposed method in this paper extends the decision-making framework developed by Fernández et al. [5], which is comprised by

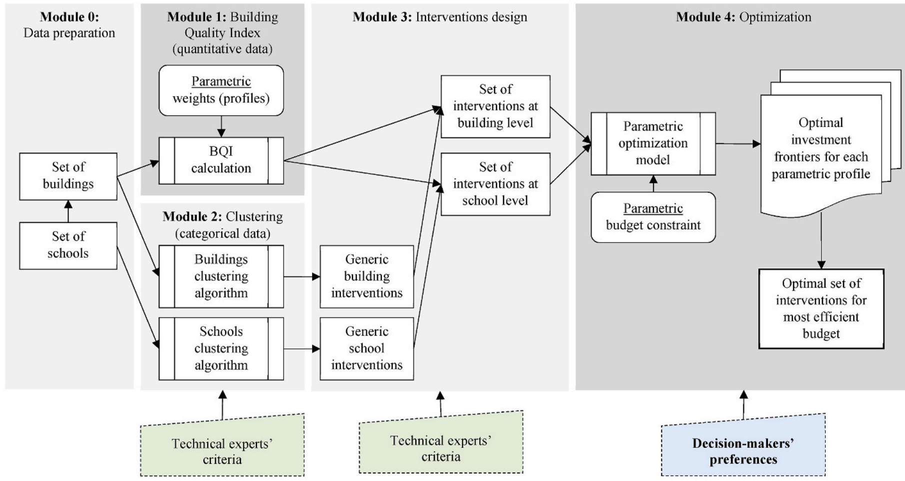


Fig. 1. Parametric decision-making framework for school infrastructure improvement with a-posteriori articulation of preferences.

five modules: 0) data preparation; 1) building quality index (BQI) estimation; 2) clustering; 3) interventions design; and 4) optimization. Module 0 includes the characterization of the school buildings' database. This module identifies the quantitative attributes of the infrastructure in terms of safety and functionality according to relevant taxonomies. Module 1 calculates the *building quality index* (BQI), which defines the current state of each building. This is the base line for improvement for each school building. In module 2, the school buildings' main typologies are identified using an unsupervised machine learning clustering algorithm, based on the construction typologies of the school buildings. Module 3 identifies a set of generic interventions for each cluster (of buildings) and evaluates their implementation in each school building identifying the total cost of the intervention and its benefit in terms of the BQI (ΔBQI) improvement. The last step of the framework, namely module 4, employs an optimization model to prioritize the interventions, subject to a set of quality and budget constraints.

The first version of this framework [5] requires key inputs from decision makers and technical experts. For instance, the preferences of the decision maker are explicitly included in module 1, as they become the a-priori weights used to calculate the BQI. Also, module 4 requires the decision-maker to express preferences in terms of the budget constraint and the minimum quality standards. However, the proposed extended framework primarily switches from an a-priori to an a-posteriori articulation of preferences approach. This extended framework uses parametric inputs in module 1 (for the BQI calculation) and in module 4. In module 1, a fixed set of weights defines a representative sample of decision-maker profiles. This takes away the responsibility from the decision-maker to define the weights a-priori. In module 4, the optimization model automatically unveils the investment frontier by solving it parametrically for the budget constraint, while the minimum quality constraints are neglected. The extended framework uses the frontier to compare the parametric profiles defined in module 1 and with an analytical procedure, it identifies the most efficient level of investment for each profile. Modules 0, 2, and 3 remain the same as in the original implementation. Fig. 1 presents the extended decision-making framework.

The main innovation of the proposed method is therefore the parametric approach that leads decision makers to be presented with valuable information that explores different tradeoffs between decision profiles and budget levels. These parametric implementations give the decision-maker a set of results that could be analyzed a-posteriori. This extension of the method changes the emphasis on eliciting input from the decision makers at an early stage in the framework (i.e., a-priori), towards one that presents the whole set of tradeoffs to the decision maker at a late stage (i.e., a-posteriori). The advantage of doing this is that the results can be used to inform the definition of programs at a formulation stage by giving insights of the possible extent of investment and the needs of the existing infrastructure. Note that this emphasis still has the decision-maker at the center of the framework, providing tools for more informed decisions regarding school improvement programs.

For sake of completeness, we present a summary of all the modules of the extended framework, including those that are not changed from the original formulation:

3.1. Module 0: Data preparation

The objective of this module is to collect all the possible information to characterize the schools, and their buildings. Two sets of information are required: quantitative and categorical data. The former includes information at the building level related to safety and functionality that could be measured and ranked. For instance, the risk level related to the main hazards in the region (e.g., the expected annual losses or the maximum probable losses for a fixed return period) or the students' density (in relation to the built area). This data is utilized to compute the quality index at the building level in Module 1. The latter set, the categorical data, is used to characterize the buildings and schools with a set of taxonomies related to safety and functionality. For example, in relation to safety, a seismic taxonomy will be used in seismic hazard prone areas. In terms of functionality, a functional taxonomy at the building level could include information related to ventilation and illumination, and a functional taxonomy at the school level could include information related to the WASH quality, the accessibility or the existence and quality of leisure spaces, among others. Several parameters can be considered in each taxonomy and their selection depends on the available information for the dataset and the aim of the intervention.

3.2. Module 1: Building Quality Index

This module calculates the Building Quality Index (BQI). This index is used to assess the quality of the educational buildings, considering functionality and safety criteria. The BQI goes from 0 to 1, where 0 is the worst quality, and 1 is the best quality in a school building. The BQI of a building b is defined as a weighted sum of the normalized value in each sub-criterion:

$$BQI_b = \sum_{c \in C} s_{b,c} \cdot w_c$$

where C is the set of criteria; $s_{b,c}$ is the normalized data of a specific building b in the criterion c; and w_c is the weight associated with

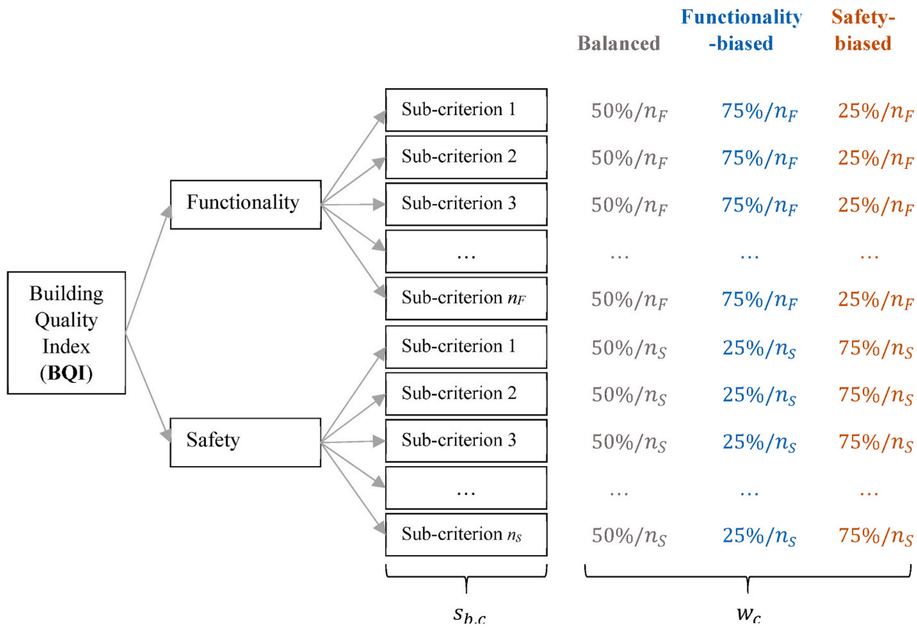


Fig. 2. Hierarchical attribute representation and parametric profiles.

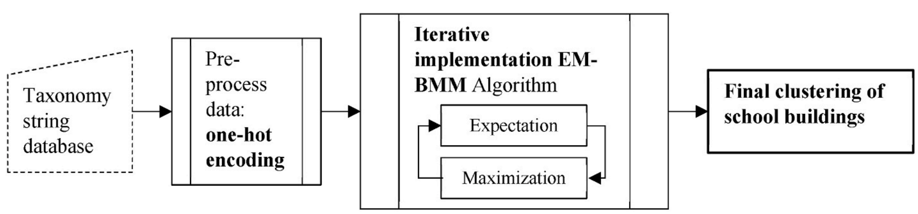


Fig. 3. Clustering algorithm. Adapted from Fernández et al. [44].

criterion *c*. The weights can be derived using methods such as the Analytic Hierarchy Process (AHP) [40] or the Optimal Scoring Method (OSM) [41]. However, input from the decision-makers is needed for the implementation of these methods. This input is usually difficult to collect specifically if the project is at an early stage of formulation. Considering this limitation, in the current proposed method the approach is to use parametric decision profiles. Three fixed profiles are chosen: a *balanced* profile, giving 50% of the weight to functionality and 50% to safety; a *functionality-biased* profile giving 75% of the total weight to functionality and 25% to safety; and a *safety-biased* profile, giving 25% of the total weight to functionality and 75% to safety. The weight of the inner sub-criteria should be divided into the number of sub-criteria (i.e., n_F and n_S, for the total number of attributes under the functionality and safety criteria). Fig. 2 shows the hierarchical attribute representation of the BQI and the proposed profiles. It is important to mention that additional decision-profiles can be included in the analysis to consider other biased scenarios, however, for sake of conciseness and clarity we limit the analysis in this paper to only three.

3.3. Module 2: Clustering

This module uses categorical taxonomies based on the information collected in Module 0 for each building and school. For each one of the categories (seismic, functional - building level, functional - school level, etc.) we implement a clustering algorithm to identify sets of buildings with common features that can be grouped into larger sets. The first step to apply the clustering algorithm is data preparation. As each building is classified by a taxonomy (i.e., categorical data), attributes' arrays are coded into binary vectors using one-hot encoding [42]. Then, we use the Expectation-Maximization (EM) implementation for the Bernoulli Mixture Model (BMM) using the binary encoding [43]. This process enables us to automatically find the clusters distribution for a defined number of clusters (K). However, to define K that better divides the data, we need to try different numbers and analyze the resulting distribution. Therefore, we implement an iterative process, starting with a small number K such as two, and increasing it until the cluster distribution is logical, interpretable, and acceptable, determined by the judgment of construction experts. This procedure is repeated for each taxonomy to identify the clusters of similar buildings and schools. At the end, each building will belong to a group (or cluster) for each one of its taxonomies. The methodology is presented in Fig. 3 and in Fernández et al. [44].

3.4. Module 3: Interventions design

Two steps comprise this module: 1) the development of generic interventions by cluster; and 2) the implementation of the generic interventions in particular buildings. In the first step, we interpret and identify the common characteristics of each cluster, to propose generic interventions applicable to all buildings within the cluster. The definition of these generic intervention should be done together with technical experts in different fields, such as architects and structural engineers, with profound understanding of school construction characteristics and country-specific or international guidelines (standards or building codes). The second step estimates the costs and the benefit improvement (in terms of the quality indicator calculated in Module 1) of implementing the generic intervention in a given building within the cluster (as the difference in BQI between the original condition and after the intervention). This module generates a database of interventions by taxonomy implemented in each building and each school.

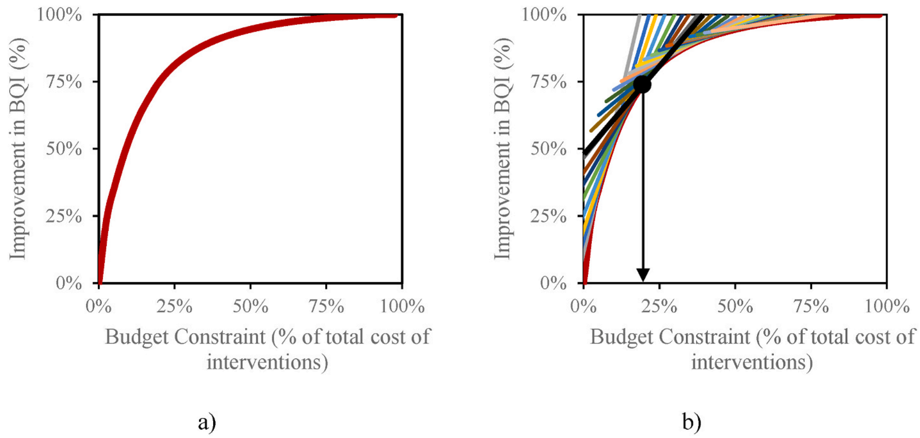


Fig. 4. Illustrative process of identifying the efficient level of investment.

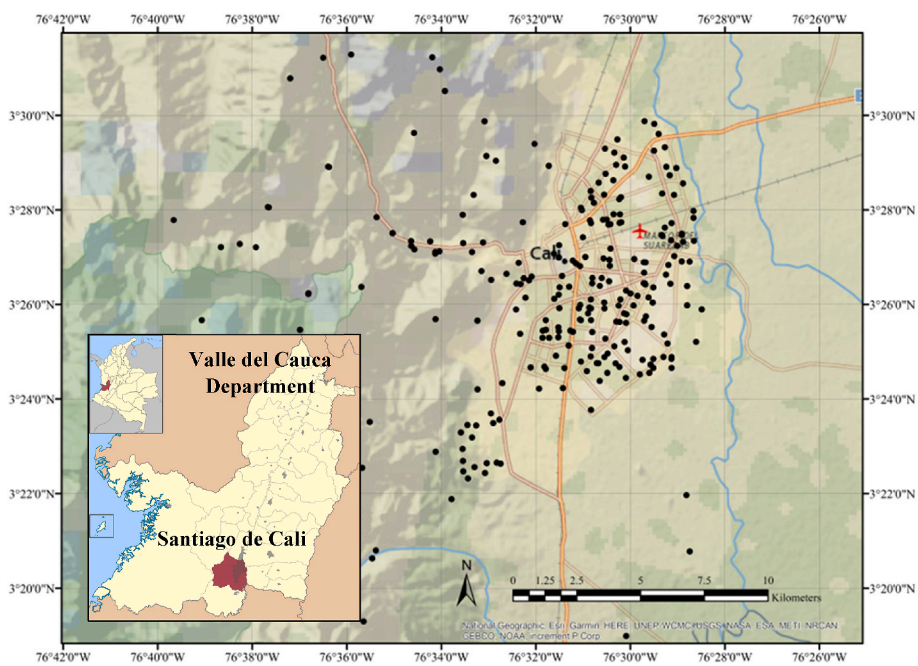


Fig. 5. Distribution of school facilities in Cali city.

3.5. Module 4: Optimization model

To select the optimal set of interventions, we define a model that finds the optimal set of interventions, maximizing the total improvement in BQI with a budget constraint. To define the optimization model, let B be the set of buildings in the portfolio; S, the set of school facilities; B_s, the set of buildings in school $s \in S$; I_b, the set of possible interventions to building $b \in B$; and I_s, the set of possible interventions to school $s \in S$. In terms of parameters, let $c_{i,b}$ be the cost of intervention $i \in I_b$ for building $b \in B$; $c_{i,s}$, the cost of intervention $i \in I_s$ for school $s \in S$; $\Delta q_{i,b}$, the *BQI* improvement in building $b \in B$ due to intervention $i \in I_b$; $\Delta \widehat{q}_{i,s}$, the *BQI* improvement in school $s \in S$ due to intervention $i \in I_s$ ($\Delta \widehat{q}_{i,s} \stackrel{\text{def}}{=} \sum_{b \in B_s} \Delta q_{i,b}$); and K, the budget limit for the investment plan. The decision variables are $x_{i,b}$, a binary variable that takes the value of 1 if building $b \in B$ is subject to intervention $i \in I_b$, and it takes the value of 0, otherwise; and $y_{i,s}$, a binary variable that takes the value of 1 if school $s \in S$ is subject to intervention $i \in I_s$, and it takes the value of 0, otherwise. The resulting (knapsack) optimization model follows:

$$\max \sum_{b \in B} \sum_{i \in I_b} \Delta q_{i,b} \cdot x_{i,b} + \sum_{s \in S} \sum_{i \in I_s} \Delta \widehat{q}_{i,s} \cdot y_{i,s} \tag{1}$$

subject to,

$$\sum_{b \in B} \sum_{i \in I_b} c_{i,b} \cdot x_{i,b} + \sum_{s \in S} \sum_{i \in I_s} c_{i,s} \cdot y_{i,s} \leq K \tag{2}$$

$$x_{i,b} \in \{0, 1\}, \forall\, b \in B, \forall\, i \in I_b \tag{3}$$

$$y_{i,s} \in \{0, 1\}, \forall\, s \in S, \forall\, i \in I_s \tag{4}$$

The objective function (1) maximizes the *BQI* improvement generated by the implementation of the selected interventions at the building and school levels in the entire portfolio. Constraint (2) guarantee that the total cost of the interventions is less than the available budget. Last, constraints (3) and (4) define the binary nature of the decision variables.

This optimization is solved iteratively for all the range of investment levels, varying the budget limit K, ranging from 0% to 100% of the summed cost of all interventions. By doing so, we obtain an optimized interventions frontier that allows us to compare alternatives (see

Table 1
Data source and normalization method.

Criterion	Sub-criterion	Quantifiable parameter; reference standard	Normalization method [0–1]
Functionality	Student density	Additional area required to achieve optimal density using constructed area measured by in-field engineer. Recommended density is taken from national standard	Direct rating technique
	Bathroom density	Number of bathrooms needed to meet density standards.	Direct rating technique
	Bathroom quality	Quality level defined by in-field engineer in categorical scale	Direct rating technique
	Lighting	Illumination and lighting equipment quality level defined based on architectural drawings	Direct rating technique
	Ventilation	Ventilation and mechanical equipment quality level defined based on architectural drawings	Direct rating technique
	Interior Finishes	Interior finishes (Floors, walls, painting, and ceiling) quality level defined by in-field engineer in categorical scale	Direct rating technique
	Furniture	Furniture and equipment quality level defined by in-field engineer in categorical scale	Direct rating technique
	Building age	Year of construction	Direct rating technique
	Water	Water supply, potable water and sewerage access identified by in-field engineer	Direct rating technique
	Connectivity	Internet and phone connection access identified by in-field engineer	Direct rating technique
Earthquake risk level	Seismic performance	Relative Average Annual Losses (AAL) obtained from a probabilistic seismic risk assessment	Inverse direct rating technique. If AAL is larger than 15‰, a value of 0 is assigned in the normalization (worst value)

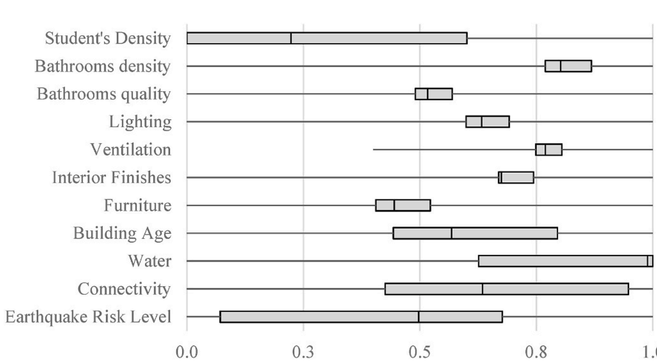


Fig. 6. Normalized data per sub-criterion.

Table 2
Taxonomies considered in the city of Cali.

Taxonomy	No.	Parameter	Attributes
Seismic Taxonomy[1]	1	Main structural system	RC1 (Bare Frame), RC2 (Infilled Frame), RC3 (Short Column Frame), RC4 (Dual or Combined Frame), RC5 (Non-Engineered Frame), A (Adobe), UCM/URM (Unconfined/Unreinforced Masonry), CM (Confined Masonry), RM (Reinforced Masonry)
	2	Height range	LR (Low Rise), MR (Mid Rise), HR (High Rise)
	3	Seismic design level	PD (Poor Design), LD (Low Design), MD (Mid Design), HD (High Design)
	4	Diaphragm type	FD (Flexible Diaphragm), RD (Rigid Diaphragm)
	5	Structural irregularity	NI (No Irregularities), HI (Horizontal Irregularities), VI (Vertical Irregularities), HV (Hor. and vert. Irregularities)
	6	Span length/Wall panel length	SS (Short Span), LS (Long Span), SP (Short Panel), LP (Long Panel)
	7	Pier type/Wall openings	SW (Weak Column), RO (Regular Column), SO (Small Openings), LO (Large Openings)
	8	Foundation type	FF (Flexible Foundation), RF (Rigid Foundation)
	9	Seismic pounding risk	PR (Pounding Risk), NP (Non-pounding Risk)
	10	Effective seismic retrofitting	OS (Original Structure), RS (Retrofitted Structure)
	11	Structural health condition	PC (Poor Condition), GC (Good Condition)
	12	Non-structural components	VN (Vulnerable non-structural elements), NN (Non-vulnerable Non-structural elements)
Functional Taxonomy – Building level	1	Main structural system	RC (Reinforced Concrete), URM (Unreinforced Masonry), CM (Confined Masonry), RM (Reinforced Masonry), A (Adobe)
	2	Height range	LR (Low Rise), MR (Mid Rise), HR (High Rise)
	3	Functionality design level	FPD (Functional Poor Design), FMD (Functional Medium Design), FGD (Functional Good Design)
	4	Ventilation	PV (Poor Ventilation), GD (Good Ventilation)
	5	Illumination	PI (Poor Illumination), GI (Good Illumination)
	6	Interior finishes	PIF (Poor Interior Finishes), GIF (Good Interior Finishes)
	7	Furniture	PF (Poor Furniture), GF (Good Furniture)
Functional Taxonomy – School level	1	Functionality design level	FPD (Functional Poor Design), FMD (Functional Medium Design), FGD (Functional Good Design)
	2	Student density	PSD (Poor Student Density), GSD (Good Student Density)
	3	Bathroom density	PBD (Poor Bathroom Density), GBD (Good Bathroom Density)
	4	Bathroom quality	PBQ (Poor Bathroom Quality), GBQ (Good Bathroom Quality)
	5	Water	PAS (Poor Water System), GAS (Good Water System)
	6	Connectivity	PIP (Poor Connectivity System), GIP (Good Connectivity System)

[1] Taxonomy based on GLOSI Taxonomy. The author is referred to the original publication for details [47].

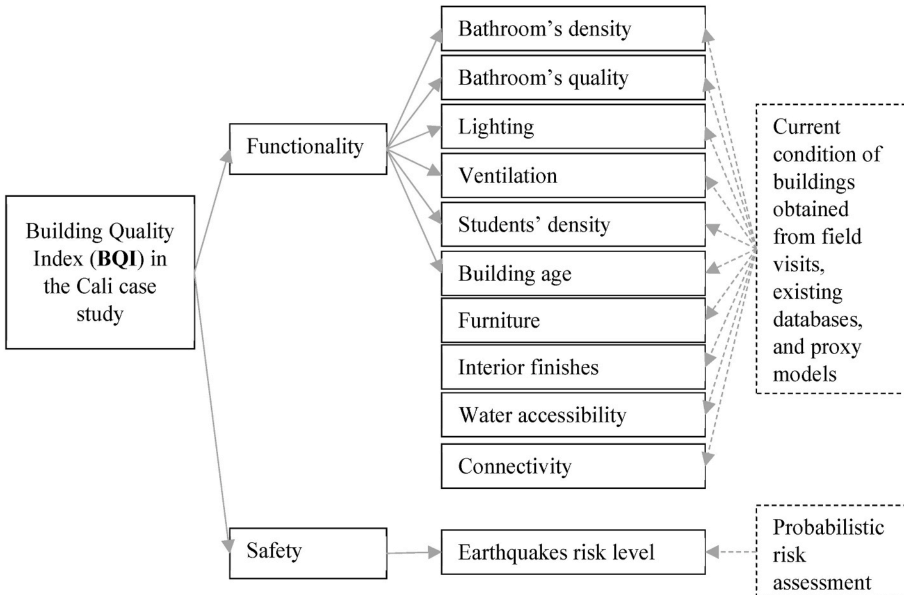


Fig. 7. Hierarchical representation of the BQI (criteria and attributes).

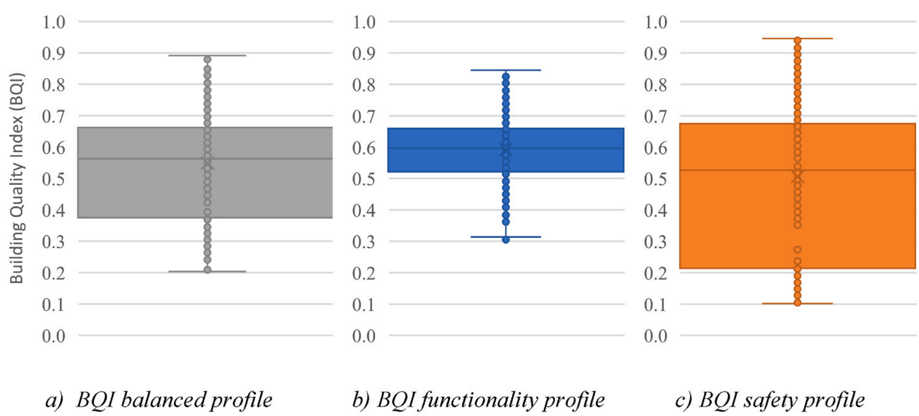


Fig. 8. Current BQI assessment per decision profile.

Fig. 4a). In addition, we estimate the most efficient level of investment by calculating the tangent line to all points in the frontier and identifying the maximum change in slope (see Fig. 4b). Thus, we present decision makers with all scenarios resulting from the parametrization of modules 1 and 4, namely, the optimized interventions frontier for the parametric profiles and the efficient levels of investment.

The results in this module also include the distribution of investment by intervention type for all intervention levels in the parametric profiles. This module presents all the information needed to make informed decisions by the relevant stakeholders. For example, a government official can use the information to select the decision profile to program the set of interventions, while a donor or multilateral agency may use it to estimate the budget to allocate to a particular country or region.

4. Case study: improving the public-school infrastructure in Cali (Colombia)

As a way of demonstrating the applicability of the framework, the public-school infrastructure of the city of Santiago de Cali (known as Cali) in Colombia, is assessed. Cali is the third most populous city in Colombia with around 2.3 million inhabitants [45], after Bogotá and Medellín. The city is the main economic pole in the southwest, located near the Pacific coastline. It has a thriving economy with large socio-economic inequalities that puts the public-school system under constant pressure.

4.1. Module 0: database

The portfolio of public schools is comprised of 373 school facilities. In this study we analyze a subset of 273 schools for which detailed information is available. This set of school facilities includes 1199 buildings, for an average of 4.39 school buildings in each facility. The total built area is around 415,000 square meters. Fig. 5 shows the geographic distribution of these school compounds in the city.

To compute the data for each sub-criterion at building and school level in Cali, we gathered information in the field and through interviews as part of a project funded by the World Bank developed in 2019 [46]. Table 1 shows, for each criterion, the choice of sub-criteria, the specific data, the compliance criterion, and the normalization method. For missing data, we used average distribution of typologies for different school sizes (small, medium, and large) to assign taxonomy strings.

Fig. 6 presents the normalized data statistics, from the worst to the best possible value, for each sub-criterion. From these results, it is possible to see that the *student's density* parameter has a larger spread compared to others. Something similar happens with the earthquake risk

Table 3
Clustering results per taxonomy.

Taxonomy	ID	Cluster name
Seismic	1	Non-engineered (URM – Poor design)
	2	Non-engineered with Retrofitting (URM – Low design)
	3	Other
	4	Confined masonry
	5	RC frames
	6	Stiff RC frames
	7	Poor design buildings (RC5)
	8	High design buildings (new buildings)
Functional (building level)	1	Interior renovations and ventilation
	2	Interior renovations and ventilation
	3	General good condition
	4	Illumination and interior finishes
	5	General bad condition
	6	Furniture, illumination, and ventilation
	7	Interior renovations
Functional (school level)	1	FGD-GSD-GBD-GBQ-GWS-GCS
	2	FGD-GSD-GBD-GBQ-GWS-PCS
	3	FGD-GSD-GBD-PBQ-GWS-GCS
	4	FGD-GSD-PBD-GBQ-GWS-GCS
	5	FGD-PSD-GBD-GBQ-GWS-GCS
	6	FMD-GSD-GBD-GBQ-PWS-PCS
	7	FMD-GSD-GBD-PBQ-GWS-PCS
	8	FMD-GSD-PBD-GBQ-GWS-PCS
	9	FMD-GSD-PBD-PBQ-GWS-GCS
	10	FMD-PSD-GBD-GBQ-GWS-PCS
	11	FMD-PSD-GBD-PBQ-GWS-GCS
	12	FMD-PSD-PBD-GBQ-GWS-GCS
	13	FPD-GSD-PBD-PBQ-GWS-PCS
	14	FPD-GSD-PBD-PBQ-PWS-PCS
	15	FPD-PSD-GBD-GBQ-PWS-PCS
	16	FPD-PSD-GBD-PBQ-GWS-PCS
	17	FPD-PSD-PBD-GBQ-GWS-PCS
	18	FPD-PSD-PBD-GBQ-PWS-PCS
	19	FPD-PSD-PBD-PBQ-GWS-GCS
	20	FPD-PSD-PBD-PBQ-GWS-PCS

[a]FPD (Functional Poor Design), FMD (Functional Medium Design), FGD (Functional Good Design), PSD (Poor Student Density), GSD (Good Student Density), PBD (Poor Bathroom Density), GBD (Good Bathroom Density), PBQ (Poor Bathroom Quality), GBQ (Good Bathroom Quality), PWS (Poor Water System), GWS (Good Water System), PCS (Poor Connectivity System), GCS (Good Connectivity System).

level, in which we can find several differences in the buildings since it depends not only on the hazard, which varies considerably, but also on the vulnerability of each typology. Less dispersion is found in the *lighting*, *ventilation*, *interior finishes*, and *furniture* criteria since this data was assigned based on typologies and not building by building. From these results it is also possible to conclude that the criteria with the worst mean scores are *student's density*, *furniture*, and *earthquake risk level*, while *bathroom's density*, *ventilation,* and *water* are the ones with better scores. This information is relevant since interventions targeting the worst criteria will increase the quality index that is discussed in the next section.

We also characterized three taxonomies for all buildings and schools in the portfolio. These taxonomies include the GLOSI seismic taxonomy [47], one functional taxonomy at the building level, and one functional taxonomy at the school level. We developed these functional taxonomies based on available field information [46]. Table 2 presents the three taxonomies, their parameters, and attributes. It is relevant to mention that each taxonomy differs in the parameters and attributes since each aim to classify different characteristics of the same building.

4.2. Module 1: building quality index (BQI)

With the database described in module 0, the following step is to compute the Building Quality Index (*BQI*) for the whole building portfolio. Fig. 7 presents a schematic representation of the BQI computation for the case study.

Table 4
Generic interventions for the seismic taxonomy clusters.

ID	Cluster name	Intervention general strategy	Type	Unitary Cost (% of a new building)	Δ*BQI*
1	Non-engineered	Replacement	Replacement	1000 US $/m^2 (100%)	Average Annual Losses (AAL) difference between current and retrofitted condition
2	Non-engineered Retrofitting	In plane strengthening Out-of-plane strengthening Ring beam Roof intervention	Extensive retrofitting	230 US $/m^2 (23%)	
3	Other	No intervention due to lack of information	No intervention	–	
4	Confined masonry	Out-of-plane strengthening	Minor retrofitting	70 US $/m^2 (7%)	
5	RC frames	Structure stiffening Masonry walls out-of-plane strengthening	Minor retrofitting	125 US $/m^2 (12.5%)	
6	Stiff RC frames	Structure stiffening Masonry walls isolation Masonry walls out-of-plane strengthening	Moderate retrofitting	150 US $/m^2 (15%)	
7	Poor design buildings	Replacement	Replacement	1000 US $/m^2 (100%)	
8	High design buildings	No intervention needed	No intervention	0 US$/m^2 (0%)	

We calculated the BQI with three decision profiles (i.e., balanced, functionality-biased and safety-biased). Fig. 8 shows the corresponding box plots of the resulting BQI distribution for each profile. From these results we can see that the quality assessment varies depending on the prism from which the decision maker sees the buildings. If the decision maker values functionality over safety, the current buildings have a decent baseline. On the contrary, if the decision maker values safety over functionality, it seems that the quality of buildings is lower and has a widespread due to the current seismic vulnerability.

4.3. Module 2: clustering

We applied the clustering algorithm to the three taxonomies in the public-school portfolio of Cali. We fine-tuned the number of clusters and analyzed the results with expert criteria to find the best distribution of clusters. For each taxonomy, we initially defined $K = 2$ and based on the results, we increased the number of clusters until the distribution was acceptable. Following this process, we found eight clusters for the seismic taxonomy, seven for the functional taxonomy at building level and 20 for the functional taxonomy at school level. For each cluster, we identified a representative building (or index building) to analyze and define a generic intervention applicable to all elements in the cluster. Table 3 shows the final distribution of clusters obtained by the implementation of the clustering algorithm (no specific order). It is relevant to mention that these 20 clusters for the functional taxonomy at school level correspond to the maximum number of clusters, which is the maximum number of typologies.

Table 5
Generic interventions for the functional taxonomy cluster (at the building level).

ID	Cluster name	Strategy	Type	Unitary Cost	ΔBQI
1	Interior renovations and ventilation	New interior finishes New furniture Ventilation system	Moderate intervention	137 US $/m^2$	Maximum value (1.0) minus current rating in Interior finishes, Furniture, and Ventilation
2	General good condition	No intervention needed	No intervention	0 US $/m^2$	
3	Illumination and interior finishes	New interior finishes Illumination system	Moderate retrofitting	83 US $/m^2$	Maximum value (1.0) minus current rating in Interior finishes, and Illumination
4	General bad condition	New interior finishes New furniture Illumination system Ventilation system	Extensive intervention	167 US $/m^2$	Maximum value (1.0) minus current rating in Interior finishes, Furniture, Illumination, and Ventilation
5	Furniture, illumination and ventilation	New furniture Illumination system Ventilation system	Moderate retrofitting	109 US $/m^2$	Maximum value (1.0) minus current rating in Furniture, Illumination, and Ventilation
6	Interior renovations	New interior finishes New furniture	Minor intervention	112 US $/m^2$	Maximum value (1.0) minus current rating in Interior finishes, and Furniture

4.4. Module 3: interventions database

With the building clusters defined, it is possible to identify the impact of a generic intervention in a particular building. Tables 4–6 show the increase in BQI (ΔBQI) and the unitary cost of the different interventions identified for the seismic and functional taxonomies, at the building and school level. Note that the unitary cost is applied to each building to obtain the total cost based on its area. This unitary cost is obtained from local budgets and consultations with local stakeholders. This valuation includes the material and personnel cost using values of 2022. Similarly, the ΔBQI is building dependent, which means that a seismic intervention in different buildings in the same cluster, will have different BQI improvements based on their location and risk assessment. The cost of each alternative was defined based on previous projects developed in school facilities in Colombia. Therefore, the unitary costs are defined for this specific case and are not generally applicable in other case studies.

After we identified the costs and ΔBQI for all buildings and all possible interventions, we compiled the input for the optimization module. In this case, we selected one intervention per cluster, leading to three possible interventions (two at the building level and one at the school level). Table 7 shows a snapshot of the interventions for the balanced profile. We generated similar tables for the other two decision profiles, but they are not shown for the sake of conciseness.

4.5. Module 4: optimal investment and decision profiles

For each decision profile, we solved (iteratively) the optimization model varying the level of investment to obtain the optimal frontiers. The cost of implementing all interventions in the database reaches US$ 174,340,395 and leads to a ΔBQI improvement of 336 points for the balanced profile, 297 *BQI* points for the functional-biased profile, and 375 *BQI* points for the safety-biased profile. Fig. 9 presents the result of the normalized optimal frontier for the three profiles. The normalization is based on the budget required to obtain the maximal ΔBQI improvement. It is possible to see from these results that the different profiles lead to slight differences in the frontier, however, the resulting curves cannot be compared directly since the BQI in each case is valued with different weights. However, what is interesting from this comparison is that each frontier varies in shape and therefore, in optimal investment level. Also, note that if we could have the full budget, we could achieve the maximal improvement regardless of the profile.

For the three frontiers in Fig. 9, we computed the slopes at each calculation point. We used the differences between neighboring tangent slopes to identify the most efficient investment level in the portfolio for each decision profile (adaptation of the elbow method used in clustering). Fig. 10 shows the most efficient investment levels at 10%, 15%, and 5% for the balanced, functionality-biased, and safety-biased decision profiles, respectively; and the corresponding investment costs are US$17.4 million, US$26.1 million, and US$8.7 million. These results can be compared to the application in the Dominican Republic in the original implementation of the methodology. In this case, the optimal level of investment is found to be 20%, which can be comparable with the functionality-biased profile in this case. This makes sense, since the decision-maker profile implemented in that case study gives 67% of the weight to the functional criteria.

Fig. 11 presents the costs distribution by intervention type for all possible investment levels over the three decision profiles. This information shows the type of interventions that are prioritized when each one of the profiles is chosen. For instance, for the balanced profile, we can see that the distribution is relatively stable and similar to the distribution of the interventions. However, as expected, at early stages of investment, the functional interventions are prioritized for the functionality-biased profile, while the seismic interventions are prioritized for the safety-biased profile. This shows the impact that decision-maker preferences have in the framework, showing the importance of defining them correctly for each case study. From the results, it can also be noted that when the resources are unlimited (100% of investment) the distribution is the same for all profiles. Although this seems trivial, it also shows how relevant is to consider decision-making profiles for limited resources. This information supports decision-makers with the definition of maximum investment levels to be included in the formulation of a financing programs. Stakeholders in this case include government officials, local infrastructure managers, and international finance and multilateral development institutions. How can this data be used for policy making is the focus of the next section.

5. Analysis: decision-maker perspective

The framework results support the decision-making processes for school infrastructure improvement. However, this improvement process involves multiple stakeholders that consider several variables at the same time. Therefore, it is crucial to have all information at hand to support decisions that would improve education quality through better infrastructure. Common stakeholders in the education service include the students, the parents (and associations), the school administration and teachers, the governments (national and local), the private sector, and the international organizations [18]. Usually, students and parents receive the educational service from schools and teachers but are also involved in the most important decisions regarding the type of education and school infrastructure development (two-way interaction). On the other hand, the private sector and international organizations usually

Table 6
Generic interventions for the functional taxonomy cluster (at the school level).

ID	Cluster name	Strategy	Unitary cost (US $/Existing m^2)	Unitary cost (US $/New m^2)	Unitary cost (US $/EBathUnit)	Unitary cost (US $/NewUnit)	Sub-criterions considered in Δ ***BQI*** (1.0 minus current rating)
1	FGD-GSD-GBD-GBQ-GWS-GCS	No intervention	$ 0	$ 0	$ 0	$ 0	–
2	FGD-GSD-GBD-GBQ-GWS-PCS	Intervention: CS	$ 17	$ 0	$ 0	$ 0	CS
3	FGD-GSD-GBD-PBQ-GWS-GCS	Intervention: BQ	$ 0	$ 0	$ 210	$ 0	BQ
4	FGD-GSD-PBD-GBQ-GWS-GCS	Intervention: BD	$ 0	$ 0	$ 0	$ 1200	BD
5	FGD-PSD-GBD-GBQ-GWS-GCS	Intervention: SD	$ 0	$ 421	$ 0	$ 0	SD
6	FMD-GSD-GBD-GBQ-PWS-PCS	Intervention: WS, CS	$ 32	$ 0	$ 0	$ 0	WS, CS
7	FMD-GSD-GBD-PBQ-GWS-PCS	Intervention: BQ, CS	$ 17	$ 0	$ 210	$ 0	BQ, CS
8	FMD-GSD-PBD-GBQ-GWS-PCS	Intervention: BD, CS	$ 17	$ 0	$ 0	$ 1200	BD, CS
9	FMD-GSD-PBD-PBQ-GWS-GCS	Intervention: BD, BQ	$ 0	$ 0	$ 210	$ 1200	BD, BQ
10	FMD-PSD-GBD-GBQ-GWS-PCS	Intervention: SD, CS	$ 17	$ 421	$ 0	$ 0	SD, CS
11	FMD-PSD-GBD-PBQ-GWS-GCS	Intervention: SD, BQ	$ 0	$ 421	$ 210	$ 0	SD, BQ
12	FMD-PSD-PBD-GBQ-GWS-GCS	Intervention: SD, BD	$ 0	$ 421	$ 0	$ 1200	SD, BD
13	FPD-GSD-PBD-PBQ-GWS-PCS	Intervention: BD, BQ, CS	$ 17	$ 0	$ 210	$ 1200	BD, BQ, CS
14	FPD-GSD-PBD-PBQ-PWS-PCS	Intervention: BD, BQ, WS, CS	$ 32	$ 0	$ 210	$ 1200	1 BD, BQ, WS, CS
15	FPD-PSD-GBD-GBQ-PWS-PCS	Intervention: SD, WS, CS	$ 32	$ 421	$ 0	$ 0	SD, WS, CS
16	FPD-PSD-GBD-PBQ-GWS-PCS	Intervention: SD, BQ, CS	$ 17	$ 421	$ 210	$ 0	SD, BQ, CS
17	FPD-PSD-PBD-GBQ-GWS-PCS	Intervention: SD, BD, CS	$ 17	$ 421	$ 0	$ 1200	SD, BD, CS
18	FPD-PSD-PBD-GBQ-PWS-PCS	Intervention: SD, BD, WS, CS	$ 32	$ 421	$ 0	$ 1200	SD, BD, WS, CS
19	FPD-PSD-PBD-PBQ-GWS-GCS	Intervention: SD, BD, BQ	$ 0	$ 421	$ 210	$ 1200	SD, BD, BQ
20	FPD-PSD-PBD-PBQ-GWS-PCS	Intervention: SD, BD, BQ, CS	$ 17	$ 421	$ 210	$ 1200	SD, BD, BQ, CS

Table 7
Illustrative example of the interventions database for the balanced decision profile.

	Seismic Interventions – Building			Functional Interventions – Building			Functional Interventions – School		
Building	Type	Cost (US$)	Δ***BQI***	Type	Cost (US$)	Δ***BQI***	Type	Cost (US$)	Δ***BQI***
1	None	$ 0	0.00	–	$ 0	0.00	CS	$ 12,128	0.05
2	Replacement	$ 293,525	0.30	IF, F, V	$ 40,330	0.06	BD, BQ	$ 8160	0.04
3	Replacement	$ 293,525	0.22	IF, F, V	$ 40,330	0.06			
	...	...	...	...	...	...	...	...	...
1198	None	$ 0	0.00	IF, F	$ 50,580	0.02	SD, BD, BQ	$ 56,525	0.09
1199	None	$ 0	0.00	IF, F	$ 50,580	0.02			

provide economic and technical resources to the government and providers of education service (one-way interaction). Similarly, government and public administration commonly support the providers in terms of economic resources and technical capacity (one-way interaction). These stakeholders, and their relationship with each other, are presented in Fig. 12.

From the stakeholders, governments and public administrations are often in charge of the school infrastructure. The different roles played by national and local governments are country dependent; while some countries rely more on national authorities, others empower local authorities. Also, the private sector and international organizations, such as NGOs and development banks, have a relevant role by supporting financially and technically the infrastructure management. To understand how the information provided by the decision-making framework is useable, let us analyze each one of these stakeholders.

At the first level, the private sector and international organizations are involved by providing the necessary funds to develop improvement programs. In some cases, these institutions have a fixed budget, but lack of information makes it uncertain to allocate more or less funds. From the proposed decision-making framework, it is possible to derive an order of magnitude for the most efficient investment levels of the school intervention program. This information is also useful to analyze the feasibility of donations or loans at an early stage of the process. However, it is important to mention that this would be only a first estimation of the amount of investment. To define the total amount precisely, additional constraints and parameters should be analyzed, for instance, the available budget, the minimum quality of the portfolio, or the minimum number of schools to be improved, among others.

At a second level, once the amount of investment is defined, it is necessary to understand the priorities for the interventions. At this step,

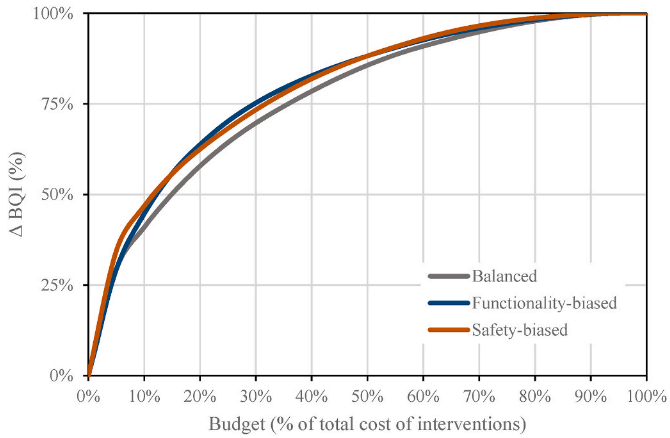


Fig. 9. Optimal investment frontier by decision profiles.

the government and public administrators need to define what type of interventions should be prioritized and in which facilities. With the framework's output, a decision maker can then decide to invest more resources (time and money) on a specific type of deficiency and intervention in a specific type of building. Also, a country can understand general deficiencies in its infrastructure to update the existing building codes to build new better infrastructure. Indeed, after the occurrence of a natural hazard event, information is usually scarce, and geographic information related to safety and functionality could be essential. This becomes very important since school facilities can be used as relief centers, storage, supply, and communication hubs in the aftermath of natural hazard events [48].

This type of analysis provides tools to decision-makers to define the correct distribution of investment types considering their own risk profiles. It is worth mentioning that the process of selecting a specific profile should consider most stakeholders in the country, including schools, teachers, students, and parents, besides the ones delegated by the government and financial partners. Also, the local context is of utmost importance. Has the region been recently affected by a natural hazard? How often do these types of events occur? Are there any gender inequalities in terms of educational completion rates? Addressing these (and other) questions from the perspective of each stakeholder is fundamental to include social, economic, cultural, and technical aspects in each project and generate a meaningful impact on education quality.

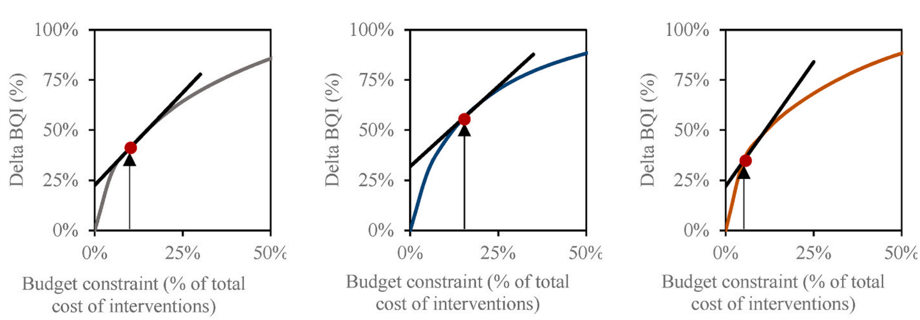
6. Conclusions

In this paper, we presented a parametric decision-making framework for large-scale school infrastructure improvement. This version of the framework allows us to unveil a frontier of solutions for a-posteriori decision-making. This extended version includes decision-maker and technical experts' input at several stages to ensure that the results are sound from a technical and economical perspective. This implementation also shows how the framework can be implemented in small portfolios at city or municipality levels where different stakeholders are involved.

The case study of the public school system in the city of Cali (Colombia) considered three decision-maker profiles: balanced, functionality-biased, and safety-biased profiles. We identified a set of interventions with a total cost of US$174 million comprised of functional interventions at the school level, functional interventions at the building level, and seismic retrofitting. We showed that the optimal level of investment should be around 10%, 15%, and 5% for the three profiles, respectively. As expected, for each profile, the investment is allocated to all types of interventions, but with different weights depending on the preferences expressed in each profile. We also presented how the distribution of interventions varies for different investment levels, showing how sensitive is to consider the decision-maker preferences at lower investment levels, when resources are scarce, and the different types of interventions compete among them.

The results are crucial for decision-making in school infrastructure improvement, involving multiple stakeholders. Comprehensive information is needed to make informed decisions leading to education quality through infrastructure improvement. Stakeholders in the education service include students, parents, school administration, governments, the private sector, and international organizations. The role of governments is to oversee infrastructure management, with local and national responsibilities varying by country. In addition, the private sector and international organizations provide financial and technical support in this process. The decision-making framework helps determine investment levels and prioritize interventions, which is fundamental for the decision-making process. It enables efficient allocation of resources, focuses on deficiencies, and informs design and building code improvements in the long term. The framework also considers the priorities of all the stakeholders, including the providers (schools and teachers) and the users (students and parents) to ensure the objective of improving educational quality in the long term.

The case study in the city of Cali (Colombia) showed the flexibility of the decision-making framework and some of its advantages. We showed how this framework can be implemented at a city scale, involving particularities of the analyzed region (e.g., seismic vulnerabilities). However, this method can also be adapted to other contexts, countries, or even other types of infrastructure as a future work. Extending the framework requires mainly changing modules 1 and 2, with taxonomies and criteria related to the specific application and context. A similar extension as the one shown here could be applied, for instance, to transportation and water infrastructure. These further developments could have many policy implications. The systematic implementation of the methodology in a country over time and across infrastructure systems can provide a dynamic indicator that reports the quality and



a) Balanced profile *b) Functionality-biased profile* *c) Safety-biased profile*

Fig. 10. Efficient levels of investment per decision profiles.

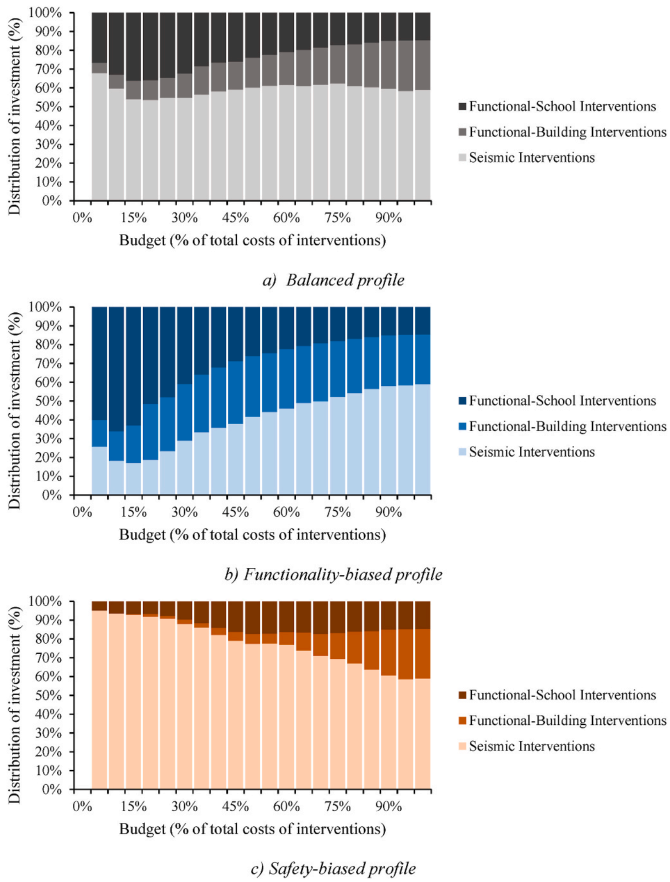


Fig. 11. Investment type distribution as a function of budget levels.

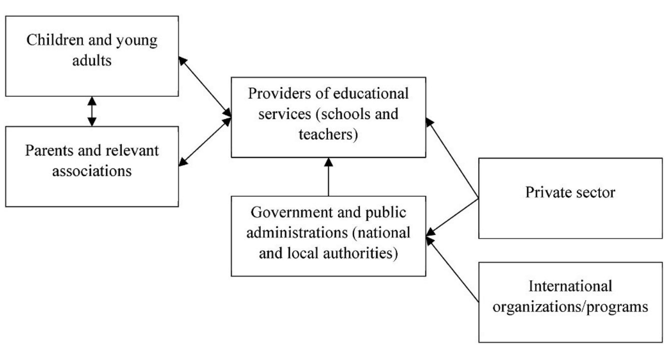


Fig. 12. Education service stakeholders.

evolution of its infrastructure. Although the methodology can be used for decision-making, it can also be used for measuring the impact of investments. This approach could be beneficial to optimize investments, improving infrastructure quality, adding transparency, and ultimately, reducing corruption by standardizing the allocation process. It is worth mentioning that technical experts' input shall be considered through all the steps of the implementation.

Last, but not least, every implementation should consider the limitations of the method, mainly related to the uncertainty in each module and the data availability. For instance, the quality of the input data will determine the quality of the results. Therefore, if data is not available for all school facilities and buildings, decision-makers should be aware of the assumptions made during the implementation of the methodology. Likewise, if the decision-making framework uses information from a probabilistic or deterministic risk assessment to identify the level of disaster risk, it is important to consider the reliability of these models. It is worth noting that this method can give a range of investment, but not specific values, since to obtain more precise estimates, further analysis is required. Finally, although this method aids the budget allocation process, it does not replace the specific technical design of each intervention.

CRediT authorship contribution statement

Rafael Fernández: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Andrés Calvo:** Data curation, Formal analysis, Software, Validation, Visualization, Writing – review & editing. **Juan Francisco Correal:** Conceptualization, Funding acquisition, Project administration, Supervision, Validation, Visualization, Writing – review & editing. **Dina D'Ayala:** Conceptualization, Methodology, Supervision, Validation, Visualization, Writing – review & editing. **Andrés L. Medaglia:** Conceptualization, Funding acquisition, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing – review & editing.

Data availability

Data will be made available on request.

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