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A Multi-Criteria Approach to Evaluate School Accessibility. AHPSort II and FlowSort: A Comparative Study

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The assessment of accessibility in educational institutions is a complex decision-making problem that involves multiple and heterogeneous criteria. In this study, Multi-Criteria Decision Making (MCDM) methods are employed to classify schools according to their level of accessibility, with particular attention to the methodological comparison between sorting techniques.

The analysis is conducted on a dataset of 131 Italian schools, for which data were collected through direct contact with the institutions in order to identify the presence and number of specific accessibility features. These features are used as evaluation criteria and include external entrances equipped with ramps, stairs compliant with current regulations, elevators for people with disabilities, stairlifts or platform lifts, accessible restrooms, accessible internal pathways and accessible external pathways.

The primary classification is performed using AHPSort II, an extension of the Analytic Hierarchy Process (AHP) specifically developed for sorting problems. AHPSort II enables the assignment of a large number of alternatives to predefined and ordered accessibility classes through the introduction of representative profiles, central and limiting profiles, thus avoiding extensive pairwise comparisons among alternatives.

Subsequently, the same dataset and criteria are analyzed using the FlowSort method, which is based on the PROMETHEE outranking approach

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and assigns alternatives to predefined categories by comparing them with reference profiles through preference flows.

A comparative analysis of the classification results obtained from AHPSort II and FlowSort is then carried out in order to evaluate the consistency of the assignments, identify potential discrepancies between the two methods and discuss their implications for accessibility assessment in educational institutions.

The contribution of this work lies in providing a methodological comparison between AHPSort II and FlowSort applied to the classification of schools according to accessibility criteria, offering insights into the strengths and limitations of different MCDM sorting approaches in the context of educational infrastructure evaluation.

Keywords: AHPSort II; FlowSort; school accessibility; multi-criteria decision making; sorting methods

1. Introduction

The accessibility of educational institutions can be assessed by considering the presence and number of devices, equipment and measures that enable people with disabilities to access school buildings, move within them and make use of the available services. These measures include, among others, ramps, elevators, stairlifts or platform lifts, accessible internal and external pathways, stairs compliant with current regulations and adequately equipped restrooms.

The simultaneous evaluation of these heterogeneous accessibility features naturally leads to a MCDM framework. In this context, the objective is not to obtain a precise quantitative measure of the accessibility level of a single educational institution, which may have limited operational relevance, but rather to classify schools into homogeneous and ordered accessibility classes, thus supporting decision-making and prioritization processes (Greco et al., 2016; Cinelli et al., 2020).

Among the most widely adopted MCDM methods, the AHP , introduced by Saaty (1980), enables the evaluation of alternatives through a hierarchical structure of criteria and pairwise comparisons. AHP allows decision-makers to derive criteria weights and to compute an overall score for each alternative. However, the traditional AHP approach becomes particularly cumbersome and difficult to apply when the number of alternatives or criteria is large, as it requires an extensive number of pairwise comparisons.

To address this limitation, several sorting methods have been developed as extensions of AHP, specifically designed to assign alternatives to predefined and ordered categories. Among these, AHPSort II (Fattoruso and Squillante, 2024; Miccoli and Ishizaka, 2017) represents a relevant advancement. AHPSort II enables the classification of alternatives into predefined classes by introducing representative category profiles, including central and limiting profiles, which characterize the boundaries and typical features of each category. By comparing alternatives with these profiles rather than with all other alternatives, the method significantly reduces the number of pairwise comparisons, making it particularly suitable for problems involving a large set of alternatives and multiple evaluation criteria, such as the assessment of accessibility in educational institutions.

In addition to AHP-based sorting methods, outranking-based approaches have also been widely applied to classification and sorting problems. In particular, FlowSort (Nemery and Lamboray, 2008), which is based on in the PROMETHEE methodology (Preference Ranking Organization METHod for Enrichment Evaluations) (Brans et al., 1986; Brans and Vincke, 1985), assigns alternatives to predefined categories by comparing them with reference profiles through preference flows. Unlike value-based methods, FlowSort relies on pairwise comparisons and preference functions to capture the intensity of preference between alternatives and category profiles, offering a different perspective on the classification problem. For this reason, the application of different MCDM sorting methods to the same accessibility assessment problem represents a valuable opportunity to analyze and compare classification outcomes. This study pursues two main objectives. The first is to apply the AHPSort II method to classify a sample of 131 Italian schools according to their level of accessibility, using data collected directly from the institutions concerning the presence and number of specific accessibility features. The second objective is to apply the FlowSort method to the same data set and criteria and to perform a comparative analysis of the results obtained from the two approaches. The comparison aims to evaluate the degree of concordance between the classifications, to identify potential differences in school assignments and to discuss the implications of adopting different MCDM sorting techniques for accessibility assessment in educational institutions.

The choice of AHPSort II and FlowSort reflects the objective of assigning schools to predefined and ordered accessibility classes rather than producing a full ranking of alternatives. The two methods are based on different decision-making logics: AHPSort II is a value-based approach, while FlowSort follows an outranking perspective derived from PROMETHEE. Their joint application allows for a comparison of classification results and for assessing the consistency and robustness of the outcomes.

The remainder of the paper is organized as follows. Section 2 presents a scoping review of the literature on MCDM sorting methods applied in educational contexts. Section 3 describes the two methodological approaches, AHPSort II and FlowSort. Section 4 presents the dataset and the accessibility criteria. Sections 5 and 6 report the application of AHPSort II and FlowSort, respectively. Section 7 discusses and compares the classification results. Section 8 draws conclusions and outlines directions for future research.

2. Related Literature

Given the still emerging nature and limited literature on the applications of multi-criteria sorting methods in education (Tosto et al., 2025), a scoping review was conducted using the Scopus database. The primary objective of this analysis was to map existing contributions using AHPSort II and FlowSort in school or university settings. The decision to adopt a scoping review addresses the need to outline the state of the art, clarify the types of decision-making problems addressed in schools using sorting approaches and, in particular, assess the possible presence of applications geared toward assessing accessibility, understood as the presence of devices and measures designed to ensure the use of school spaces by students with disabilities.

The bibliographic search was conducted on Scopus applying a specific search string to the title, abstract and keywords fields, formulated as *TITLE-ABS-KEY ((“AHPSort” OR “AHP Sort” OR “AHP-Sort” OR “AHPSort II” OR “AHPSort2” OR “FlowSort”) AND (school* OR education* OR “educational institution*” OR “school building*” OR universit* OR “higher education” OR “master* degree” OR “high school*”)) AND NOT TITLE-ABS-KEY (intralogistic* OR conveyor* OR sortation OR warehouse* OR diverter* OR parcel* OR logistics).* The string was defined to combine terms referring to multi-criteria sorting methods with keywords representative of the educational context, while simultaneously excluding contributions related to industrial and logistics domains, where the terms ”sorting” or ”FlowSort” are frequently used with a purely operational meaning and not related to MCDM methods applied to the educational field. No time restrictions were applied to the search, thus ensuring that the entire time span covered by the database was included.

Following the initial screening, the query returned a total of three records. Subsequent analysis of titles and abstracts, supplemented by reading the full text, allowed us to distinguish between studies truly relevant to the school or university context and contributions inconsistent with the focus of this analysis.

Among the identified works, Fattoruso et al. (2025) applies an extension of AHPSort II, called q-AHPSort II, to the classification of STEM master’s degree programs. The study demonstrates the validity of a sorting approach, based on the assignment of alternatives to predefined classes, to support evaluation decisions in educational contexts, distinguishing it from more traditional ranking-oriented approaches. However, the scope of the analysis is limited to the evaluation of educational programs and does not involve the infrastructural or building dimensions of educational institutions.

Another relevant contribution uses FlowSort, integrated with fuzzy components and PROMETHEE type modeling, to support the planning of technology transfer measures in universities (Tibay et al., 2022). Again, the study confirms the applicability of sorting methods to complex decision-making problems in higher education contexts; however, the analysis focuses on strategic-organizational aspects and not on the evaluation of school buildings, spaces or services.

The third record returned by the query includes AHPSort II within the methodological framework, but addresses the competitive evaluation of patents in the field of water pollution abatement (Fan et al., 2023). Since this is a non-educational domain, this contribution was considered a false positive and, consequently, excluded from the summary of applications in the school environment.

Overall, the results of the scoping review show that AHPSort II and FlowSort have been applied, albeit to a very limited extent, to decision-making problems in educational contexts, predominantly at the university level and with reference to organizational programs, measures, or strategies. At the same time, there is no evidence of applications aimed at assessing the *physical accessibility or inclusiveness of school buildings*, such as, for example, the classification of schools based on accessibility levels or compliance with requirements for the removal of architectural barriers. This absence represents a significant gap in the literature, especially considering that accessibility assessment naturally lends itself to a sorting-type approach, based on the assignment of alternatives to predefined classes or standards (Fattoruso et al., 2025; Tibay et al., 2022). In this sense, the extension of multi-criteria sorting methods to the domain of accessibility of educational institutions appears to be a coherent, innovative and methodologically sound research direction.

In this sense, the extension of multicriteria sorting methods to the domain of accessibility of educational institutions appears to be a coherent, innovative and methodologically sound research direction.

The choice of AHPSort II and FlowSort as the two methods to be compared is motivated by their complementary theoretical foundations. AHPSort II belongs to the family of value-based sorting methods: it derives a synthetic score for each alternative through a weighted additive function and assigns it to a class by comparing the score with limiting thresholds (Miccoli and Ishizaka, 2017; Fattoruso and Squillante, 2024). FlowSort, on the other hand, belongs to the outranking family and is grounded in the PROMETHEE methodology (Nemery and Lamboray, 2008; Ishizaka and Nemery, 2013): it assigns alternatives to classes by comparing their preference flows with those of reference profiles, without assuming full compensability between criteria. The two methods thus represent the two main paradigms of multicriteria sorting and their joint application to the same data set enables a rigorous cross-methodological validation of the classification outcomes.

Table 1 provides a structured overview of the most relevant contributions, highlighting applications of MCDM methods related to accessibility, inclusiveness, and decision support in educational contexts.

Table 1: Overview of studies applying MCDM methods in education and related decision contexts.

Method	**Authors**	**Title**	**Purpose**
q-AHPSort II	Fattoruso et al. (2025)	A new q-AHPSort II to classify STEM master's degree programme	*To classify STEM master's degree programs into predefined categories using an extension of AHPSort II. The study highlights the effectiveness of sorting methods in educational evaluation, although it focuses on academic programs rather than infrastructural aspects.*

AHP	Baba et al. (2024)	A comprehensive framework for assessing the sustainability of public schools in conflict areas	*To assess sustainability of public schools in conflict zones, focusing on the West Bank (Palestine).*
AHP	Shahraki et al. (2016)	Distributional planning of educational places in developing cities with case studies	*To analyze school distribution and propose redistribution using AHP and GIS.*
AHP	Chan et al. (2023)	Assessing urban sustainability and the potential to improve the quality of education and gender equality in Phnom Penh, Cambodia	*To assess sustainability and identify improvements for education and gender equality aligned with the SDGs.*
AHP	Tahura et al. (2025)	Evaluating the online and offline learning effectiveness in Bangladesh using Analytic Hierarchy Process	*To compare online and offline learning effectiveness using AHP.*
AHP	Teoh et al. (2022)	Analysis of ICT Implementation in Teaching and Learning using Analytic Hierarchy Process (AHP)	*To rank barriers to ICT implementation in rural and urban schools.*
AHP + GIS	Abd El Karim and Awawdeh (2020)	Integrating GIS Accessibility and Location-Allocation Models with MCDA for quality of life in Buraidah	*To assess accessibility to public services, including schools, through spatial multicriteria analysis.*
Fuzzy AHP	Gulzar et al. (2023)	A fuzzy analytic hierarchy process for usability requirements of online education systems	*To evaluate usability requirements of online learning platforms.*

Fuzzy AHP	Chang et al. (2013)	Factors influencing sociability in educational MMORPGs - a fuzzy AHP approach	*To identify and rank sociability factors in educational digital environments.*
Fuzzy AHP	Incekara (2021)	Post-COVID-19 ergonomic school furniture design under fuzzy logic	*To design ergonomic and inclusive school furniture.*
PROMETHEE	Rogulj and Jajac (2021)	Achieving a construction barrier-free environment: decision support to policy selection	*To support prioritization of accessibility improvements in school environments.*
TOPSIS	Kumar and Banerji (2024)	Comparing priority ranking of inclusive education indicators using MCDM methods	*To rank inclusive education indicators according to different disability conditions.*

As can be observed from Table 1, FlowSort has not been applied in the context of school and educational evaluation. Within the broader landscape of sorting methods, it nevertheless emerges as a well-established and flexible approach based on the PROMETHEE outranking framework, designed to assign alternatives to predefined ordered categories. Its subsequent extensions, including group decision support configurations (Lolli et al., 2015), fuzzy formulations for handling uncertainty (Campos et al., 2015), and hybrid models integrating advanced techniques (Tibay et al., 2022), further confirm its methodological robustness and adaptability to complex decision-making problems. Existing applications are mainly oriented toward strategic or organizational decision-making, especially in higher education settings. This highlights a gap in the literature, suggesting that FlowSort represents a promising and still underexplored tool for classification problems in the educational domain, particularly with respect to the assessment of school infrastructures, accessibility, and safety, and this paper represents, to the best of the authors' knowledge, the first contribution in this specific domain.

The choice of AHPSort II and FlowSort as the two methods to be compared is motivated by their complementary theoretical foundations. AHPSort II belongs to the family of value-based sorting methods: it derives a synthetic score for each alternative through a weighted additive function and assigns it to a class by comparing the score with limiting thresholds (Miccoli and Ishizaka, 2017; Fattoruso and Squillante, 2024). FlowSort, on the other hand, belongs to the outranking family and is grounded in the PROMETHEE methodology (Nemery and Lamboray, 2008; Ishizaka and Nemery, 2013): it assigns alternatives to classes by comparing their preference flows with those of reference profiles, without assuming full compensability among criteria. The two methods thus represent the two main paradigms of multicriteria sorting and their joint application to the same dataset enables a rigorous cross-methodological validation of the classification outcomes.

3. Methods

3.1. AHPSort II

Evaluating the accessibility of educational institutions requires the simultaneous consideration of a variety of heterogeneous criteria, making the use of MCDM methods appropriate, which allow the decision problem to be structured in an analytical and transparent manner (Greco et al., 2016).

Among MCDM methods, the AHP, introduced by Saaty (1980), makes it possible to derive the weights of the criteria through pairwise comparisons and to identify the best alternative. However, traditional AHP is not well suited for use when the number of alternatives is large, because as the number of pairwise comparisons increases, the inconsistency of the decision maker's judgments grows and the model becomes particularly burdensome to manage.

To overcome these limitations, this work adopts the AHPSort II method, an extension of AHP designed to address classification problems rather than choice or ranking problems (Miccoli and Ishizaka, 2017; Fattoruso and Squillante, 2024). The aim of AHPSort II is not to identify the best alternative, but to assign each alternative to a predefined and ordered class.

Let $A = \{a_1, \dots, a_n\}$ be the set of alternatives, which in our study are represented by schools, and let $G = \{g_1, \dots, g_m\}$ be the set of evaluation criteria. The element $g_j(a_i)$ represents the evaluation of alternative a_i with respect to criterion g_j. Furthermore, let $C = \{C_1, \dots, C_o\}$ denote the predefined set of classes into which the alternatives will be sorted.

For each criterion g_j, an ordered set of representative profiles is defined. These are ideal values within the range of values taken by that specific criterion, which we denote by

$$RP_j = \{rp_{1j}, rp_{2j}, \dots, rp_{sj}\},$$

where rp_{sj} denotes the value of representative profile s for criterion g_j.

It is also necessary to define, for each class C_k and for each criterion g_j, the set of limiting profiles lp_{kj} and central profiles cp_{kj}. These profiles are not defined for individual alternatives, but constitute reference values common to all alternatives and are used in the final phase of assigning alternatives to classes.

The criterion weights w_j, the local priorities of the representative profiles and the local priorities of the central profiles are determined through pairwise comparison matrices, solved using the geometric mean method, as in traditional AHP.

Let $A = [a_{ij}]$ be the $m \times m$ pairwise comparison matrix, where each element a_{ij} represents the relative importance of criterion i with respect to criterion j, according to Saaty's semantic scale. The geometric mean GM_i associated with criterion i is computed as:

$$GM_i = \left(\prod_{j=1}^{m} a_{ij} \right)^{\frac{1}{m}}. \tag{1}$$

The criteria weights are then obtained by normalizing the geometric means:

$$w_i = \frac{GM_i}{\sum_{k=1}^{m} GM_k}, \tag{2}$$

where w_i represents the normalized weight associated with criterion i.

After computing the criterion weights using the geometric mean method, the consistency of the pairwise comparison matrix was assessed. Let m denote the number of criteria and let $C = (c_{ij})$ be a complete pairwise comparison matrix. Consistency was evaluated using the triad-based inconsistency index proposed by Cavallo and D'Apuzzo (2009), which assesses the coherence of judgments by examining all possible triads of elements. This index has been further investigated and applied in subsequent studies, including Lundby et al. (2017).

For each triad (i, j, k), with $i < j < k$, local inconsistency is measured by comparing the direct judgment c_{ik} with the indirect judgment obtained as the product $c_{ij}c_{jk}$. The overall inconsistency index is defined as:

$$I(C) = \left(\prod_{i<j<k} \max \left\{ \frac{c_{ik}}{c_{ij}c_{jk}}, \frac{c_{ij}c_{jk}}{c_{ik}} \right\} \right)^{\frac{6}{m(m-1)(m-2)}}. \tag{3}$$

The index satisfies $I(C) \geq 1$, where $I(C) = 1$ corresponds to perfect consistency and larger values indicate increasing levels of inconsistency.

The literature does not provide universally accepted threshold values for the triad-based inconsistency index proposed by Cavallo and D'Apuzzo (2009). The index attains its minimum value of 1 under perfect consistency, whereas larger values indicate increasing inconsistency. In applied decision-making problems, moderate deviations from 1 are generally considered acceptable and reflect the inherent uncertainty of real judgment elicitation.

Once the pairwise comparison matrices between the representative profiles and the central profiles were defined for each criterion g_j, the local priorities associated with the representative and central profiles were determined using the geometric mean method. Let n_p denote the total number of profiles considered for criterion g_j. The geometric mean of the values in the corresponding row of the matrix was calculated for each profile s:

$$GM_s^{(j)} = \left(\prod_{r=1}^{n_p} a_{sr}^{(j)} \right)^{\frac{1}{n_p}}. \tag{4}$$

The local priorities of the profiles with respect to criterion g_j are obtained by normalizing the geometric means:

$$p_s^{(j)} = \frac{GM_s^{(j)}}{\sum_{r=1}^{n_p} GM_r^{(j)}}. \tag{5}$$

In the next step, for each alternative a_i and each criterion g_j, the local priority of the alternative with respect to the criterion under consideration is calculated by means of linear interpolation. Given the observed value $g_j(a_i)$, two consecutive profiles s and $s+1$ are identified such that

$$rp_{sj} \leq g_j(a_i) \leq rp_{(s+1)j}.$$

The local priority of alternative a_i with respect to criterion g_j is then computed as:

$$p_{ij} = p_s^{(j)} + \frac{p_{s+1}^{(j)} - p_s^{(j)}}{rp_{(s+1)j} - rp_{sj}} \left(g_j(a_i) - rp_{sj}\right). \tag{6}$$

The global priority of alternative a_i is calculated through a weighted additive value function:

$$P_i = \sum_{j=1}^{m} w_j \, p_{ij}, \qquad \sum_{j=1}^{m} w_j = 1. \tag{7}$$

Similarly, the global priority of a class profile k is defined as:

$$P_k = \sum_{j=1}^{m} w_j \, p_{kj}. \tag{8}$$

Subsequently, the limiting profiles lp_1 and lp_2 are determined and used as thresholds for assigning the alternatives to the predefined classes. Let P_{CP1}, P_{CP2} and P_{CP3} denote the global priorities of the central profiles of the *Low*, *Moderate* and *High* classes, respectively. The limiting profiles are computed as:

$$lp_1 = \frac{P_{CP1} + P_{CP2}}{2}, \tag{9}$$

$$lp_2 = \frac{P_{CP2} + P_{CP3}}{2}. \tag{10}$$

The final assignment of alternative a_i to an accessibility class C_k is obtained by comparing its global priority P_i with the limiting profiles. In particular, an alternative a_i is assigned to the *Low* class if

$$P_i < lp_1,$$

to the *Moderate* class if

$$lp_1 \leq P_i < lp_2,$$

and to the *High* class if

$$P_i \geq lp_2.$$

In this way, each school is classified into an ordered class that represents its level of accessibility.

3.2. FlowSort

FlowSort is a MCDM sorting method belonging to the PROMETHEE family (Nemery and Lamboray, 2008, 2013), designed to assign a set of alternatives to predefined, ordered categories. Unlike ranking methods, FlowSort does not aim to construct a complete ordering of the alternatives, but focuses on assigning them to categories based on reference profiles (Ishizaka and Nemery, 2013).

The first phase of the method consists of formally defining the decision problem. Let $A = \{a_1, \ldots, a_n\}$ be the set of n alternatives to be evaluated, and let $C = \{C_1, \ldots, C_k\}$ be the ordered set of predefined categories to which these alternatives are to be assigned. The categories are delimited by a set of reference profiles $B = \{b_1, \ldots, b_h\}$, which define the boundaries between adjacent classes. In the case of limiting profiles, the number of profiles is equal to $k + 1$, since each category is identified by the interval between two successive thresholds; in the case of central profiles, however, each category is represented by a single central profile, so the number of profiles coincides with the number of categories, i.e. k. Let $G = \{g_1, \ldots, g_m\}$ be the set of evaluation criteria considered, each of which is associated with a weight w_j, with $\sum_{j=1}^{m} w_j = 1$, which expresses its relative importance in the decision-making process.

The second phase consists of defining the extended set

$$B_i^* = B \cup \{a_i\},$$

consisting of the reference profiles to which the alternative a_i to be classified is added. For each criterion g_j and for each pair of elements $a, b \in B_i^*$, the gap is calculated

$$d_j(a, b) = g_j(a) - g_j(b).$$

Subsequently, a preference function $P_j(a, b) = F_j(d_j(a, b))$ is defined, which expresses the degree of preference of element a over element b as a function of the difference in their respective performances.

The aggregate preference index between two elements a and b is then calculated as a weighted additive function:

$$\pi(a, b) = \sum_{j=1}^{m} w_j P_j(a, b).$$

The third phase consists in calculating the positive and negative outranking flows for each element $a \in B_i^*$:

$$\phi^+(a) = \frac{1}{|B_i^*| - 1} \sum_{x \in B_i^*} \pi(a, x), \qquad \phi^-(a) = \frac{1}{|B_i^*| - 1} \sum_{x \in B_i^*} \pi(x, a).$$

The terms $\phi^+(a)$ and $\phi^-(a)$ represent the positive and negative outranking flows of element a, respectively. The positive flow measures how much element a dominates the other elements of the extended set B_i^*, while the negative flow measures how much element a is dominated by the other elements of the extended set B_i^*.

The net flow is defined as

$$\phi(a) = \phi^{+}(a) - \phi^{-}(a).$$

The fourth step consists of assigning alternatives to predefined categories. In the FlowSort method, the assignment of an alternative a_i to a category C_h is determined by comparing the alternative's outranking flows with the corresponding flows of the reference profiles that delimit adjacent categories.

In the case of limiting profiles, the alternative is assigned to the category whose consecutive profiles delimit the interval in which the alternative's flow falls. In the case of central profiles, however, the alternative is assigned to the category whose central profile presents the closest flow, according to a distance criterion applied to positive and negative flows or, alternatively, to net flows.

This procedure allows for a classification of alternatives into ordered and predefined categories.

4. Data

The data used in this study were collected through a direct survey carried out in Italian schools, with the aim of acquiring detailed information on the presence and number of equipment and structural features designed to ensure the accessibility of school buildings. The collection of count-type data was necessary for the application of the AHPSort II method.

The resulting dataset consists of 131 Italian schools. For each institution, information was collected on the following accessibility criteria: the number of external entrances equipped with ramps, the number of stairs compliant with current regulations, the number of elevators for people with disabilities, the number of stairlifts or lifting platforms, the number of accessible restrooms for people with disabilities, the number of accessible internal pathways and the number of accessible external pathways.

The choice of these seven criteria is grounded in the Italian regulatory framework governing accessibility in public buildings, in particular D.M. 236/1989 and D.P.R. 503/1996, which define the technical requirements for removing architectural barriers in school facilities. Each criterion captures a distinct dimension of physical accessibility: *external entrances with ramps* (g_1) and *accessible external pathways* (g_7) concern the reachability of the school building from public space; *compliant staircases* (g_2), *elevators* (g_3), *stairlifts or platform lifts* (g_4) and *accessible internal pathways* (g_6) address vertical and horizontal mobility within the building; *accessible restrooms* (g_5) measure the availability of services adapted for users with disabilities. Together, these criteria provide a comprehensive and legally grounded picture of a school's structural accessibility.

The sample of schools analyzed includes institutions distributed across different regions of the national territory.

A detailed description of the dataset is provided in Appendix A.

The regional distribution of the schools included in the dataset is shown in Figure 1, which reports the number of schools per region for which complete information was collected.

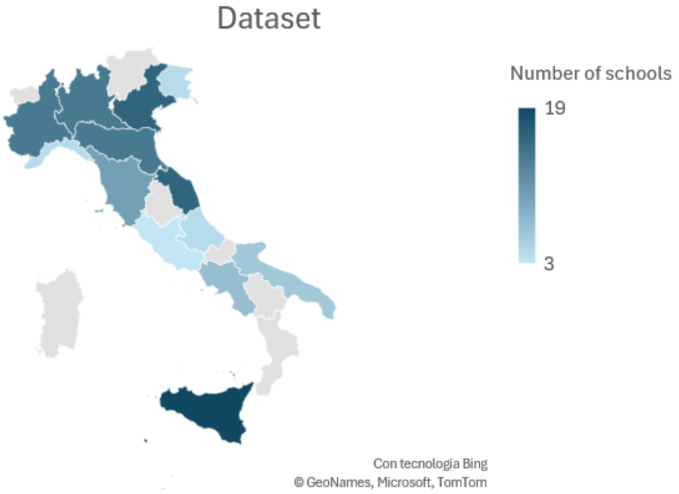

Figure 1: Regional distribution of the 131 Italian schools included in the dataset. Each region is shaded according to the number of schools for which complete accessibility data were collected (darker shades indicate a higher number of schools). Data collected through direct contact with the institutions.

This dataset was used to classify schools according to their level of accessibility.

5. Application of the AHPSort II method

This section describes the application of the AHPSort II method to the collected dataset, with the aim of classifying the educational institutions analyzed based on their level of accessibility.
The first application phase involved the collection and organization of the data necessary to assess the level of accessibility of the schools included in the study sample.
The AHPSort II method is applied to the dataset described in Section 4, as it allows handling a large number of alternatives and criteria, avoiding direct comparisons among all alternatives and facilitating their classification into ordered accessibility classes.
After the data collection phase, a summary table was constructed reporting, for each evaluation criterion, the observed range of values in the dataset, namely the minimum and maximum values across the 131 schools analyzed.
Subsequently, for each criterion, three central profiles CP_k representative of the accessibility levels were identified, as required by the AHPSort II method. In particular, three central profiles were defined:

- a *Low* profile, denoted as CP_1, representative of a low level of accessibility;
- a *Moderate* profile, denoted as CP_2, representative of an intermediate level of accessibility;
- a *High* profile, denoted as CP_3, representative of a high level of accessibility.

The central profiles CP_k were defined for each criterion within the observed range. Table 3 reports, for each evaluation criterion, the range of the observed values and the positions of the three identified central profiles (CP_1, CP_2, and CP_3).

Table 3: Criteria ranges and core profiles used in the AHPSort II method

Criteria	Min	Max	High (CP3)	Moderate (CP2)	Low (CP1)
g_1	0	8	4.00	2.00	1.00
g_2	0	7	3.00	2.00	1.00
g_3	0	3	2.00	1.00	0.00
g_4	0	2	2.00	1.00	0.00
g_5	0	9	4.00	3.00	1.00
g_6	0	11	5.00	3.00	1.00
g_7	0	8	4.00	2.00	1.00

Subsequently, a pairwise comparison matrix was constructed between the evaluation criteria to determine the weights of each criterion. To this end, a qualified decision maker with specific expertise in the field of school building accessibility was identified and asked to express preference judgments between each criterion and the other criteria. Preferences were elicited through pairwise comparisons, using the semantic scale proposed by Saaty (1980), which allows us to quantify the intensity of preference for one criterion over another. The judgments thus collected were organized into a square pairwise comparison matrix, from which the weights of the criteria were subsequently derived. Table 5 reports the pairwise comparison matrix used in the present study.

Table 5: Pairwise comparison matrix among the evaluation criteria

	g_1	g_2	g_3	g_4	g_5	g_6	g_7
g_1	1	2	1/3	3	2	1/2	1
g_2	1/2	1	1/6	2	1	1/3	1/2
g_3	3	6	1	6	4	2	4
g_4	1/3	1/2	1/6	1	1/2	1/5	1/2
g_5	1/2	1	1/4	2	1	1/3	1
g_6	2	3	1/2	5	3	1	2
g_7	1	2	1/4	2	1	1/2	1

Once the pairwise comparison matrix between the criteria was constructed, the relative weights were calculated using the geometric mean method. Applying this procedure to the pairwise comparison matrix defined in this study, we obtain the vector of criterion weights.

Table 7: Criteria and weights.

Criterion	Weight
g_1	0.125
g_2	0.068
g_3	0.364
g_4	0.044
g_5	0.080
g_6	0.216
g_7	0.103

The resulting weight vector reflects the relative importance assigned by the decision maker to each criterion.

The consistency analysis of the pairwise comparison matrix was performed using Python in a Google Colab environment. Consistency was evaluated using the triad-based inconsistency index proposed by Cavallo and D'Apuzzo (2009). Considering $m = 7$ criteria, the inconsistency index computed was $I(C) = 1.307$. Given that $I(C) \geq 1$ and that $I(C) = 1$ corresponds to perfect consistency, the observed value reflects a moderate and acceptable deviation from full consistency, as typically encountered in real decision-making contexts.

Subsequently, representative profiles were identified for each evaluation criterion. In accordance with the approach proposed by Miccoli and Ishizaka (2017), the representative profiles were obtained by equidistantly dividing the range of observed values for each criterion.

Table 8 shows, for each criterion, the distribution of representative profiles within the range of observed values.

Table 8: Reference profiles used for the criteria in the AHPSort II application

	g_1	g_2	g_3	g_4	g_5	g_6	g_7
RP1	0	0	0	0	0	0	0
RP2	1.6	1.4	0.6	0.4	1.8	2.2	1.6
RP3	3.2	2.8	1.2	0.8	3.6	4.4	3.2
RP4	4.8	4.2	1.8	1.2	5.4	6.6	4.8
RP5	6.4	5.6	2.4	1.6	7.2	8.8	6.4
RP6	8	7	3	2	9	11	8

At this point, pairwise comparisons were elicited between the representative profiles and the central profiles for each evaluation criterion.

Pairwise comparison matrices between the representative profiles and the central profiles were constructed for each criterion, using Saaty's semantic scale. The pairwise comparisons were performed by evaluating the intensity of preference for one profile over another.

For each criterion, pairwise comparison matrices between the representative profiles and the central profiles were constructed. The consistency of these matrices was verified through an analysis performed in a Python Google Colab environment, using the triad-based inconsistency index proposed by Cavallo and D'Apuzzo (2009). The pairwise comparison matrices together with the corresponding inconsistency indices are provided in Appendix C.

Once the pairwise comparison matrices between the representative profiles and the central profiles were defined for each criterion, we proceeded to determine the local priorities associated with the representative and central profiles. To this end, we used the geometric mean method and subsequent normalization.

Below, for each evaluation criterion, are the local priority vectors associated with the representative profiles and the central profiles.

$$\mathbf{p}^{(g_1)} = \begin{bmatrix} \text{RP6} & 0.238 \\ \text{RP5} & 0.220 \\ \text{CP3} & 0.137 \\ \text{RP4} & 0.141 \\ \text{CP2} & 0.071 \\ \text{RP3} & 0.092 \\ \text{CP1} & 0.032 \\ \text{RP2} & 0.045 \\ \text{RP1} & 0.024 \end{bmatrix} \quad \mathbf{p}^{(g_2)} = \begin{bmatrix} \text{RP6} & 0.245 \\ \text{RP5} & 0.185 \\ \text{CP3} & 0.112 \\ \text{RP4} & 0.164 \\ \text{CP2} & 0.074 \\ \text{RP3} & 0.107 \\ \text{CP1} & 0.037 \\ \text{RP2} & 0.054 \\ \text{RP1} & 0.023 \end{bmatrix} \quad \mathbf{p}^{(g_3)} = \begin{bmatrix} \text{RP6} & 0.176 \\ \text{CP3} & 0.176 \\ \text{RP5} & 0.176 \\ \text{RP4} & 0.176 \\ \text{RP3} & 0.103 \\ \text{CP2} & 0.088 \\ \text{CP1} & 0.023 \\ \text{RP2} & 0.060 \\ \text{RP1} & 0.023 \end{bmatrix}$$

$$\mathbf{p}^{(g_4)} = \begin{bmatrix} \text{RP6} & 0.213 \\ \text{CP3} & 0.180 \\ \text{RP5} & 0.180 \\ \text{RP4} & 0.160 \\ \text{CP2} & 0.096 \\ \text{RP3} & 0.075 \\ \text{RP2} & 0.042 \\ \text{CP1} & 0.026 \\ \text{RP1} & 0.027 \end{bmatrix} \quad \mathbf{p}^{(g_5)} = \begin{bmatrix} \text{RP6} & 0.234 \\ \text{RP5} & 0.190 \\ \text{CP3} & 0.098 \\ \text{RP4} & 0.176 \\ \text{CP2} & 0.098 \\ \text{RP3} & 0.098 \\ \text{CP1} & 0.031 \\ \text{RP2} & 0.053 \\ \text{RP1} & 0.023 \end{bmatrix} \quad \mathbf{p}^{(g_6)} = \begin{bmatrix} \text{RP6} & 0.222 \\ \text{RP5} & 0.206 \\ \text{CP3} & 0.118 \\ \text{RP4} & 0.156 \\ \text{CP2} & 0.076 \\ \text{RP3} & 0.097 \\ \text{CP1} & 0.039 \\ \text{RP2} & 0.058 \\ \text{RP1} & 0.027 \end{bmatrix}$$

$$\mathbf{p}^{(g_7)} = \begin{bmatrix} \text{RP6} & 0.227 \\ \text{RP5} & 0.221 \\ \text{CP3} & 0.123 \\ \text{RP4} & 0.133 \\ \text{CP2} & 0.062 \\ \text{RP3} & 0.123 \\ \text{CP1} & 0.034 \\ \text{RP2} & 0.049 \\ \text{RP1} & 0.026 \end{bmatrix}$$

For each criterion, summary tables were constructed showing the values of the representative and central profiles together with the corresponding local priorities; these tables are reported in Appendix D.

In the next step, for each alternative a_i and each criterion g_j, the local priority of the alternative with respect to the criterion under consideration was calculated through linear interpolation, starting from the local priorities of the profiles that delimit the observed value of the criterion for the alternative.

The complete table of local priorities is reported in Table 26 in Appendix E.

Subsequently, for each alternative a_i, the global priority P_i was calculated using a weighted additive value function, aggregating the local priorities with respect to each criterion g_j with the corresponding weights w_j.

The global priorities of each alternative are reported in Table 27 in Appendix F.

After determining the global priorities of the individual alternatives, the global priorities of the central profiles of each accessibility class were determined. Table 10 reports the local priorities and global priorities of the central profiles.

Table 10: Local and global priorities of central profiles (CP)

	$p_k^{(1)}$	$p_k^{(2)}$	$p_k^{(3)}$	$p_k^{(4)}$	$p_k^{(5)}$	$p_k^{(6)}$	$p_k^{(7)}$	$P(\mathrm{CP}_k)$
CP1	0.032	0.037	0.023	0.026	0.031	0.039	0.034	0.030
CP2	0.071	0.074	0.088	0.096	0.098	0.076	0.062	0.080
CP3	0.137	0.112	0.176	0.180	0.098	0.118	0.123	0.140

Subsequently, the limiting profiles lp_1 and lp_2 were determined and used as thresholds for assigning the alternatives to the predefined classes. The values of the limiting profiles are reported in Table 11.

Table 11: Limiting profiles used for class assignment

Limiting profile	Value
lp_1 (L1)	0.055
lp_2 (L2)	0.110

Finally, the alternatives were assigned to the predefined accessibility classes by comparing the global priority of each alternative with the limiting profiles lp_1 and lp_2, thus obtaining the classification into the *Low*, *Moderate* and *High* classes.

In this way, each alternative is ranked based on the value of its global priority with respect to the ranges defined by the limiting profiles, ensuring consistency with the AHPSort II method setting and with the class ordering established a priori.

The final results of the classification of alternatives into the accessibility classes *Low*, *Moderate* and *High*, based on the comparison between the global priorities and the limiting profiles, are reported in Table 12.

Table 12: AHPSort II classification results: global priorities and assignment to accessibility classes

Alternative	$P(a_i)$	Class	Alternative	$P(a_i)$	Class	Alternative	$P(a_i)$	Class
a_1	0.047	Low	a_{45}	0.065	Moderate	a_{89}	0.063	Moderate
a_2	0.029	Low	a_{46}	0.073	Moderate	a_{90}	0.071	Moderate
a_3	0.034	Low	a_{47}	0.047	Low	a_{91}	0.028	Low
a_4	0.034	Low	a_{48}	0.035	Low	a_{92}	0.033	Low
a_5	0.034	Low	a_{49}	0.039	Low	a_{93}	0.029	Low
a_6	0.031	Low	a_{50}	0.047	Low	a_{94}	0.032	Low
a_7	0.034	Low	a_{51}	0.046	Low	a_{95}	0.030	Low
a_8	0.034	Low	a_{52}	0.036	Low	a_{96}	0.027	Low
a_9	0.029	Low	a_{53}	0.041	Low	a_{97}	0.030	Low
a_{10}	0.047	Low	a_{54}	0.032	Low	a_{98}	0.028	Low
a_{11}	0.157	High	a_{55}	0.032	Low	a_{99}	0.054	Low
a_{12}	0.047	Low	a_{56}	0.028	Low	a_{100}	0.026	Low
a_{13}	0.113	High	a_{57}	0.027	Low	a_{101}	0.027	Low
a_{14}	0.115	High	a_{58}	0.027	Low	a_{102}	0.053	Low
a_{15}	0.040	Low	a_{59}	0.027	Low	a_{103}	0.030	Low
a_{16}	0.064	Moderate	a_{60}	0.036	Low	a_{104}	0.061	Moderate
a_{17}	0.032	Low	a_{61}	0.038	Low	a_{105}	0.055	Moderate
a_{18}	0.073	Moderate	a_{62}	0.048	Low	a_{106}	0.031	Low
a_{19}	0.027	Low	a_{63}	0.037	Low	a_{107}	0.109	Moderate
a_{20}	0.025	Low	a_{64}	0.079	Moderate	a_{108}	0.092	Moderate
a_{21}	0.090	Moderate	a_{65}	0.057	Moderate	a_{109}	0.068	Moderate
a_{22}	0.057	Moderate	a_{66}	0.036	Low	a_{110}	0.034	Low
a_{23}	0.051	Low	a_{67}	0.035	Low	a_{111}	0.034	Low
a_{24}	0.055	Low	a_{68}	0.055	Low	a_{112}	0.068	Moderate
a_{25}	0.034	Low	a_{69}	0.070	Moderate	a_{113}	0.045	Low
a_{26}	0.034	Low	a_{70}	0.055	Low	a_{114}	0.030	Low
a_{27}	0.045	Low	a_{71}	0.073	Moderate	a_{115}	0.031	Low
a_{28}	0.081	Moderate	a_{72}	0.063	Moderate	a_{116}	0.049	Low
a_{29}	0.038	Low	a_{73}	0.068	Moderate	a_{117}	0.029	Low
a_{30}	0.059	Moderate	a_{74}	0.062	Moderate	a_{118}	0.030	Low
a_{31}	0.028	Low	a_{75}	0.095	Moderate	a_{119}	0.033	Low
a_{32}	0.029	Low	a_{76}	0.057	Moderate	a_{120}	0.049	Low
a_{33}	0.069	Moderate	a_{77}	0.063	Moderate	a_{121}	0.049	Low
a_{34}	0.063	Moderate	a_{78}	0.061	Moderate	a_{122}	0.033	Low
a_{35}	0.033	Low	a_{79}	0.080	Moderate	a_{123}	0.028	Low
a_{36}	0.026	Low	a_{80}	0.067	Moderate	a_{124}	0.028	Low
a_{37}	0.025	Low	a_{81}	0.030	Low	a_{125}	0.067	Moderate
a_{38}	0.026	Low	a_{82}	0.047	Low	a_{126}	0.058	Moderate
a_{39}	0.044	Low	a_{83}	0.063	Moderate	a_{127}	0.061	Moderate
a_{40}	0.025	Low	a_{84}	0.037	Low	a_{128}	0.045	Low
a_{41}	0.026	Low	a_{85}	0.111	High	a_{129}	0.150	High
a_{42}	0.025	Low	a_{86}	0.070	Moderate	a_{130}	0.054	Low
a_{43}	0.025	Low	a_{87}	0.058	Moderate	a_{131}	0.059	Moderate
a_{44}	0.089	Moderate	a_{88}	0.062	Moderate			

6. Application of FlowSort

In this section, the FlowSort method is applied to the empirical dataset reported in Appendix B. The decision matrix includes $n = 131$ educational institutions, denoted by a_i $(i = 1, \ldots, n)$, evaluated with respect to $m = 7$ criteria, denoted by g_j $(j = 1, \ldots, m)$. All criteria are assumed to be maximized. The criterion weights w_j adopted in the FlowSort model are those previously derived through the AHP Sort II procedure (Table 7). Maintaining the same weighting structure ensures consistency in the representation of the decision-maker's preferences across methods and enhances the comparability of the classification results. The weights satisfy the normalization condition $\sum_{j=1}^{m} w_j = 1$.

Let $A = \{a_1, \ldots, a_n\}$ denote the set of schools and $C = \{C_1, C_2, C_3\}$ the ordered set of predefined accessibility categories, where $C_1 = Low$, $C_2 = Moderate$, and $C_3 = High$. In line with the methodological setting adopted in this study, we use the *central profiles* version of FlowSort. Hence, the reference set is $B = \{\mathrm{CP}_1, \mathrm{CP}_2, \mathrm{CP}_3\}$, where each central profile represents one target class. The numerical performances of the three central profiles on each criterion are those reported in Table 3.

In the empirical application, each school a_i $(i = 1, \ldots, n)$ is evaluated jointly with the three reference profiles. Accordingly, the corresponding extended set consists of the three fixed reference vectors together with the institution under consideration.

The structure of the family of extended sets $\mathcal{B}^* = \{B_i^*\}_{i=1}^{131}$ is reported in Table 13.

Table 13: Extended sets.

a_i	Extended set B_i^*
a_1	$\{(1,1,0,0,1,1,1),\ (2,2,1,1,3,3,2),\ (4,3,2,2,4,5,4),\ a_1\}$
a_2	$\{(1,1,0,0,1,1,1),\ (2,2,1,1,3,3,2),\ (4,3,2,2,4,5,4),\ a_2\}$
a_3	$\{(1,1,0,0,1,1,1),\ (2,2,1,1,3,3,2),\ (4,3,2,2,4,5,4),\ a_3\}$
$\vdots$	$\vdots$
a_{131}	$\{(1,1,0,0,1,1,1),\ (2,2,1,1,3,3,2),\ (4,3,2,2,4,5,4),\ a_{131}\}$

For each pair $(a, b) \in B_i^*$ and each criterion g_j, deviations are computed as $d_j(a, b) = g_j(a) - g_j(b)$. Since all criteria are maximized, positive deviations indicate a preference of a over b.

We adopt the linear V-shape preference function with indifference.

For each criterion g_j, the thresholds are set equal to the empirical minimum and maximum observed in the sample of 131 institutions, i.e., $q_j = \min(g_j)$ and $p_j = \max(g_j)$, thus ensuring that the thresholds are calibrated directly on the empirical range of the dataset. This specification was adopted in order to ensure comparability with the AHPSort II results and to avoid introducing additional subjective parameters into the model.

The unicriterion preference degrees $P_j(a, b)$ are then aggregated into a global preference index via the weighted additive formulation $\pi(a, b) = \sum_{j=1}^{7} w_j P_j(a, b)$.

After computing $\pi(a, b)$ for all pairs $(a, b) \in B_i^*$, we determine the PROMETHEE positive, negative and net flows on the extended set. Since $|B_i^*| = 4$ in our application, flows

are computed by averaging over $|B_i^*| - 1 = 3$ comparisons.
For the illustrative extended set B_1^*, the resulting net flows are:

$$\phi(a_1) = -0.138, \qquad \phi(\mathrm{CP}_1) = -0.267, \qquad \phi(\mathrm{CP}_2) = 0.032, \qquad \phi(\mathrm{CP}_3) = 0.373.$$

These values summarize the relative outranking strength of each element within the extended set and constitute the basis for the assignment rule.
Finally, each alternative is assigned to the class whose central profile has the closest net flow in absolute value:

$$\min_{h\in\{1,2,3\}} \left|\phi(a_i) - \phi(\mathrm{CP}_h)\right|.$$

For a_1 we obtain:

$$|\phi(a_1) - \phi(\mathrm{CP}_1)| = 0.130, \quad |\phi(a_1) - \phi(\mathrm{CP}_2)| = 0.170, \quad |\phi(a_1) - \phi(\mathrm{CP}_3)| = 0.511.$$

Hence, a_1 is assigned to class C_1 (*Low*).
The same procedure is applied to all 131 schools. The final FlowSort classification results, based on net flow values and comparison with limiting profiles, are reported in Table 14.

Table 14: FlowSort classification results: net flow values and final assignment of schools to accessibility classes

Alternative	$\phi(a_i)$	Class	Alternative	$\phi(a_i)$	Class	Alternative	$\phi(a_i)$	Class
a_1	-0.138	Low	a_{45}	-0.040	Moderate	a_{89}	-0.072	Moderate
a_2	-0.259	Low	a_{46}	-0.016	Moderate	a_{90}	0.010	Moderate
a_3	-0.230	Low	a_{47}	-0.135	Low	a_{91}	-0.268	Low
a_4	-0.230	Low	a_{48}	-0.225	Low	a_{92}	-0.234	Low
a_5	-0.230	Low	a_{49}	-0.189	Low	a_{93}	-0.259	Low
a_6	-0.246	Low	a_{50}	-0.128	Low	a_{94}	-0.243	Low
a_7	-0.230	Low	a_{51}	-0.140	Low	a_{95}	-0.249	Low
a_8	-0.230	Low	a_{52}	-0.215	Low	a_{96}	-0.272	Low
a_9	-0.259	Low	a_{53}	-0.175	Low	a_{97}	-0.249	Low
a_{10}	-0.138	Low	a_{54}	-0.248	Low	a_{98}	-0.272	Low
a_{11}	0.439	High	a_{55}	-0.242	Low	a_{99}	-0.104	Moderate
a_{12}	-0.098	Moderate	a_{56}	-0.276	Low	a_{100}	-0.294	Low
a_{13}	0.172	High	a_{57}	-0.285	Low	a_{101}	-0.288	Low
a_{14}	0.246	High	a_{58}	-0.275	Low	a_{102}	-0.115	Moderate
a_{15}	-0.193	Low	a_{59}	-0.285	Low	a_{103}	-0.266	Low
a_{16}	-0.043	Moderate	a_{60}	-0.208	Low	a_{104}	-0.062	Moderate
a_{17}	-0.240	Low	a_{61}	-0.150	Low	a_{105}	-0.088	Moderate
a_{18}	0.006	Moderate	a_{62}	-0.103	Moderate	a_{106}	-0.249	Low
a_{19}	-0.287	Low	a_{63}	-0.210	Low	a_{107}	0.176	High
a_{20}	-0.300	Low	a_{64}	0.170	High	a_{108}	0.119	High
a_{21}	0.091	Moderate	a_{65}	-0.107	Moderate	a_{109}	-0.061	Moderate
a_{22}	-0.090	Moderate	a_{66}	-0.176	Low	a_{110}	-0.230	Low
a_{23}	-0.106	Moderate	a_{67}	-0.230	Low	a_{111}	-0.230	Low
a_{24}	-0.106	Moderate	a_{68}	-0.113	Moderate	a_{112}	-0.049	Moderate
a_{25}	-0.201	Low	a_{69}	0.015	Moderate	a_{113}	-0.059	Moderate
a_{26}	-0.208	Low	a_{70}	-0.102	Moderate	a_{114}	-0.249	Low
a_{27}	-0.164	Low	a_{71}	-0.032	Moderate	a_{115}	-0.240	Low
a_{28}	0.067	Moderate	a_{72}	-0.075	Moderate	a_{116}	-0.128	Low
a_{29}	-0.174	Low	a_{73}	-0.031	Moderate	a_{117}	-0.259	Low
a_{30}	-0.080	Moderate	a_{74}	-0.052	Moderate	a_{118}	-0.249	Low
a_{31}	-0.287	Low	a_{75}	0.103	Moderate	a_{119}	-0.239	Low
a_{32}	-0.277	Low	a_{76}	-0.082	Moderate	a_{120}	-0.128	Low
a_{33}	-0.057	Moderate	a_{77}	-0.068	Moderate	a_{121}	-0.128	Low
a_{34}	-0.079	Moderate	a_{78}	-0.058	Moderate	a_{122}	-0.230	Low
a_{35}	-0.239	Low	a_{79}	0.029	Moderate	a_{123}	-0.272	Low
a_{36}	-0.292	Low	a_{80}	0.013	Moderate	a_{124}	-0.272	Low
a_{37}	-0.307	Low	a_{81}	-0.249	Low	a_{125}	-0.046	Moderate
a_{38}	-0.292	Low	a_{82}	-0.141	Low	a_{126}	-0.093	Moderate
a_{39}	-0.167	Low	a_{83}	-0.074	Moderate	a_{127}	-0.084	Moderate
a_{40}	-0.307	Low	a_{84}	-0.191	Low	a_{128}	-0.148	Low
a_{41}	-0.292	Low	a_{85}	0.166	High	a_{129}	0.287	High
a_{42}	-0.307	Low	a_{86}	-0.029	Moderate	a_{130}	-0.096	Moderate
a_{43}	-0.307	Low	a_{87}	-0.077	Moderate	a_{131}	-0.036	Moderate
a_{44}	0.086	Moderate	a_{88}	-0.071	Moderate			

7. Discussion of Results

This section discusses the classification results obtained with AHPSort II and FlowSort, applied to the same dataset of $n = 131$ educational institutions and the same $m = 7$ criteria. For the sake of comparability, the FlowSort application adopts the same criterion weights estimated in AHPSort II (Table 7), thereby preserving the decision maker's preference structure.

The two methods produce an overall similar distribution of classes, although with some differences in the number of schools assigned to each category. AHPSort II assigns 86 schools to the *Low* class, 40 to the *Moderate* class and 5 to the *High* class. FlowSort assigns 76 schools to *Low*, 47 to *Moderate* and 8 to *High*. Hence, FlowSort shows a slightly greater tendency to assign schools to higher accessibility levels compared to AHPSort II.

Despite these differences, the overall level of agreement between the two methods is high. Out of 131 schools, 118 receive the same classification, corresponding to an agreement rate of 90.1%. The chance-corrected agreement, measured by Cohen's index (Cohen, 1960) ($\kappa = 0.804$), confirms a strong consistency between the two sorting procedures.

Table 15: Contingency table of class assignments obtained with AHPSort II and FlowSort (V-shape).

AHPSort II \ FlowSort	**Low**	**Moderate**	**High**
Low	76	10	0
Moderate	0	37	3
High	0	0	5

The contingency table shows that disagreements occur exclusively between adjacent classes. Ten schools move from *Low* (AHPSort II) to *Moderate* (FlowSort), and three schools move from *Moderate* (AHPSort II) to *High* (FlowSort). No downgrading is observed, nor are there jumps of two classes. This pattern indicates that differences arise mainly for schools located close to the decision thresholds separating the categories.

These discrepancies can be interpreted in light of the different underlying decision logics. AHPSort II is based on an additive value function, where global priorities are derived from local priorities obtained through linear interpolation between reference profiles and compared with limiting thresholds. FlowSort, in contrast, follows an outranking approach: performance differences are transformed into preference degrees through preference functions and aggregated into PROMETHEE flows, which capture the relative dominance of each school with respect to the class profiles.

A particularly noteworthy result concerns the *High* class. All schools classified as *High* by AHPSort II are confirmed in the same class by FlowSort, and no downgrading from *High* to lower categories is observed. Moreover, FlowSort identifies three additional schools as *High*, previously classified as *Moderate* by AHPSort II. More generally, all observed differences correspond to upward reassignments, while no demotions occur.

Overall, the high level of agreement confirms the robustness of the classification, while the limited number of divergent cases highlights borderline situations deserving further analysis. The combined use of the two approaches therefore not only provides a classification consistent with the decision maker's preferences, but also helps to identify areas of potential decisional uncertainty.
Table 16 summarises the main strengths and limitations of the two methods along five key dimensions, providing a structured basis for method selection in future accessibility studies.

Table 16: Comparison of strengths and limitations of AHPSort II and FlowSort.

Dimension	**AHPSort II**	**FlowSort**
Decision logic	Additive value function; full compensability among criteria	Outranking flows; partial compensability via preference functions
Input requirements	Pairwise comparisons for criteria weights and profile priorities; structured elicitation process	Criterion weights and preference function parameters (p_j, q_j); calibration on empirical range
Handling of trade-offs	Allows trade-offs: strong performance on one criterion can offset weakness on another	Limits trade-offs: dominance logic may penalise alternatives with uneven profiles
Sensitivity to thresholds	Classification depends on the position of limiting profiles, derived from central profile priorities	Classification sensitive to the definition of preference and indifference thresholds
Interpretability	High: global priorities are scores directly comparable to limiting thresholds	Moderate: net flows require understanding of outranking logic; less intuitive for non-specialists

7.1. Managerial implications.

The classification results produced by both methods have direct practical implications for public decision-makers at the school, local authority, and national ministry levels. Schools assigned to the *Low* accessibility class — which represent the large majority of the sample — should be considered priority targets for structural investment, with particular attention to the criteria receiving the highest weights: elevators (g_3, weight 0.364) and accessible internal pathways (g_6, weight 0.216). Schools in the *Moderate* class are partially compliant and may require targeted interventions on specific deficient features rather than comprehensive renovation. Schools in the *High* class can serve as benchmarks of best practice. When the two methods agree on a classification, as is the case for 90.1% of the sample, the assignment can be considered robust and can directly inform funding priority decisions. When they disagree — which occurs exclusively for schools near class boundaries — a more in-depth case-by-case assessment is advisable before allocating resources. More broadly, the combined use of AHPSort II and FlowSort offers public administrators a methodologically rigorous and transparent tool for monitoring progress toward full accessibility compliance across a large school system, supporting evidence-based planning of remediation interventions.

8. Conclusions

This study compared two multi-criteria sorting methods, AHPSort II and FlowSort, applied to the classification of 131 Italian schools based on their accessibility level. The analysis was conducted using the same dataset, the same criteria, and the same weights, so that any differences could be attributed exclusively to the different operating logic of the two approaches.

The results show a high level of convergence between the obtained classifications. Over 90% of schools receive the same assignment with both methods, and the *High* class is completely stable. The differences found concern exclusively cases located near the thresholds between adjacent classes and manifest themselves as promotions to higher categories in the case of FlowSort. Overall, this indicates that, despite being based on different theoretical approaches, the two methods provide largely consistent results in the application context considered.

The differences between AHPSort II and FlowSort reflect two different ways of interpreting the decision-making process. AHPSort II aggregates performance using a weighted value function, allowing for trade-offs between criteria: a weakness in one aspect can be offset by good performance in others. FlowSort, on the other hand, relies on pairwise comparisons and a dominance logic, in which some weaknesses can limit assignment even in the presence of significant strengths. This makes the two approaches complementary rather than alternative.

Both methods have strengths and limitations, which must be evaluated in relation to the objectives of the analysis and the preferences of the decision maker.

Based on the results obtained, no one method emerges as intrinsically superior. The choice between AHPSort II and FlowSort should depend on the type of decision-making rationale one intends to adopt and the degree of trade-offs deemed acceptable among the evaluation criteria. The combined use of the two approaches can be a useful strategy for strengthening the robustness of the analysis: when the classifications coincide, the result appears more robust; when they diverge, boundary situations are identified that merit specific investigation.

Ultimately, the value of this paper lies not in the identification of a superior method, but in demonstrating how different approaches can offer complementary perspectives and, together, contribute to a more informed and nuanced assessment of the accessibility of educational institutions.

Declarations

Conflict of interest. The authors declare that they have no conflict of interest.

A. Dataset Description

Table 17: Dataset of the 131 analyzed schools, including their geographical origin.

A	**Region**	**Area**	A	**Region**	**Area**
a_1	EMILIA ROMAGNA	North	a_{67}	LOMBARDIA	North
a_2	EMILIA ROMAGNA	North	a_{68}	LOMBARDIA	North
a_3	EMILIA ROMAGNA	North	a_{69}	LOMBARDIA	North
a_4	EMILIA ROMAGNA	North	a_{70}	LOMBARDIA	North
a_5	EMILIA ROMAGNA	North	a_{71}	LOMBARDIA	North
a_6	EMILIA ROMAGNA	North	a_{72}	LOMBARDIA	North
a_7	EMILIA ROMAGNA	North	a_{73}	LOMBARDIA	North
a_8	EMILIA ROMAGNA	North	a_{74}	LOMBARDIA	North
a_9	EMILIA ROMAGNA	North	a_{75}	VENETO	North
a_{10}	EMILIA ROMAGNA	North	a_{76}	SICILIA	South
a_{11}	ABRUZZO	South	a_{77}	SICILIA	South
a_{12}	ABRUZZO	South	a_{78}	PIEMONTE	North
a_{13}	ABRUZZO	South	a_{79}	PIEMONTE	North
a_{14}	ABRUZZO	South	a_{80}	VENETO	North
a_{15}	CAMPANIA	South	a_{81}	VENETO	North
a_{16}	CAMPANIA	South	a_{82}	VENETO	North
a_{17}	CAMPANIA	South	a_{83}	VENETO	North
a_{18}	CAMPANIA	South	a_{84}	VENETO	North
a_{19}	CAMPANIA	South	a_{85}	LOMBARDIA	North
a_{20}	CAMPANIA	South	a_{86}	LOMBARDIA	North
a_{21}	EMILIA ROMAGNA	North	a_{87}	LOMBARDIA	North
a_{22}	EMILIA ROMAGNA	North	a_{88}	LOMBARDIA	North
a_{23}	EMILIA ROMAGNA	North	a_{89}	SICILIA	South
a_{24}	EMILIA ROMAGNA	North	a_{90}	SICILIA	South
a_{25}	PUGLIA	South	a_{91}	SICILIA	South
a_{26}	PUGLIA	South	a_{92}	SICILIA	South
a_{27}	PUGLIA	South	a_{93}	SICILIA	South
a_{28}	FRIULI VENEZIA GIULIA	North	a_{94}	SICILIA	South
a_{29}	FRIULI VENEZIA GIULIA	North	a_{95}	PIEMONTE	North
a_{30}	FRIULI VENEZIA GIULIA	North	a_{96}	PIEMONTE	North
a_{31}	FRIULI VENEZIA GIULIA	North	a_{97}	PIEMONTE	North
a_{32}	MARCHE	Centre	a_{98}	PIEMONTE	North
a_{33}	PUGLIA	South	a_{99}	PIEMONTE	North
a_{34}	PUGLIA	South	a_{100}	PIEMONTE	North
a_{35}	PUGLIA	South	a_{101}	PIEMONTE	North
a_{36}	TOSCANA	Centre	a_{102}	PIEMONTE	North
a_{37}	TOSCANA	Centre	a_{103}	PIEMONTE	North
a_{38}	TOSCANA	Centre	a_{104}	LAZIO	Centre
a_{39}	TOSCANA	Centre	a_{105}	LAZIO	Centre
a_{40}	TOSCANA	Centre	a_{106}	LAZIO	Centre
a_{41}	TOSCANA	Centre	a_{107}	VENETO	North
a_{42}	TOSCANA	Centre	a_{108}	VENETO	North
a_{43}	TOSCANA	Centre	a_{109}	SICILIA	South
a_{44}	TOSCANA	Centre	a_{110}	SICILIA	South
a_{45}	TOSCANA	Centre	a_{111}	SICILIA	South
a_{46}	MARCHE	Centre	a_{112}	SICILIA	South
a_{47}	MARCHE	Centre	a_{113}	SICILIA	South
a_{48}	MARCHE	Centre	a_{114}	SICILIA	South

A	**Region**	**Area**	A	**Region**	**Area**
a_{49}	MARCHE	Centre	a_{115}	SICILIA	South
a_{50}	MARCHE	Centre	a_{116}	SICILIA	South
a_{51}	MARCHE	Centre	a_{117}	SICILIA	South
a_{52}	MARCHE	Centre	a_{118}	SICILIA	South
a_{53}	MARCHE	Centre	a_{119}	SICILIA	South
a_{54}	MARCHE	Centre	a_{120}	PIEMONTE	North
a_{55}	MARCHE	Centre	a_{121}	PIEMONTE	North
a_{56}	LIGURIA	North	a_{122}	VENETO	North
a_{57}	LIGURIA	North	a_{123}	VENETO	North
a_{58}	LIGURIA	North	a_{124}	VENETO	North
a_{59}	LIGURIA	North	a_{125}	VENETO	North
a_{60}	CAMPANIA	South	a_{126}	VENETO	North
a_{61}	MARCHE	Centre	a_{127}	VENETO	North
a_{62}	MARCHE	Centre	a_{128}	VENETO	North
a_{63}	MARCHE	Centre	a_{129}	LOMBARDIA	North
a_{64}	MARCHE	Centre	a_{130}	PIEMONTE	North
a_{65}	MARCHE	Centre	a_{131}	VENETO	North
a_{66}	LOMBARDIA	North			

B. Decision Matrix

Table 18: Decision matrix of the 131 schools with respect to the considered accessibility criteria.

Alternative (a_i)	g_1	g_2	g_3	g_4	g_5	g_6	g_7
a_1	1	0	1	0	1	1	1
a_2	1	0	0	0	1	1	1
a_3	2	0	0	0	1	1	2
a_4	2	0	0	0	1	1	2
a_5	2	0	0	0	1	1	2
a_6	1	0	0	0	1	1	2
a_7	2	0	0	0	1	1	2
a_8	2	0	0	0	1	1	2
a_9	1	0	0	0	1	1	1
a_{10}	1	0	1	0	1	1	1
a_{11}	4	7	3	0	3	8	6
a_{12}	4	6	0	2	3	0	2
a_{13}	2	4	2	0	8	4	2
a_{14}	1	1	2	1	2	11	3
a_{15}	2	0	0	0	3	2	2
a_{16}	1	1	1	0	4	4	1
a_{17}	1	1	0	0	2	1	1
a_{18}	1	1	1	0	5	6	1
a_{19}	0	3	0	0	0	0	0
a_{20}	1	0	0	0	0	0	0
a_{21}	8	3	1	1	2	4	1
a_{22}	2	1	1	1	1	1	1
a_{23}	1	1	1	1	1	1	1
a_{24}	0	4	1	0	2	1	1
a_{25}	1	6	0	0	1	1	1
a_{26}	1	3	0	1	1	1	1
a_{27}	2	3	0	0	3	2	2
a_{28}	1	6	1	0	2	8	1
a_{29}	1	0	0	0	4	4	1
a_{30}	1	1	1	0	2	3	1
a_{31}	0	1	0	0	0	1	0
a_{32}	0	0	0	0	0	2	0
a_{33}	2	2	1	0	1	2	3
a_{34}	2	2	1	0	0	2	2
a_{35}	2	0	0	0	0	1	2
a_{36}	1	0	0	0	1	0	0
a_{37}	0	0	0	0	1	0	0
a_{38}	1	0	0	0	1	0	0
a_{39}	0	1	1	0	2	0	0
a_{40}	0	0	0	0	1	0	0
a_{41}	1	0	0	0	1	0	0
a_{42}	0	0	0	0	1	0	0
a_{43}	0	0	0	0	1	0	0
a_{44}	0	4	2	1	3	3	1
a_{45}	1	3	1	1	4	2	1
a_{46}	0	2	1	0	4	5	2
a_{47}	0	2	0	0	5	4	3
a_{48}	0	0	0	0	3	2	2
a_{49}	1	2	0	0	3	2	2
a_{50}	1	2	0	0	4	4	3

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Alternative (a_i)	g_1	g_2	g_3	g_4	g_5	g_6	g_7
a_{51}	0	2	0	0	3	4	4
a_{52}	0	1	0	0	3	2	2
a_{53}	1	2	0	0	1	3	3
a_{54}	0	2	0	0	1	2	0
a_{55}	0	0	0	0	1	2	2
a_{56}	0	1	0	0	2	0	1
a_{57}	0	1	0	0	1	0	1
a_{58}	0	1	0	1	1	0	0
a_{59}	0	1	0	0	1	0	1
a_{60}	2	0	0	1	1	1	2
a_{61}	1	2	0	0	1	1	8
a_{62}	2	1	0	0	1	7	2
a_{63}	0	0	0	0	1	3	3
a_{64}	4	1	3	0	2	1	1
a_{65}	2	0	1	0	2	0	3
a_{66}	0	0	0	0	2	1	8
a_{67}	0	1	0	0	2	1	3
a_{68}	0	1	1	0	3	1	2
a_{69}	1	1	2	0	2	1	2
a_{70}	1	1	1	0	1	1	3
a_{71}	2	2	1	1	2	3	1
a_{72}	2	1	1	0	3	2	1
a_{73}	2	1	1	1	1	4	1
a_{74}	1	0	1	0	4	4	1
a_{75}	6	5	1	1	7	1	4
a_{76}	1	1	1	0	4	2	1
a_{77}	3	1	1	0	2	2	1
a_{78}	1	0	1	2	2	3	0
a_{79}	5	1	1	0	5	4	1
a_{80}	1	3	2	0	1	1	1
a_{81}	1	1	0	0	1	1	1
a_{82}	1	1	1	0	1	1	0
a_{83}	1	2	1	0	3	3	0
a_{84}	1	2	0	1	1	3	0
a_{85}	0	2	2	0	5	7	3
a_{86}	1	3	1	1	3	3	1
a_{87}	1	1	1	1	2	2	1
a_{88}	1	3	1	0	3	2	1
a_{89}	2	2	1	1	2	1	1
a_{90}	2	2	2	0	0	1	1
a_{91}	1	0	0	0	0	1	1
a_{92}	2	1	0	0	1	1	1
a_{93}	1	0	0	0	1	1	1
a_{94}	2	0	0	0	1	1	1
a_{95}	1	1	0	0	1	1	1
a_{96}	0	0	0	1	1	0	1
a_{97}	1	1	0	0	1	1	1
a_{98}	1	0	0	0	1	1	0
a_{99}	0	1	1	0	1	3	1
a_{100}	0	0	0	0	1	0	1
a_{101}	0	0	0	0	1	1	0
a_{102}	0	1	1	0	2	2	1
a_{103}	0	0	0	0	2	1	1
a_{104}	6	2	1	0	0	1	0
a_{105}	5	2	1	0	1	0	0
a_{106}	3	0	0	0	0	1	0

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Alternative (a_i)	g_1	g_2	g_3	g_4	g_5	g_6	g_7
a_{107}	5	3	2	0	8	1	4
a_{108}	1	4	2	0	9	1	3
a_{109}	2	2	1	0	2	2	2
a_{110}	2	0	0	0	1	1	2
a_{111}	2	0	0	0	1	1	2
a_{112}	1	2	1	0	3	3	2
a_{113}	8	0	0	0	1	1	8
a_{114}	1	1	0	0	1	1	1
a_{115}	1	2	0	0	1	1	1
a_{116}	1	1	1	0	1	1	1
a_{117}	1	0	0	0	1	1	1
a_{118}	1	1	0	0	1	1	1
a_{119}	2	0	0	0	0	1	2
a_{120}	1	1	1	0	1	1	1
a_{121}	1	1	1	0	1	1	1
a_{122}	0	1	0	1	1	1	2
a_{123}	0	1	0	0	1	0	2
a_{124}	0	1	0	0	1	0	2
a_{125}	1	5	1	0	3	1	3
a_{126}	1	2	1	0	1	1	3
a_{127}	1	2	1	0	2	1	3
a_{128}	1	1	1	0	1	0	1
a_{129}	2	4	2	2	5	7	5
a_{130}	1	2	1	1	1	1	1
a_{131}	2	7	0	1	4	3	5

C. Pairwise Comparison Matrices between Representative and Central Profiles

C.1. External entrances with ramp (g_1)

The pairwise comparison matrix for criterion g_1 is reported below.

	$RP6$	$RP5$	$CP3$	$RP4$	$RP3$	$CP2$	$RP2$	$CP1$	$RP1$
$RP6$	1	1	1	1	2	2	4	6	6
$RP5$	1	1	1	1	2	2	4	6	6
$CP3$	1	1	1	1	2	2	4	6	6
$RP4$	1	1	1	1	2	2	4	6	6
$RP3$	1/2	1/2	1/2	1/2	1	1	2	6	6
$CP2$	1/2	1/2	1/2	1/2	1	1	2	3	3
$RP2$	1/4	1/4	1/4	1/4	1/2	1/2	1	6	6
$CP1$	1/6	1/6	1/6	1/6	1/6	1/3	1/6	1	1
$RP1$	1/6	1/6	1/6	1/6	1/6	1/3	1/6	1	1

$$I(C) = 1.4162.$$

C.2. Compliant stairways (g_2)

The pairwise comparison matrix for criterion g_2 is reported below.

	$RP6$	$RP5$	$RP4$	$CP3$	$RP3$	$CP2$	$RP2$	$CP1$	$RP1$
$RP6$	1	2	2	2	3	3	5	5	6
$RP5$	1/2	1	1	2	2	3	4	6	6
$RP4$	1/2	1	1	2	2	2	3	4	6
$CP3$	1/2	1/2	1/2	1	1	2	2	3	6
$RP3$	1/3	1/2	1/2	1	1	2	2	3	6
$CP2$	1/3	1/3	1/2	1/2	1/2	1	2	2	4
$RP2$	1/5	1/4	1/3	1/2	1/2	1/2	1	2	3
$CP1$	1/5	1/6	1/4	1/3	1/3	1/2	1/2	1	2
$RP1$	1/6	1/6	1/6	1/6	1/6	1/4	1/3	1/2	1

$$I(C) = 1.4296.$$

C.3. Elevators for persons with disabilities (g_3)

The pairwise comparison matrix for criterion g_3 is reported below.

	$RP6$	$CP3$	$RP5$	$RP4$	$CP2$	$RP3$	$RP2$	$CP1$	$RP1$
$RP6$	1	1	1	2	3	3	6	6	6
$CP3$	1	1	1	1	2	3	4	6	6
$RP5$	1	1	1	1	2	3	4	6	6
$RP4$	1/2	1	1	1	2	2	4	6	6
$CP2$	1/3	1/2	1/2	1/2	1	1	3	6	4
$RP3$	1/3	1/3	1/3	1/2	1	1	2	3	3
$RP2$	1/6	1/4	1/4	1/4	1/3	1/2	1	2	2
$CP1$	1/6	1/6	1/6	1/6	1/6	1/3	1/2	1	1
$RP1$	1/6	1/6	1/6	1/6	1/4	1/3	1/2	1	1

$$I(C) = 1.3022.$$

C.4. Stairlifts or lifting platforms (g_4)

The pairwise comparison matrix for criterion g_4 is reported below.

	$RP6$	$CP3$	$RP5$	$RP4$	$CP2$	$RP3$	$RP2$	$CP1$	$RP1$
$RP6$	1	1	1	2	3	3	6	6	6
$CP3$	1	1	1	1	2	3	4	6	6
$RP5$	1	1	1	1	2	3	4	6	6
$RP4$	1/2	1	1	1	2	2	4	6	6
$CP2$	1/3	1/2	1/2	1/2	1	1	3	6	4
$RP3$	1/3	1/3	1/3	1/2	1	1	2	3	3
$RP2$	1/6	1/4	1/4	1/4	1/3	1/2	1	2	2
$CP1$	1/6	1/6	1/6	1/6	1/6	1/3	1/2	1	1
$RP1$	1/6	1/6	1/6	1/6	1/4	1/3	1/2	1	1

$$I(C) = 1.3050.$$

C.5. Accessible restrooms for persons with disabilities (g_5)

The pairwise comparison matrix for criterion g_5 is reported below.

	$RP6$	$RP5$	$RP4$	$CP3$	$RP3$	$CP2$	$RP2$	$CP1$	$RP1$
$RP6$	1	1	2	3	3	3	4	6	6
$RP5$	1	1	1	2	2	2	4	6	6
$RP4$	1/2	1	1	2	2	2	4	6	6
$CP3$	1/3	1/2	1/2	1	1	1	2	3	6
$RP3$	1/3	1/2	1/2	1	1	1	2	3	6
$CP2$	1/3	1/2	1/2	1	1	1	2	3	6
$RP2$	1/4	1/4	1/4	1/2	1/2	1/2	1	2	3
$CP1$	1/6	1/6	1/6	1/3	1/3	1/3	1/2	1	1
$RP1$	1/6	1/6	1/6	1/6	1/6	1/6	1/3	1	1

$$I(C) = 1.2844.$$

C.6. Accessible internal pathways (g_6)

The pairwise comparison matrix for criterion g_6 is reported below.

	$RP6$	$RP5$	$RP4$	$CP3$	$RP3$	$CP2$	$RP2$	$CP1$	$RP1$
$RP6$	1	1	2	2	2	3	4	6	6
$RP5$	1	1	1	2	2	3	4	6	6
$RP4$	1/2	1	1	1	2	2	3	4	6
$CP3$	1/2	1/2	1	1	1	2	2	3	4
$RP3$	1/2	1/2	1/2	1	1	1	2	2	4
$CP2$	1/3	1/3	1/2	1/2	1	1	1	2	4
$RP2$	1/4	1/4	1/3	1/2	1/2	1	1	2	2
$CP1$	1/6	1/6	1/4	1/3	1/2	1/2	1/2	1	2
$RP1$	1/6	1/6	1/6	1/4	1/4	1/4	1/2	1/2	1

$$I(C) = 1.2993.$$

C.7. Accessible external pathways (g_7)

The pairwise comparison matrix for criterion g_1 is reported below.

	$RP6$	$RP5$	$RP4$	$CP3$	$RP3$	$CP2$	$RP2$	$CP1$	$RP1$
$RP6$	1	1	2	2	2	4	5	6	6
$RP5$	1	1	2	2	2	4	4	6	6
$RP4$	1/2	1/2	1	1	1	2	4	4	6
$CP3$	1/2	1/2	1	1	1	2	2	4	6
$RP3$	1/2	1/2	1	1	1	2	2	4	6
$CP2$	1/4	1/4	1/2	1/2	1/2	1	1	2	3
$RP2$	1/5	1/4	1/4	1/2	1/2	1	1	2	1
$CP1$	1/6	1/6	1/4	1/4	1/4	1/2	1/2	1	2
$RP1$	1/6	1/6	1/6	1/6	1/6	1/3	1	1/2	1

$$I(C) = 1.2945.$$

D. Reference Values and Local Priorities of Representative and Central Profiles

D.1. External entrances with ramp (g_1)

Table 19: Reference values and local priorities for representative and central profiles with respect to criterion g_1.

Profile	**Reference value**	**Local priority**
RP1	0.0	0.024
CP1	1.0	0.032
RP2	1.6	0.045
CP2	2.0	0.071
RP3	3.2	0.092
CP3	4.0	0.137
RP4	4.8	0.141
RP5	6.4	0.220
RP6	8.0	0.238

D.2. Compliant stairways (g_2)

Table 20: Reference values and local priorities for representative and central profiles with respect to criterion g_2.

Profile	**Reference value**	**Local priority**
RP1	0.0	0.023
CP1	1.0	0.037
RP2	1.4	0.054
CP2	2.0	0.074
RP3	2.8	0.107
CP3	3.0	0.112
RP4	4.2	0.164
RP5	5.6	0.185
RP6	7.0	0.245

D.3. Elevators for persons with disabilities (g_3)

Table 21: Reference values and local priorities for representative and central profiles with respect to criterion g_3.

Profile	Reference value	Local priority
RP1	0.0	0.023
CP1	0.0	0.023
RP2	0.6	0.060
CP2	1.0	0.088
RP3	1.2	0.103
RP4	1.8	0.176
CP3	2.0	0.176
RP5	2.4	0.176
RP6	3.0	0.176

D.4. Stairlifts or lifting platforms (g_4)

Table 22: Reference values and local priorities for representative and central profiles with respect to criterion g_4.

Profile	Reference value	Local priority
RP1	0.0	0.027
CP1	0.0	0.026
RP2	0.4	0.042
RP3	0.8	0.075
CP2	1.0	0.096
RP4	1.2	0.160
RP5	1.6	0.180
CP3	2.0	0.180
RP6	2.0	0.213

D.5. Accessible restrooms for persons with disabilities (g_5)

Table 23: Reference values and local priorities for representative and central profiles with respect to criterion g_5.

Profile	**Reference value**	**Local priority**
RP1	0.0	0.023
CP1	1.0	0.031
RP2	1.8	0.053
CP2	3.0	0.098
RP3	3.6	0.098
CP3	4.0	0.098
RP4	5.4	0.176
RP5	7.2	0.190
RP6	9.0	0.234

D.6. Accessible internal pathways (g_6)

Table 24: Reference values and local priorities for representative and central profiles with respect to criterion g_6.

Profile	**Reference value**	**Local priority**
RP1	0.0	0.027
CP1	1.0	0.039
RP2	2.2	0.058
CP2	3.0	0.076
RP3	4.4	0.097
CP3	5.0	0.118
RP4	6.6	0.156
RP5	8.8	0.206
RP6	11.0	0.222

D.7. Accessible external pathways (g_7)

Table 25: Reference values and local priorities for representative and central profiles with respect to criterion g_7.

Profile	**Reference value**	**Local priority**
RP1	0.0	0.026
CP1	1.0	0.034
RP2	1.6	0.049
CP2	2.0	0.062
RP3	3.2	0.123
CP3	4.0	0.123
RP4	4.8	0.133
RP5	6.4	0.221
RP6	8.0	0.227

E. Local Priorities of the Alternatives

Table 26: Local priorities of the alternatives.

Alternative (a_i)	g_1	g_2	g_3	g_4	g_5	g_6	g_7
a_1	0.032	0.023	0.088	0.027	0.031	0.039	0.034
a_2	0.032	0.023	0.023	0.027	0.031	0.039	0.034
a_3	0.071	0.023	0.023	0.027	0.031	0.039	0.062
a_4	0.071	0.023	0.023	0.027	0.031	0.039	0.062
a_5	0.071	0.023	0.023	0.027	0.031	0.039	0.062
a_6	0.032	0.023	0.023	0.027	0.031	0.039	0.062
a_7	0.071	0.023	0.023	0.027	0.031	0.039	0.062
a_8	0.071	0.023	0.023	0.027	0.031	0.039	0.062
a_9	0.032	0.023	0.023	0.027	0.031	0.039	0.034
a_{10}	0.032	0.023	0.088	0.027	0.031	0.039	0.034
a_{11}	0.137	0.245	0.176	0.027	0.098	0.188	0.199
a_{12}	0.137	0.202	0.023	0.213	0.098	0.027	0.062
a_{13}	0.071	0.155	0.176	0.027	0.210	0.091	0.062
a_{14}	0.032	0.037	0.176	0.096	0.060	0.222	0.113
a_{15}	0.071	0.023	0.023	0.027	0.098	0.055	0.062
a_{16}	0.032	0.037	0.088	0.027	0.098	0.091	0.034
a_{17}	0.032	0.037	0.023	0.027	0.060	0.039	0.034
a_{18}	0.032	0.037	0.088	0.027	0.153	0.142	0.034
a_{19}	0.024	0.112	0.023	0.027	0.023	0.027	0.026
a_{20}	0.032	0.023	0.023	0.027	0.023	0.027	0.026
a_{21}	0.238	0.112	0.088	0.096	0.060	0.091	0.034
a_{22}	0.071	0.037	0.088	0.096	0.031	0.039	0.034
a_{23}	0.032	0.037	0.088	0.096	0.031	0.039	0.034
a_{24}	0.024	0.155	0.088	0.027	0.060	0.039	0.034
a_{25}	0.032	0.202	0.023	0.027	0.031	0.039	0.034
a_{26}	0.032	0.112	0.023	0.096	0.031	0.039	0.034
a_{27}	0.071	0.112	0.023	0.027	0.098	0.055	0.062
a_{28}	0.032	0.202	0.088	0.027	0.060	0.188	0.034
a_{29}	0.032	0.023	0.023	0.027	0.098	0.091	0.034
a_{30}	0.032	0.037	0.088	0.027	0.060	0.076	0.034
a_{31}	0.024	0.037	0.023	0.027	0.023	0.039	0.026
a_{32}	0.024	0.023	0.023	0.027	0.023	0.055	0.026
a_{33}	0.071	0.074	0.088	0.027	0.031	0.055	0.113
a_{34}	0.071	0.074	0.088	0.027	0.023	0.055	0.062
a_{35}	0.071	0.023	0.023	0.027	0.023	0.039	0.062
a_{36}	0.032	0.023	0.023	0.027	0.031	0.027	0.026
a_{37}	0.024	0.023	0.023	0.027	0.031	0.027	0.026
a_{38}	0.032	0.023	0.023	0.027	0.031	0.027	0.026
a_{39}	0.024	0.037	0.088	0.027	0.060	0.027	0.026
a_{40}	0.024	0.023	0.023	0.027	0.031	0.027	0.026
a_{41}	0.032	0.023	0.023	0.027	0.031	0.027	0.026
a_{42}	0.024	0.023	0.023	0.027	0.031	0.027	0.026
a_{43}	0.024	0.023	0.023	0.027	0.031	0.027	0.026
a_{44}	0.024	0.155	0.176	0.096	0.098	0.076	0.034
a_{45}	0.032	0.112	0.088	0.096	0.098	0.055	0.034
a_{46}	0.024	0.074	0.088	0.027	0.098	0.118	0.062
a_{47}	0.024	0.074	0.023	0.027	0.153	0.091	0.113
a_{48}	0.024	0.023	0.023	0.027	0.098	0.055	0.062
a_{49}	0.032	0.074	0.023	0.027	0.098	0.055	0.062
a_{50}	0.032	0.074	0.023	0.027	0.098	0.091	0.113
a_{51}	0.024	0.074	0.023	0.027	0.098	0.091	0.123
a_{52}	0.024	0.037	0.023	0.027	0.098	0.055	0.062

Alternative (a_i)	g_1	g_2	g_3	g_4	g_5	g_6	g_7
a_{53}	0.032	0.074	0.023	0.027	0.031	0.076	0.113
a_{54}	0.024	0.074	0.023	0.027	0.031	0.055	0.026
a_{55}	0.024	0.023	0.023	0.027	0.031	0.055	0.062
a_{56}	0.024	0.037	0.023	0.027	0.060	0.027	0.034
a_{57}	0.024	0.037	0.023	0.027	0.031	0.027	0.034
a_{58}	0.024	0.037	0.023	0.096	0.031	0.027	0.026
a_{59}	0.024	0.037	0.023	0.027	0.031	0.027	0.034
a_{60}	0.071	0.023	0.023	0.096	0.031	0.039	0.062
a_{61}	0.032	0.074	0.023	0.027	0.031	0.039	0.227
a_{62}	0.071	0.037	0.023	0.027	0.031	0.165	0.062
a_{63}	0.024	0.023	0.023	0.027	0.031	0.076	0.113
a_{64}	0.137	0.037	0.176	0.027	0.060	0.039	0.034
a_{65}	0.071	0.023	0.088	0.027	0.060	0.027	0.113
a_{66}	0.024	0.023	0.023	0.027	0.060	0.039	0.227
a_{67}	0.024	0.037	0.023	0.027	0.060	0.039	0.113
a_{68}	0.024	0.037	0.088	0.027	0.098	0.039	0.062
a_{69}	0.032	0.037	0.176	0.027	0.060	0.039	0.062
a_{70}	0.032	0.037	0.088	0.027	0.031	0.039	0.113
a_{71}	0.071	0.074	0.088	0.096	0.060	0.076	0.034
a_{72}	0.071	0.037	0.088	0.027	0.098	0.055	0.034
a_{73}	0.071	0.037	0.088	0.096	0.031	0.091	0.034
a_{74}	0.032	0.023	0.088	0.027	0.098	0.091	0.034
a_{75}	0.200	0.176	0.088	0.096	0.188	0.039	0.123
a_{76}	0.032	0.037	0.088	0.027	0.098	0.055	0.034
a_{77}	0.088	0.037	0.088	0.027	0.060	0.055	0.034
a_{78}	0.032	0.023	0.088	0.213	0.060	0.076	0.026
a_{79}	0.151	0.037	0.088	0.027	0.153	0.091	0.034
a_{80}	0.032	0.112	0.176	0.027	0.031	0.039	0.034
a_{81}	0.032	0.037	0.023	0.027	0.031	0.039	0.034
a_{82}	0.032	0.037	0.088	0.027	0.031	0.039	0.026
a_{83}	0.032	0.074	0.088	0.027	0.098	0.076	0.026
a_{84}	0.032	0.074	0.023	0.096	0.031	0.076	0.026
a_{85}	0.024	0.074	0.176	0.027	0.153	0.165	0.113
a_{86}	0.032	0.112	0.088	0.096	0.098	0.076	0.034
a_{87}	0.032	0.037	0.088	0.096	0.060	0.055	0.034
a_{88}	0.032	0.112	0.088	0.027	0.098	0.055	0.034
a_{89}	0.071	0.074	0.088	0.096	0.060	0.039	0.034
a_{90}	0.071	0.074	0.176	0.027	0.023	0.039	0.034
a_{91}	0.032	0.023	0.023	0.027	0.023	0.039	0.034
a_{92}	0.071	0.037	0.023	0.027	0.031	0.039	0.034
a_{93}	0.032	0.023	0.023	0.027	0.031	0.039	0.034
a_{94}	0.071	0.023	0.023	0.027	0.031	0.039	0.034
a_{95}	0.032	0.037	0.023	0.027	0.031	0.039	0.034
a_{96}	0.024	0.023	0.023	0.096	0.031	0.027	0.034
a_{97}	0.032	0.037	0.023	0.027	0.031	0.039	0.034
a_{98}	0.032	0.023	0.023	0.027	0.031	0.039	0.026
a_{99}	0.024	0.037	0.088	0.027	0.031	0.076	0.034
a_{100}	0.024	0.023	0.023	0.027	0.031	0.027	0.034
a_{101}	0.024	0.023	0.023	0.027	0.031	0.039	0.026
a_{102}	0.024	0.037	0.088	0.027	0.060	0.055	0.034
a_{103}	0.024	0.023	0.023	0.027	0.060	0.039	0.034
a_{104}	0.200	0.074	0.088	0.027	0.023	0.039	0.026
a_{105}	0.151	0.074	0.088	0.027	0.031	0.027	0.026
a_{106}	0.088	0.023	0.023	0.027	0.023	0.039	0.026
a_{107}	0.151	0.112	0.176	0.027	0.210	0.039	0.123
a_{108}	0.032	0.155	0.176	0.027	0.234	0.039	0.113
a_{109}	0.071	0.074	0.088	0.027	0.060	0.055	0.062
a_{110}	0.071	0.023	0.023	0.027	0.031	0.039	0.062

Alternative (a_i)	g_1	g_2	g_3	g_4	g_5	g_6	g_7
a_{111}	0.071	0.023	0.023	0.027	0.031	0.039	0.062
a_{112}	0.032	0.074	0.088	0.027	0.098	0.076	0.062
a_{113}	0.238	0.023	0.023	0.027	0.031	0.039	0.227
a_{114}	0.032	0.037	0.023	0.027	0.031	0.039	0.034
a_{115}	0.032	0.074	0.023	0.027	0.031	0.039	0.034
a_{116}	0.032	0.037	0.088	0.027	0.031	0.039	0.034
a_{117}	0.032	0.023	0.023	0.027	0.031	0.039	0.034
a_{118}	0.032	0.037	0.023	0.027	0.031	0.039	0.034
a_{119}	0.071	0.023	0.023	0.027	0.023	0.039	0.062
a_{120}	0.032	0.037	0.088	0.027	0.031	0.039	0.034
a_{121}	0.032	0.037	0.088	0.027	0.031	0.039	0.034
a_{122}	0.024	0.037	0.023	0.096	0.031	0.039	0.062
a_{123}	0.024	0.037	0.023	0.027	0.031	0.027	0.062
a_{124}	0.024	0.037	0.023	0.027	0.031	0.027	0.062
a_{125}	0.032	0.176	0.088	0.027	0.098	0.039	0.113
a_{126}	0.032	0.074	0.088	0.027	0.031	0.039	0.113
a_{127}	0.032	0.074	0.088	0.027	0.060	0.039	0.113
a_{128}	0.032	0.037	0.088	0.027	0.031	0.027	0.034
a_{129}	0.071	0.155	0.176	0.213	0.153	0.165	0.144
a_{130}	0.032	0.074	0.088	0.096	0.031	0.039	0.034
a_{131}	0.071	0.245	0.023	0.096	0.098	0.076	0.144

F. Global Priorities of the Alternatives ($P(a_i)$)

Table 27: Global priorities of the alternatives.

Alternative	$P(a_i)$	Alternative	$P(a_i)$	Alternative	$P(a_i)$	Alternative	$P(a_i)$
a_1	0.047	a_{34}	0.063	a_{67}	0.035	a_{100}	0.026
a_2	0.029	a_{35}	0.033	a_{68}	0.055	a_{101}	0.027
a_3	0.034	a_{36}	0.026	a_{69}	0.070	a_{102}	0.053
a_4	0.034	a_{37}	0.025	a_{70}	0.055	a_{103}	0.030
a_5	0.034	a_{38}	0.026	a_{71}	0.073	a_{104}	0.061
a_6	0.031	a_{39}	0.044	a_{72}	0.063	a_{105}	0.055
a_7	0.034	a_{40}	0.025	a_{73}	0.068	a_{106}	0.031
a_8	0.034	a_{41}	0.026	a_{74}	0.062	a_{107}	0.109
a_9	0.029	a_{42}	0.025	a_{75}	0.095	a_{108}	0.092
a_{10}	0.047	a_{43}	0.025	a_{76}	0.057	a_{109}	0.068
a_{11}	0.157	a_{44}	0.089	a_{77}	0.063	a_{110}	0.034
a_{12}	0.047	a_{45}	0.065	a_{78}	0.061	a_{111}	0.034
a_{13}	0.113	a_{46}	0.073	a_{79}	0.080	a_{112}	0.068
a_{14}	0.115	a_{47}	0.047	a_{80}	0.067	a_{113}	0.045
a_{15}	0.040	a_{48}	0.035	a_{81}	0.030	a_{114}	0.030
a_{16}	0.064	a_{49}	0.039	a_{82}	0.047	a_{115}	0.031
a_{17}	0.032	a_{50}	0.047	a_{83}	0.063	a_{116}	0.049
a_{18}	0.073	a_{51}	0.046	a_{84}	0.037	a_{117}	0.029
a_{19}	0.027	a_{52}	0.036	a_{85}	0.111	a_{118}	0.030
a_{20}	0.025	a_{53}	0.041	a_{86}	0.070	a_{119}	0.033
a_{21}	0.090	a_{54}	0.032	a_{87}	0.058	a_{120}	0.049
a_{22}	0.057	a_{55}	0.032	a_{88}	0.062	a_{121}	0.049
a_{23}	0.051	a_{56}	0.028	a_{89}	0.063	a_{122}	0.033
a_{24}	0.055	a_{57}	0.027	a_{90}	0.071	a_{123}	0.028
a_{25}	0.034	a_{58}	0.027	a_{91}	0.028	a_{124}	0.028
a_{26}	0.034	a_{59}	0.027	a_{92}	0.033	a_{125}	0.067
a_{27}	0.045	a_{60}	0.036	a_{93}	0.029	a_{126}	0.058
a_{28}	0.081	a_{61}	0.038	a_{94}	0.032	a_{127}	0.061
a_{29}	0.038	a_{62}	0.048	a_{95}	0.030	a_{128}	0.045
a_{30}	0.059	a_{63}	0.037	a_{96}	0.027	a_{129}	0.150
a_{31}	0.028	a_{64}	0.079	a_{97}	0.030	a_{130}	0.054
a_{32}	0.029	a_{65}	0.057	a_{98}	0.028	a_{131}	0.059
a_{33}	0.069	a_{66}	0.036	a_{99}	0.054		

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