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Multi-Criteria Decision Making and Artificial Intelligence for the School System: A Systematic Literature Review

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Abstract

The growing availability of data in school systems has sparked a broad academic debate [Garzón et al., 2025, Melo-López et al., 2025] on the use of advanced quantitative tools to support decision-making processes related to the planning and management of school infrastructure. This paper fits within this analytical framework, exploring, in particular, the role of Multi-Criteria Decision Making (MCDM) models and Artificial Intelligence (AI) in school systems, particularly whether these tools are used to assess the accessibility of school buildings. To this end, this paper presents a systematic review of the literature on the use of MCDM methods and AI. The analysis was conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [Moher et al., 2015], analyzing 416 scientific contributions in detail. The main contribution of this study is to analyze the current scientific landscape on the use of quantitative tools

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(with a focus on MCDM and AI tools) in the school system, with the aim of highlighting the main current, emerging, and potential research areas. The results show that MCDM methods and AI techniques have numerous applications in the education sector; for example, they are used to assess sustainability [Kabassi, 2021], and in information and communication technologies (ICT) [Voultsiou and Moussiades, 2025]. However, the use of MCDM and AI tools in assessing school accessibility is still limited. This latter application area may represent a potential new research field in which the use of combined tools such as MCDM methods and AI techniques can be used to classify schools based on their level of accessibility, thus further enriching the academic debate on school systems.

Keywords: Multi-criteria decision making, AI, Decision Analysis, accessibility, school. [1]

1 Introduction

In recent years, the growing availability of data within school systems [Schildkamp, 2019] has fueled a broad academic debate on the use of advanced quantitative tools to support decision-making processes related to the planning and management of school infrastructure [Barrett et al., 2019]. In this context, the topic of school building accessibility has assumed an increasingly important role in the issue of school inclusion. School accessibility represents a key dimension of modern education policies and a pillar of the 2030 Agenda for Sustainable Development [Weiland et al., 2021, UNESCO, 2020]. However, its assessment is particularly complex because it involves the integration of heterogeneous criteria and the management of a plurality of actions, including, for example, the removal of architectural barriers [Pivik, 2010], which requires extensive timescales, planning, and structural interventions that require significant financial resources [Forman et al., 2009]. Analyzing school accessibility therefore requires tools capable of combining different, often conflicting, perspectives [Cinelli et al., 2014], and processing large amounts of data from diverse fields to provide a systemic and accurate view of the phenomenon. This aspect is not only attributable to school accessibility but also to other key aspects of the school system, such as building safety and sustainability [Marinković et al., 2024], energy efficiency [Ashrafian et al., 2023], the quality of learning environments [Barrett et al., 2015], and so on. In this sense, schools are increasingly using quantitative tools that allow them to analyze decision-making problems characterized by high dimensionality (in terms of the number of alternatives and decision criteria) [Ishizaka and Nemery, 2013],

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leveraging tools related to Multi-Criteria Decision Making (MCDM) [Greco et al., 2016] and AI [Russell and Norvig, 2021]. It is well established in the literature that these tools are widely used to analyze several decision-making problems, in a variety of application fields such as manufacturing [Fattoruso et al., 2022], public tender analysis [Marcarelli and Squillante, 2020], behavioral finance [Martino et al., 2023, Ventre et al., 2024, Cruz Rambaud and González Fernández, 2018], healthcare [Esteva et al., 2019], transportation [Iyer et al., 2021] and energy management [Safari et al., 2024]. This work aims to explore how and in which contexts related to the school system, MCDM methods and AI techniques have been used, as well as to explore whether and how these tools have been used in an integrated manner. One of the focuses of this work, in the context of the use of quantitative tools in school systems, is school accessibility.

We note that the topic of school accessibility can also be considered within the Quadruple Helix Model [Carayannis and Campbell, 2010], which highlights the existing collaboration between universities, industry, government, and civil society to develop inclusive and sustainable solutions. In this model, universities have the role of providing the scientific and methodological knowledge and expertise that can be used to make school institutions more inclusive; the government can outline policies to be adopted and the available financial resources; industry can contribute by supporting universities and government; and civil society, particularly families and students, can provide concrete feedback on the current situation of school institutions and the needs that need to be addressed. This framework allows us to envision the development of tools for assessing the accessibility of schools that are not only scientifically and methodologically sound, but also effectively respond to societal needs by actively involving all stakeholders involved in decision-making processes at various levels.

The aim of this paper is to define, through a systematic literature review, the state of the art of existing literature in the school system, providing an overview of the main MCDM and AI tools used in several areas of application in the school context. This analysis aims to provide an overview that allows us to identify the main lines of research already developed by scholars but also to identify potential new areas of research that could be initiated. Studies as systematic literature review [Fattoruso, 2022, Yüksel et al., 2023, Sahoo and Goswami, 2023, Tahiru, 2021, Shams et al., 2024], allow us to understand how quantitative tools can contribute to strategic decisions by the various stakeholders involved in decision-making processes in different fields of application.

The paper is organized as follows: Section 2 describes the search strategy, the material, and the eligibility criteria; Section 3 reports the main results on the relevant scientific landscape and subsequent analysis of the main contents; Section 4 concludes the paper.

2 Search Strategy, Material and Eligibility Criteria

This systematic literature review aims to provide an overview of the use of multi-criteria decision-making methods and AI in the evaluation of the accessibility of school institutions, both individually and in combination. An exploratory approach will be applied to understand the state of the art and identify potential future directions. In selecting documents we used the PRISMA (Preferred Reporting Items for Systematic Review and Meta-Analyses) guidelines [Moher et al., 2015]. The PRISMA guidelines aim to ensure that the process of systematic literature review is carried out in a transparent manner [Moher et al., 2015, Liberati et al., 2009].

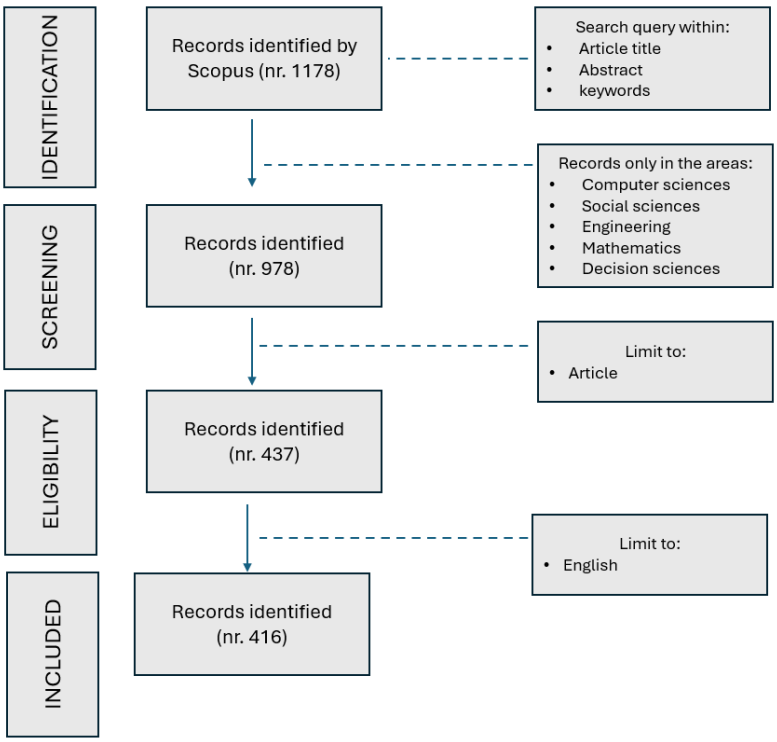

Figure 1: Stages of the systematic literature review process (database search, primary screening, and secondary screening) following PRISMA 2020 extended flow diagram (Preferred Reporting Items for Systematic Review and Meta-Analyses) flowchart. Source: our elaboration.

Academic articles from the Scopus database were analyzed, considering only English-language publications, with no temporal restrictions. A total of 416 relevant articles were found, meeting the criteria specified in the search string (“multi-criteria decision making” OR mcdm OR ”multi-criteria analysis” OR ”multi-

attribute decision making" OR madm OR AHP OR "analytic hierarchy process" OR "artificial intelligence" OR "ai") AND (access* OR inclus* OR "universal design" OR "barrier-free" OR "buildings") AND (school* OR "educational institution*" OR "learning environment*" OR "educational facilit*"). The search string is intentionally broad since in the first instance we tried to narrow the search by looking for applications of multi-criteria methods and AI to the accessibility of school institutions but the number of publications was null or irrelevant. For this reason we opted for a broader search that also included similar applications. The search was further refined using the keywords Artificial Intelligence, Machine Learning, Deep Learning, Decision Making, AI, Decision Support Systems, School, Machine-learning, Inclusive Education, AHP, Schools, Accessibility, Inclusion, Multicriteria Analysis, Analytical Hierarchy Process, Analytic Hierarchy Process, Natural Languages, Educational Institutions.

The identified articles were analyzed for the purpose of the ongoing literature review [Van Eck and Waltman, 2010, for History and Media, 2024]. The collected data were exported in CSV format for analysis using the VOSviewer software, to examine the relationships among article keywords, and in RIS format for further analysis using Zotero. During the export process, the following information was included: Citation information (Author(s), Document title, Year, EID, Source title, Volume, Issues, Pages, Citation count, Source and document type, Publication stage, DOI, Open access) and Abstract and keywords (Abstract, Author keywords, Indexed keywords).

3 Results

This section aims to provide a detailed and critical analysis of the current state of the literature. In the Sub-section 3.2 we provide an analysis of the current scientific landscape, highlighting the relationships between the keywords considered, identifying those that have been the main focus of the authors and examining how the scientific literature related to the research topic has evolved over time. In the Sub-section 3.3 is proposed an analysis on the main contributions in the school field to evaluate the accessibility of school institutions using multi-criteria decision-making methods and AI. More generally, an overview of the use of such methods in the education sector is provided by identifying unexplored and potential application areas.

3.1 Review Process and Selection Criteria

The review process was conducted in line with the PRISMA guidelines, which allowed us to perform a rigorous systematic literature review. The literature search

was conducted using the Scopus database, which was chosen because it represents one of the main sources of scientific literature. Initially, keywords were entered into the search string and combined with Boolean operators (AND, OR) to find scientific articles related to the use of multi-criteria methods and AI in the educational setting. Subsequently, the articles were screened, considering only those in the areas of interest to our research which are computer sciences, social sciences, engineering, mathematics and decision sciences. Only articles in this type of publication are subject to methodological review, ensuring their scientific validity. Furthermore, only articles written in English were selected. Articles not related to the educational setting or concerning areas that do not concern the areas of interest we indicated were excluded. Finally, after selecting the articles, they were exported from Scopus and imported into VOSviewer. Using this software, we performed a quantitative analysis of the bibliography, identifying the main nodes and the relationships between keywords.

3.2 Current Scientific Landscape

In order to analyze the current scientific landscape, we used the VOSviewer software.
After processing the data imported from the Scopus database, the VOSviewer application allowed us to generate a map of the relationships between the keywords within the selected articles. A total of 3,519 keywords were selected. Of these, 178 met the threshold of at least 5 occurrences to be included in the visualization. Among these keywords, the following were selected: *artificial intelligence, machine learning, education, deep learning, school, decision making, learning environment, generative AI, higher education, convolutional neural networks, natural language processing, decision support systems, high school, quantitative analysis, inclusive education, AI technologies, accessibility, special education, school institutions, quality of life, AI tools, AI in education, secondary schools, AHP, analytic hierarchy process, inclusion, AI learning, multi-criteria analysis, sustainability*. The result is presented in Figure 2, which illustrates the scientific landscape of the keywords.

The cluster function is essential. The VOSviewer software uses a clustering algorithm to divide keywords into thematic groups. Keywords are placed into thematic groups based on co-occurrence, that is, how many times they appear in the same article. The logical connection between documents and keywords is precisely these co-occurrences, so if two keywords appear frequently within the article, the software connects them with a line. The distances between words on the map reflect the frequency of co-occurrences, so the closer the words, the more frequently they co-occur. Furthermore, the color of the clusters serves to visually distinguish the various groupings. It is very important to correctly interpret the

map generated by the VOSviewer software because this allows us to analyze the research lines and any connections.

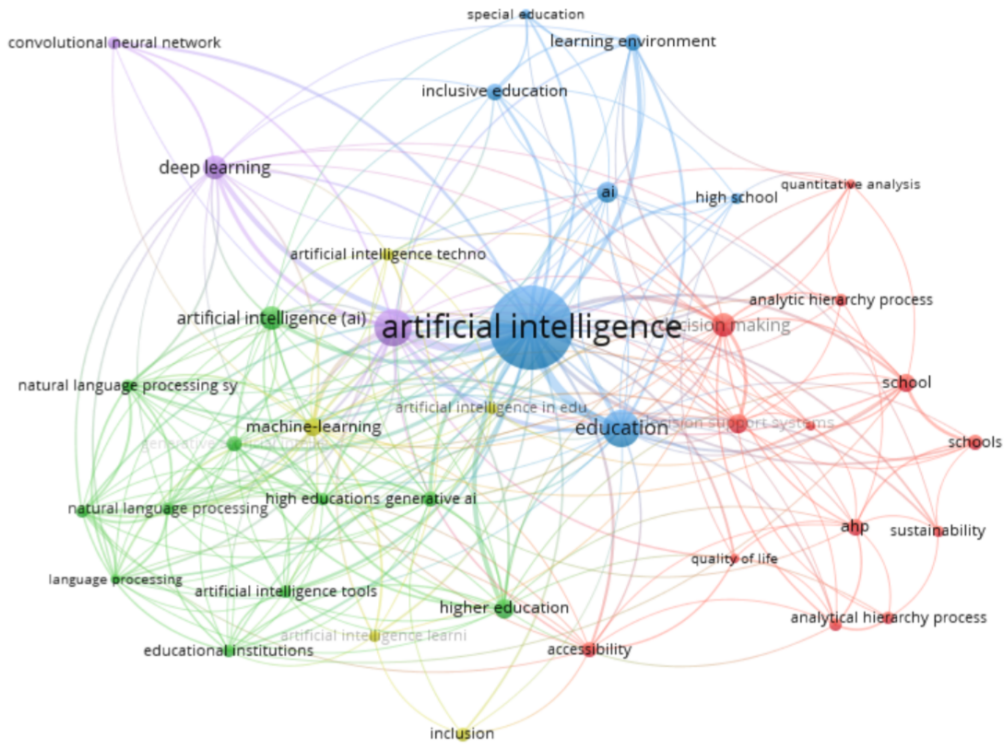

Figure 2: Scientific landscape of AI and MCDM in the school system obtained by Software VOSviewer.

As shown in the Figure 2, it is possible to identify five main clusters in which the words are classified (Cluster 1 - red, Cluster 2 - green, Cluster 3 - blue, Cluster 4 - yellow and Cluster 5 - purple). The Table 1 presents the classification of the keywords by cluster.

Table 1: Classification of keywords in five thematic clusters obtained through VOSviewer.

Cluster 1 — Red	**Cluster 2 — Green**	**Cluster 3 — Blue**	**Cluster 4 — Yellow**	**Cluster 5 — Purple**
accessibility	artificial intelligence (ai)	ai	artificial intelligence in education	convolutional neural networks
AHP	artificial intelligence tools	artificial intelligence	artificial intelligence learning	deep learning
analytic hierarchy process	educational institutions	education	artificial intelligence technologies	machine learning
analytical hierarchy process	generative ai	high school	inclusion	
decision making	generative artificial intelligence	inclusive education	machine-learning	
decision support systems	high educations	learning environment		
multicriteria analysis	higher education	special education		
quality of life	language processing			
quantitative analysis	natural language processing			
school	natural language processes			
schools	natural languages			
secondary schools				
sustainability				

In particular, analyzing the clusters specifically reported in Table 1 we can observe that:

- Cluster 1 - RED, focuses on multi-criteria decision making methods (MCDM) applied in school contexts. We can observe relationships between the elements of this cluster and artificial intelligence.
- Cluster 2 - GREEN, focuses on various AI technologies (such as natural language processing and generative AI) that have been applied in school settings, but not specifically for assessing the accessibility of school institutions.
- Cluster 3 - BLUE, focuses on school environments and inclusiveness. We also see connections between AI and education in this cluster.
- Cluster 4 - YELLOW, highlights connections between inclusion and AI.
- Cluster 5 - PURPLE, focuses exclusively on AI methods.

From the analysis of the map shown in Figure 2, we observe that the central node of the network is the keyword *"artificial intelligence"*. This represents the largest node, indicating that this keyword appears frequently in the analyzed articles and has a high number of connections with other keywords. In the analysis of the scientific landscape, we notice that there are various connections among the clusters. The themes we are focusing on MCDM, AI and school inclusion are interconnected, although the theme of inclusion appears to be more marginal. It is evident that MCDM methods and AI have been more extensively applied in other school-related areas. Looking at the map, we can observe a cohesive network, with few peripheral nodes and many connections among the keywords. From the analysis of the network, we observe strong interest in the use of AI in the school context [McMahon and Walker, 2019, Lin et al., 2024]. It is appropriate to proceed with the analysis of the Density Visualization map as well that measures the number of published documents and the strength of the relationships between keywords. The density map allows us to observe the keywords in the analyzed literature. The yellow and light green colors indicate the most relevant keywords, while the other colors correspond to lower relevance.

As can be seen in Figure 3, there is a predominance of the keyword *artificial intelligence*, indicating a strong focus. The second keyword highlighted by the density map is *education*.

Clearly, the keyword "artificial intelligence" is by far the most relevant: it is located at the center of the map and is surrounded by a bright yellow cloud. This means it appears very frequently in the analyzed articles and has many connections with other keywords. It is clearly the central thematic core of the network:

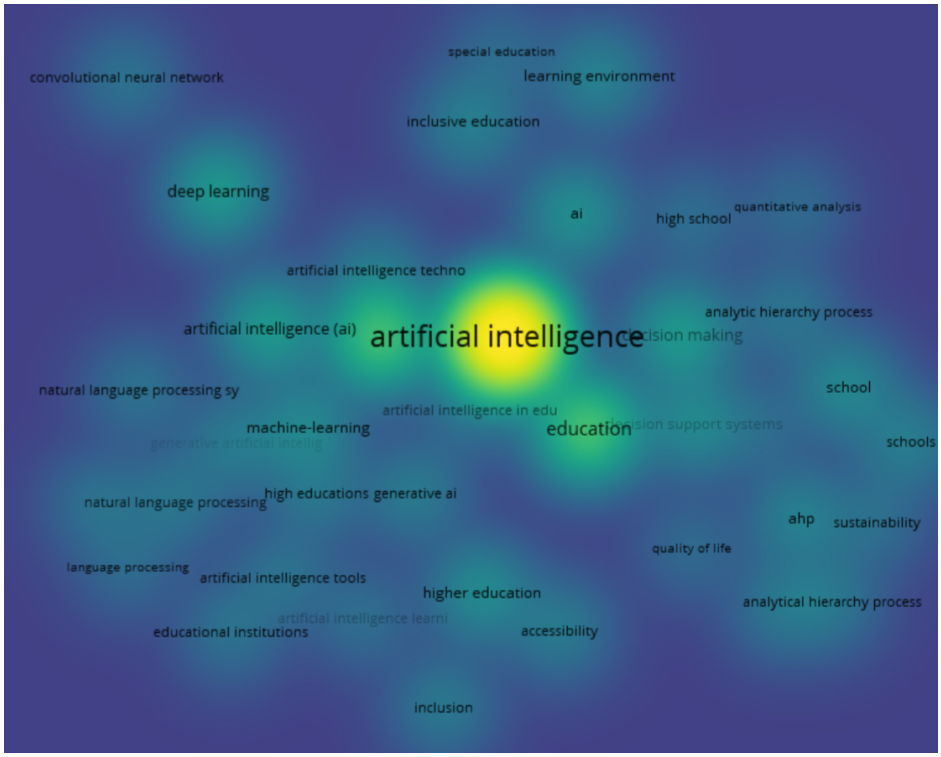

Figure 3: Density Visualization.

its central position and yellow color indicate that it occurs frequently in the documents and is highly interconnected with other terms.

Then we have education and AI, which are also surrounded by a slightly less intense but still significant yellow cloud. This suggests that AI is being used in school contexts.

The keywords machine learning, decision making, natural language processing, and higher education are located in intermediate-density areas, meaning they are fairly relevant, though not as central as those mentioned above.

Keywords such as inclusive education, learning environment, decision support systems, analytic hierarchy process, and sustainability are present with lower intensity. Therefore, they are likely less frequent in the scientific articles being analyzed.

Finally, the keywords neural network, deep learning, language processing, school institutions, inclusion, accessibility, and quality of life are the least relevant, occurring less frequently and showing fewer connections compared to the most prominent keywords. In particular, keywords such as “accessibility” and “inclusion” are low-density, which confirms that the topic of school institution accessibility in relation to AI and MCDM methods is still marginal [Gulzar et al.,

2023, Chang et al., 2013].

In Figure 4, we report the graph represents the Overlay Visualization obtained by VOSviewer.

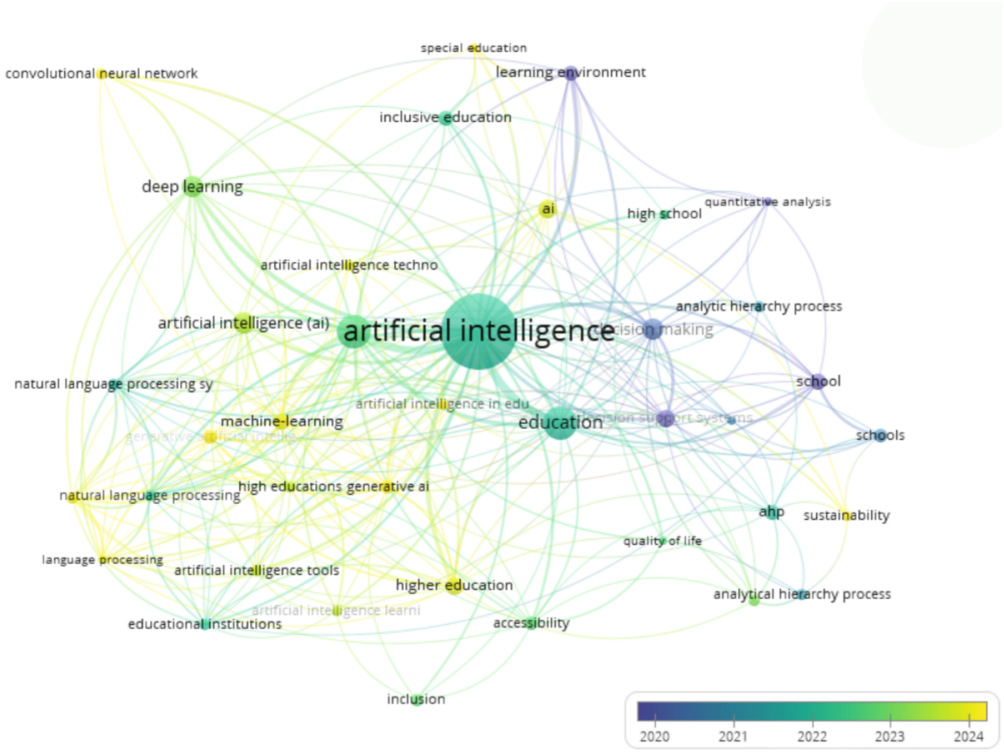

Figure 4: Overlay visualization of the keywords obtained with VOSviewer (2020–2024).

The Overlay Visualization generated by VOSviewer allows us to visualize, through a map, how the scientific literature related to the research topics has evolved over time. In this graph, the colors represent the average publication year of the scientific articles for each keyword. We distinguish three main colors:

- Blue keywords have an average publication year around 2020. Among the blue keywords, we find: decision making, analytic hierarchy process, sustainability, school, quantitative analysis. This is expected, as these are well-established topics in the scientific literature.

- Green keywords are transversal, meaning they have remained consistent across the years. Among the green keywords, we find: education, accessibility, higher education, machine learning, language processing. These are themes that have been addressed continuously over time and are still relevant today.

- Yellow keywords are those that approach 2024, indicating their recent emergence. Among the yellow keywords, we find: AI, natural language processing, artificial intelligence tools, generative AI, deep learning, convolutional neural network. These terms have recently appeared in the scientific landscape, indicating emerging areas of research.

3.3 Content Analysis

In this Section we analyze the scientific articles published in the school field with reference to the use of multi-criteria methods and AI. The focus is represented by the use of these methods individually and combined with each other to evaluate the accessibility of school institutions understood as the absence of architectural barriers that in fact limit or prevent access to people with disabilities. As we said in the section "Materials and methods", 416 articles were selected on Scopus using the keywords. We downloaded these articles in RIS format to analyze them using Zotero software.

At this point we analyzed the main contributions considering four macrogroups that concern the areas of analysis of our interest reported in Table 2.

Table 2: Keyword frequency by thematic category.

Category	**Keyword**	**Nr.**
MCDM methods	Decision Making	52
	AHP	26
	Multicriteria	11
AI	Artificial intelligence	354
	Machine learning	93
	Deep learning	43
Accessibility	Access	310
	Inclus	164
	Inclusion	75
	Accessibility	72
	Building	21
	Barrier free	4
	Universal Design	4
Educational Institutes	School	242
	Education	311

In particular, in the Table 2 we have reported for each keyword that we entered in the Zotero search field how many times it appeared (the frequency). For the MCDM methods category we note that the frequency of the keywords is low;

in fact Decision Making appears 52 times, AHP appears 26 times and Multicriteria only 11 times. As for the AI category we note that the keyword Artificial intelligence appears 354 times, Machine learning 93 times and Deep learning 43 times. This denotes that they represent the focus of the selected articles. The Accessibility category is also very relevant. In fact the keyword Access appears 310 times, Inclus 164, Inclusion 75 and Accessibility 72. We can deduce that the themes of inclusion and accessibility are very present in the articles [Abd El Karim and Awawdeh, 2020, Rogulj and Jajac, 2021]. The terms Universal Design and Barrier free are also present, even if to a lesser extent. Finally we have the School Institutes category which highlights the fact that the applications were made in a school environment. In fact, the terms Education and School are present in most of the articles; this is because our research was oriented precisely towards applications in a school environment. For the analysis of the main contributions we believe it is appropriate to provide an overview of the temporal evolution of the articles published regarding our research (see Figure 5), in order to evaluate the evolution of scientific research.

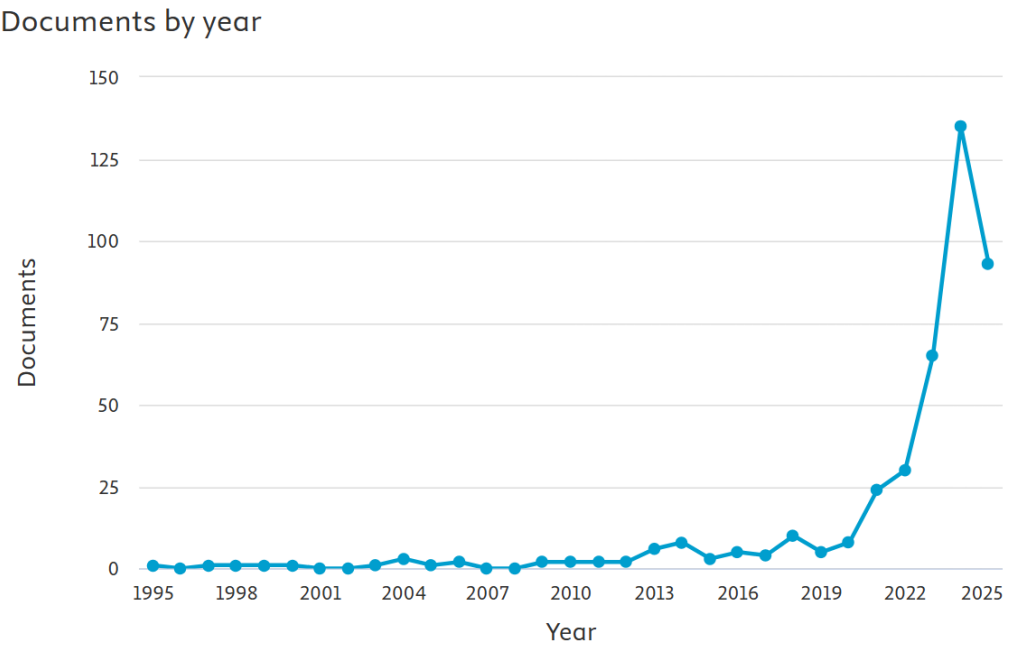

Figure 5: Documents by year. Source: Scopus.

From the analysis of the graph in Figure 5, which represents the trend of articles published over time, we can see that from 1995 to 2016 the publications

related to the object of our research had few publications, demonstrating a low or non-current interest. In recent years, from 2016 to 2020 the number of published articles has gradually grown. In recent years, however, there has been an exponential growth. This is certainly due to the growing interest both at European and International level towards the issues of inclusiveness and accessibility but also to the development of multi-criteria methods and the growing applications of AI.

Analyzing the direct applications of AI on the topic of accessibility of school institutions we notice a notable discrepancy between the large scientific production related to the topic of AI in the school environment and its direct applications on the topic of school accessibility. In fact, by doing a search for the terms artificial intelligence and accessibility we obtain only 5 articles; artificial intelligence and inclusion 7 articles of which only 1 refers to the school environment. Even with the combination artificial intelligence, accessibility and education we do not obtain any results. It is clear that the applications of artificial intelligence to evaluate the accessibility of school institutions must be explored in depth.

Furthermore, analyzing the combinations between the terms multicriteria methods and accessibility of school institutions we note that the scientific applications are even more scarce. In fact, the search for the term multicriteria combined with accessibility provides only one result while the other combinations with inclusion and barrier free do not even produce one result. Even the keyword AHP (Analytic Hierarchy Process) searched in combination with accessibility or with inclusion provides only one result. No results with the combination barrier free. This highlights that multicriteria methods have currently been scarcely used to evaluate the accessibility of school institutions. Finally, we note that the combination of the keywords accessibility, multicriteria and artificial intelligence do not produce any results.

Now we can analyze (Table 3), within the scientific articles we have selected, what have been the main applications of artificial intelligence and multi-criteria methods in the school environment or in relation to issues related to accessibility.

Table 3: Overview of studies applying MCDM and AI methods in education.

Method	**Authors**	**Title**	**Purpose**
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 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 SDGs.*
AHP	Tahura et al. [2025]	Evaluating the online and offline learning effectiveness in Bangladesh using AHP	*To compare online and offline learning effectiveness using AHP.*
AHP	Teoh et al. [2022]	Analysis of ICT Implementation in Teaching and Learning using AHP	*To rank barriers to ICT implementation in rural and urban schools.*
AHP	Abd El Karim and Awawdeh [2020]	Integrating GIS and location-allocation models with MCDA for quality of life in Buraidah	*To assess accessibility to public services (schools, hospitals, etc.) as part of Vision 2030.*
AHP	Naccarella [2003]	Evaluation of the rural South Australian tri-division Adolescent Health Project	*To evaluate health project impact in rural areas on GP-adolescent relationships.*
Fuzzy AHP	Gulzar et al. [2023]	A Fuzzy AHP for Usability Requirements of Online Education Systems	*To evaluate usability of online learning platforms with fuzzy AHP.*
Fuzzy AHP	Chang et al. [2013]	Factors influencing sociability in educational MMORPGs – a fuzzy AHP approach	*To identify and rank sociability factors in educational MMORPGs.*

Fuzzy AHP	Incekara [2021]	Post-COVID-19 ergonomic school furniture design under fuzzy logic	*To design ergonomic furniture based on health, safety, and post-COVID needs.*
PROMETHEE	Rogulj and Jajac [2021]	Achieving a Construction Barrier-Free Environment: Decision Support to Policy Selection	*To support prioritization of accessibility improvements in schools.*
TOPSIS	Kumar and Banerji [2024]	Comparing inclusive education indicators: locomotor vs physical disabilities	*To rank inclusive education indicators based on disability type.*
DEA	Davies and Lewis [2020]	Children as researchers: An Appreciative Inquiry with primary-aged children	*To improve classroom communication using Appreciative Inquiry with students.*
DEA	McMahon and Walker [2019]	Leveraging emerging technology for inclusive education with UDL	*To explore how AI, robotics, and immersive tech support inclusive education.*
Generic AI	McMahon and Walker [2019]	Leveraging emerging technology to design an inclusive future with universal design for learning	*To explore opportunities and challenges from new technologies and propose an inclusive framework for experimentation.*
Automated analysis AI	Acosta-Vargas et al. [2022]	Accessibility Analysis of Worldwide COVID-19-Related Information Portals	*To evaluate accessibility of 199 official COVID-19 information websites related to medical education.*
Qualitative study AI	Castro et al. [2025]	Identifying Rural Elementary Teachers' Perception Challenges and Opportunities in Integrating Artificial Intelligence in Teaching Practices	*To investigate rural teachers' perceptions of using AI in education.*

Geospatial AI	Knoblauch et al. [2025]	Crime-associated inequality in geographical access to education: Insights from the municipality of Rio de Janeiro	*To examine the impact of crime on school access in Rio de Janeiro.*
Generic AI	Lin et al. [2024]	An Exploratory Study on the Efficacy and Inclusivity of AI Technologies in Diverse Learning Environments	*To analyze students' experiences and use of AI tools in education.*
Machine Learning, Deep Learning	Wagan et al. [2023]	Artificial Intelligence-Enabled Game-Based Learning and Quality of Experience: A Novel and Secure Framework (B-AIQoE)	*To propose a blockchain-secured AI-based game learning environment for education.*
Conceptual AI design	Xia et al. [2022]	A self-determination theory (SDT) design approach for inclusive and diverse artificial intelligence (AI) education	*To investigate how SDT-based teacher support and student attributes affect AI learning in schools.*
Generative AI	Jauhiainen and Guerra [2023]	Generative AI and ChatGPT in School Children's Education: Evidence from a School Lesson	*To examine the use of generative AI in primary school education.*
Machine Learning	Ulrich et al. [2024]	SIGNIFY: Leveraging Machine Learning and Gesture Recognition for Sign Language Teaching Through a Serious Game	*To present an ML-based educational tool for teaching sign language through a serious game.*

In the selected articles we can see that multi-criteria methods (MCDM) and AI

are used in the school environment separately. The most relevant applications regarding multi-criteria methods are the Analytic Hierarchy Process (AHP) which has been used [Baba et al., 2024] to evaluate the sustainability of public schools in conflict areas and [Shahraki et al., 2016] to analyze the distribution of school buildings in developing cities. Chan et al. [2023] also use AHP to evaluate the relationship between urban sustainability and quality of education, Tahura et al. [2025] use AHP to compare the effectiveness of online and offline learning. Teoh et al. [2022] studied the barriers to the use of ICT (Information and Communication Technologies) in urban and rural schools, while Abd El Karim and Awawdeh [2020] combined AHP with GIS (Geographic Information System) to evaluate the accessibility of school services in Saudi Arabia. The study by Naccarella [2003] used AHP in the healthcare sector.
Fuzzy AHP [Gulzar et al., 2023] was used to evaluate how the accessibility of online platforms [Chang et al., 2013] can promote socialization in educational role-playing games and [Incekara, 2021] to design ergonomic school furniture post-pandemic. The PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluations) method was used by Rogulj and Jajac [2021] in policies to eliminate architectural barriers in schools. TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) has been applied by Kumar and Banerji [2024] to classify school inclusion indicators according to the type of disability, while Davies and Lewis [2020] use DEA (Data Envelopment Analysis) to improve communication between students in participatory teaching. McMahon and Walker [2019] explored the use of technologies for inclusion purposes. As for AI, McMahon and Walker [2019] proposed an integration of AI, robotics and immersive learning for inclusion purposes, while Acosta-Vargas et al. [2022] evaluated.

4 Conclusion

This work fits within the framework of school systems by investigating the use of advanced quantitative tools to support decision-making processes related to the planning and management of school infrastructure. To do so, this article presents a systematic review of the literature on the use of MCDM methods and AI in the school system, with a focus on their use in assessing the accessibility of school buildings. From this perspective, the goal is to gain a comprehensive overview of the main current, emerging and potential research areas.
The systematic literature review was conducted following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, focusing on 416 scientific contributions. The results of our investigation reveal that the academic debate focuses on the diverse areas of application of MCDM methods

and AI techniques in the school context. For example, to assess the sustainability of public schools in conflict-affected areas [Baba et al., 2024], to study the spatial distribution of school buildings in developing cities [Shahraki et al., 2016], to assess barriers to the use of ICT in rural and urban school contexts [Teoh et al., 2022] and also to measure the accessibility of school services from a geospatial perspective [Abd El Karim and Awawdeh, 2020].

Our analysis also revealed that the use of quantitative tools on issues related to school accessibility is still limited. However, given the relevance of the topic [Talen, 2001, Zhang et al., 2020, UNESCO, 2020], it can be considered that this area could represent a potential new line of research, of great social relevance, in which quantitative tools such as MCDM methods and AI can be used. It should be noted that there is a consolidated literature demonstrating the effectiveness of MCDM and AI tools in supporting decision makers in public and private strategic decisions [Saaty, 2008, Zavadskas et al., 2014].

For example, they could be used to classify schools based on various criteria, such as the presence of ramps, elevators, compliant restrooms, accessible internal routes and so on. The integrated use of AI and multi-criteria methods could also be considered to obtain even more powerful and effective tools [Cinelli et al., 2020].

We also note how the use of these tools and their integration could be incorporated into the Quadruple Helix model, which considers the joint contribution of academia, industry, government, and civil society in evaluating and improving the accessibility of school institutions [Carayannis and Campbell, 2010]. This would allow the definition and use of integrated tools that involve all stakeholders involved in decision-making processes affecting the school system. In line with this perspective, the outcomes of this study may also serve as a valuable reference for stakeholders such as families and local authorities, supporting their efforts to foster inclusive, safe and sustainable school environments.

Declarations

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

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