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Artificial Intelligence (AI) Integration in Urban Decision-Making Processes: Convergence and Divergence with the Multi-Criteria Analysis (MCA)

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Abstract: The dynamics underpinning the urban landscape change are primarily driven by social, economic, and environmental issues. Owing to the population's fluctuating needs, a new and dual perspective of urban space emerges. The Artificial Intelligence (AI) of a territory, or the system of technical diligence associated with the anthropocentric world, makes sense in the context of this temporal mismatch between territorial processes and utilitarian apparatus. This creates cerebral connections between several concurrent decision-making systems, leading to numerous perspectives of the same urban environment, often filtered by the people whose interests direct the information flow till the transformability. In contrast to the conventional methodologies of decision analysis, which are employed to facilitate convenient judgments between alternative options, innovative Artificial Intelligence tools are gaining traction as a means of more effectively evaluating and selecting fast-track solutions. The study's goal is to investigate the cross-functional relationships between Artificial Intelligence (AI) and current decision-making support systems, which are increasingly being used to interpret urban growth and development from a multi-dimensional perspective, such as a multi-criteria one. Individuals in charge of administering and governing a territory will gain from artificial intelligence techniques because they will be able to test resilience and responsibility in decision-making circumstances while also responding fast and spontaneously to community requirements. The study evaluates current grading techniques and recommends areas for future upgrades via the lens of the potentials afforded by AI technology to the establishment of digitization pathways for technological advancements in the urban valuation.

Keywords: AI; MCDA; urban environment; scoping review

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1. Introduction

People's everyday lives are drastically changed by Artificial Intelligence (AI), which is currently defined as machine intelligence with human-like cognitive abilities [1]. Urban environments have great aspirations for it, but not much is known about how AI especially impacts interurban cohesion and development. AI-powered systems have the potential to help create more efficient procedures, conserving resources while enhancing productivity. AI technology would contribute up to USD 15 billion to the global economy by 2030 [2].

Cities have denser infrastructure networks, greater electrical and internet access, and a huge population of data producers, developers, and users, making them ideal for leveraging this potential. Metropolitan areas will see the most AI-driven innovation. Urban landscapes should be able to enhance and arrange the entire spectrum of services they offer to their residents more transparently by taking use of AI's potential benefits [3]. They will be able to optimize their infrastructure by fitting more sensors in order to generate practical data. Urban planning and taxation processes may become more efficient and evidence-based through the ongoing collection of pertinent information, and the potential for artificial intelligence to improve the comprehensiveness and efficacy of monitoring systems. Additionally, longer infrastructure lifespans may be possible with AI [4]. Applications are already being employed to assist cities in improving the services they offer to citizens. There is a great deal of promise for improving the efficacy and transparency of public involvement using AI-powered solutions. For instance, by grouping and finding all citizen comments on a certain topic, machine learning algorithms are able to categorize them all. This contributes to the creation of a more complete image of the city, and accounting for everyone's input produces results that are more inclusive and well-integrated. Simultaneously, the ability to visualise proposed initiatives and their impacts on many aspects influencing a city would aid in the building of co-creative inhabitant's engagement. This allows the potential of defining multiple realities to be chosen based on how well they meet actual needs [5]. The city government of Hamburg has experimented with AI-enabled public involvement, including imagery. It may identify potential development regions using its location finder tool [6]. Those affected by development projects should be given the chance to engage through direct consultation/support. Some hybrid systems capture data utilising non-digital interfaces, such as mobile phone buttons or voice-to-text, depending on the group's needs. The Digital Principles for Development, notably the one about 'designing with users', provide significant direction in this.

The study of why AI systems make the decisions they do is one of the main areas of investigation. It has been challenging to clearly define in academic papers how a machine learning system learns, reaches conclusions, identifies relevant data, stores that information, and assesses its impact on the system's decision-making. This has led to the emergence of the "black box" dilemma, which brings with it the need to find useful operational strategies to ensure a certain level of transparency and effective communication of results.

We often have limited knowledge of why AI systems make decisions or exhibit specific behaviours. Many machine learning (ML) strategies used to construct these systems are difficult to understand, particularly deep learning neural network approaches, which have become a prominent class of ML algorithms. This ambiguity can undermine users' faith in the system, particularly in situations with serious repercussions, and lead to system rejection. It has also hampered the uncovering of algorithmic biases caused by poorly generated processes that are biased to specific populations.

Therefore, it could be necessary to look into how well-known analytical decision support tools, such hierarchical multi-criteria ones, might be adjusted to the operational stylistics of AI in order to overcome the ambiguity that arises from the usage of AI tools and analysis techniques. Prior to artificial intelligence's inevitable advent and its prospective applications in urban environments, human attentiveness relied on techniques and instruments that could capture a city's multidimensionality. Although multi-criteria and multi-objective analysis have been widely used, are they still relevant and suitable for the demands of the digitalization and AI's intrinsic speed of execution?

It is imperative to rationalize the blind process under the AI mechanism, particularly when it comes to the urban landscape development process, taking the population and potential involvement into account. Rational methods implemented inside the formal framework of the combined assessment methods and approaches related to urban development have to be interfaced to artificial intelligence mechanisms in a multiverse configuration and in a co-creative and shared knowledge crossing point. Investigating novel approaches to digitise decision-making processes and judgment-making mechanisms in the face of various decision-making contexts is imperative. Does artificial intelligence present a chance to digitise the repetitive processes of multi-dimensional assessments when faced with the centralized and multiple application of multi-criteria choice methods/tools?

Based on a scoping review of the sector-scientific literature, which focused on the multi-criteria analysis and AI, respectively, the aim of this work is to identify the main windows of knowledge and the degree to which they overlap within the decision-making processes in urban landscapes. It aims to identify the primary domains of Artificial Intelligence (AI) and multidimensional analysis in connection to urban systems, as well as suggest potential paths of technological and digital renovation of the multi-criteria analysis and evaluation methodologies most commonly used in urban assessments to date. This is to develop novel multidimensional matrix analysis methods integrated with the main AI tools and processes in the optic of the fast digitalization of urban decisions. By analyzing the navigation routes followed in AI and multi-criteria analysis for urban assessments through a scoping review, it is possible to trace paths of conceptual, methodological, and operational integration between what is commonly used in multi-dimensional urban evaluation practices and what AI offers in terms of speed, accuracy of execution, and quality of results by comparing the two fields of investigation.

To substantiate the thematic areas related to AI and multi-criteria analysis for establishing feasible bridges of communication between them to monitor future digitalization-technological value routes, the manuscript is organised as follows: the primary semantic AI domains and multi-dimensional assessment methods related to urban analysis are outlined in Section 2; in Section 3, the knowledge windows related to AI and decision multi-dimensional analysis are performed, with a focus on the connections with the urban decision-making process. The results are discussed in Section 4, and Section 5 outlines the conclusions of the work.

2. Materials and Method

The goal of the work is to develop the cognitive underpinnings necessary to replace the usage of standalone assessment instruments and methodologies with an artificial intelligence-based collateral border. This will assist in defining the parameters for the creation of multidimensional and inter-operational assessment instruments that seek to take into account several evaluation case characteristics in a cooperative way, their connections, and the cumulative, positive-negative effects produced over time. Following this, evidence is provided on the AI operational application navigation routes (Section 2.1) and the principal assessment strategies suitable for capturing the urban dynamics in multi-collateral and -dimensional views (Section 2.2). The depiction of the methodological flow behind AI techniques and instruments, as well as multi-criteria analysis, is intended to emphasize the key qualities of these analysis types. This is also done to identify the essential criteria for the development of MCDA/AI-based methodological and instrumental apparatuses targeted at improving the accuracy and understanding of the results of an ordered assessment process that will give the operator greater trust.

2.1. AI Semantics

Artificial Intelligence (AI) has advanced steadily, enabling intelligent and expert systems to make better decisions more quickly (*Reaction*), with higher quality (*Accuracy*), and with greater creativity (*Originality*).

Reaction. Individuals take their time making decisions because they have demanding jobs that need them to multitask or because approval the decision involves several steps and the participation of other decision-makers, which slows down the process. The productivity and profitability may suffer as a result of these circumstances. Intelligent systems cut down on the amount of time needed for analysis and frequently even decision-making.

Accuracy. The decision-maker deliberates under extreme time restrictions and in high-stress environments frequently. According to psychological research, people's decision-making skills significantly deteriorate when faced with a large number of decisions to make in a short amount of time [7]. Though they are not affected by human variables, AI systems do not display inconsistencies or absorb pressures. However, there is a chance that intelligent systems are biased by design in some circumstances.

Originality. Artificial intelligence can analyze vast amounts of data and information that is helpful for processing the output of decision-making, which may enable managers to make completely different decisions than they have in the past. It can also spot anomalies and inconsistencies in decisions that have already been made. Decision support systems will be able to examine both prior user reactions to similar circumstances in the past and combine historical data with a sophisticated new dataset to produce whole new options for decision-makers. Employees inside the company may become more creative and develop their analytical and decision-making skills with the use of artificial intelligence [8].

These unique characteristics are enhanced by the application of cutting-edge artificial intelligence techniques. An intelligent system that assists or substitutes decision-makers claims to have a better and more objective interpretation of reality and a better representation of uncertainty, as well as an improved codification of knowledge, including tacit knowledge [9]. Additionally, an intuitive human–machine interface enhances the transferability of information [10].

An organization can create expert systems using a range of methods and resources. They are primarily divided between (*i*) simpler mechanisms and (*ii*) more intricate processes (*learning systems*).

(*i*) Simple mechanisms, like rule-based systems, follow predetermined rules established by an expert rather than building their own models.
(*ii*) Conversely, learning systems generate their own models, have an infinite ability to simulate intelligence, and exhibit adaptive intelligence—that is, an intelligence that can both learn new things and change the world by creating new things. However, there are a number of drawbacks to these intricate systems, the most significant being the challenge of deciphering the logic that generated the model and, consequently, the outcome. As a result, consumers are unable to adequately analyse, explain, and comprehend them. This is why learning systems are sometimes referred to as "black boxes", which helps to explain why certain intelligent systems take a while to become market-ready [11].

The review by Tan et al. (2024) in [12] that deals with the deployment of AI in real-world situations may be used to illustrate the operational impacts and limitations of AI tools in real-world urban assessments, strengthening the link between theory and practice.

Artificial intelligence functions in decision-making processes, including those pertaining to urban environments, in accordance with four standard and sequential phases, regardless of the methodological approach of reference [11]:

a. AI has the ability to gather and arrange data from the decision-making sphere of reference. AI operating systems base their development and functioning on the data treated as input information, regardless of the strategy a general operator chooses to use. The correctness of the input data preconditions the quality of the findings obtained, regardless of the type of analysis to be done. The trustworthiness of the data that artificial intelligence systems rely on must be addressed;
b. AI processes the data using suitable models and algorithms to determine relevant relationships between the variables of interest;
c. AI also handles the transfer, representation, and simple replication of the data, suggesting actions based on the problem of decision-making problem to be resolved;
d. finally, AI automatically learns the updated data, adapting processing models to the constantly changing real-world scenario.

Figure 1 illustrates the actions-flow for a hypothetical AI-powered decision-making process that goes through the preceding four stages.

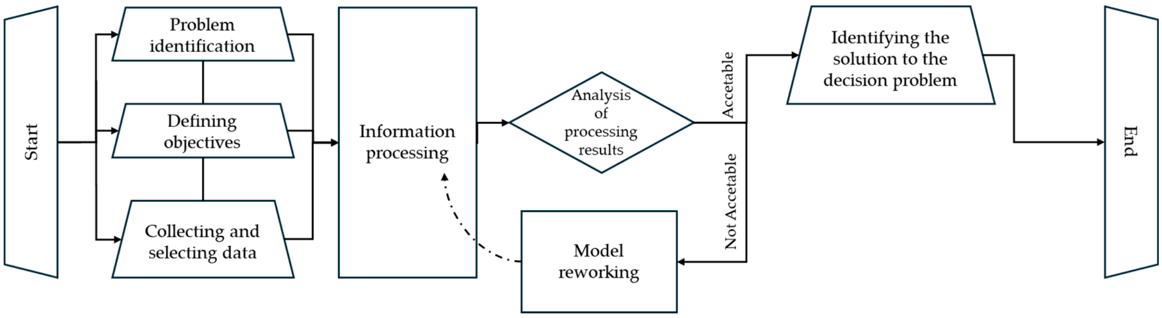

Figure 1. Flow-chart of a decision making process AI-based. *Source*: authors' elaboration.

2.2. Assessments in Urban Environments

Evaluation techniques that aid in decision-making generally fall into the following categories: (i) Mono-criterial approaches enable the financial and/or economic aspect of the initiative to be considered during the assessment phase by using monetary performance indicators that can synthetically include the effects produced on the market in environmental, social, and cultural nature, but obviously only those that can be quantified monetarily with reference to a time period; (ii) Multi-criteria approaches enable the assessment of land transformation initiatives by considering multiple indicators of a financial, environmental, social, and cultural nature during the assessment phase, either contextually or individually, often referring to qualitative–quantitative parameters of a performance type. The particular problem that needs to be solved determines the best evaluation technique. This can involve social (improving citizens' psychophysical well-being), environmental (reducing pollutant concentrations in the atmosphere), or strictly financial issues (finding the best way to allocate available funds among project alternatives) in a single or collaborative manner.

By using mathematical models, assessment may be configured as a pertinent operational support for managing complex decision-making systems to decide which intervention programs or projects to undertake so as to achieve multiple, often conflicting goals. Analytical models can be structured in various ways, such as Goal Programming (GL) or by combining the use of standard multi-criteria analysis tools (e.g., non-exhaustive, AHP, TOPSIS, ELECTRE). These models can be employed to address complex cases where scarce resources and competing interests must be managed optimally. This enables operators—public and private—to create investment plans that guarantee the region's sustainability in terms of the economy, society, and environment. Regarding GL, there has been a resurgence of interest in developing models for operational research, a subfield of applied mathematics that includes goal programming models, to address intricate decision-making processes marked by high levels of uncertainty [13–15]. Specifically, the requirement to find legitimate solutions for competing goals—economic, environmental, and social—has made GL one of the most popular multi-criteria decision-making approaches [16]. Several research have utilized the Geographic Information System (GIS) for environmental purposes, such as enhancing the administration of public green areas and monitoring the natural water quality [17]. Several scholars have examined the advantages of GL in choosing investments within the region, specifically in relation to social welfare, historic center revitalization strategies [18,19], public road funding allocation [20], social housing sustainability initiatives, public building enhancement [21], and urban regeneration interventions [22].

A growing number of advanced models in the reference literature have been used to process information on trends, preferences, tastes, and social and commercial behaviours of the community, as expressed through evaluations on the most popular social networks, such as Facebook, Twitter, Instagram, and others. Social media are open platforms for crowdsourcing [23]. These are sources of heterogeneous data, whose effective interpretation through the use of techniques known as sentiment analysis procedures can produce models with high predictive capacity for shifts in consumer preferences in the wake of abrupt shocks to the economy and social system (consider the ongoing COVID-19 pandemic and the subprime crisis). Modern research on sophisticated analytics methods emphasises how these tools can be used to define resilient urban systems—those that can meet community needs while mitigating the harmful effects of extreme stressors [24,25]. Specifically, 'static' data analysis prevents resilient solutions that ensure cities function even under unusual circumstances [26–29]. This is because "static" data analysis precludes 'dynamic' approaches like advanced analytics.

By means of sophisticated sentiment analysis models that are based on community experiences and preferences, implementation databases are continuously monitored and updated. This allows for the development of a comprehensive model that can interpret the dynamics of urban systems, respond to unexpected economic shocks, and assist in making future sustainable urban planning decisions.

Technique also determines the level of analysis complexity, from the most common multi-criteria methods to the more modern implementation and application research techniques. Operational complexity is the result of taking into account several analytical factors and their interdependencies simultaneously during the evaluation stage. The AI approaches and procedures, in addition to being laborious to set up and necessitating a high processing load, typically involve the use of logical–operational processes. These processes provide the chance to determine the reciprocal relationships between the elements that characterize the phases (planning, design, construction, management, and eventual decommissioning) that make up the individual initiative's life cycle, and to evaluate the suitability of the solutions chosen in light of the sustainability objectives aligned with the environmental and socio-economic context of reference.

By referencing three complementary types of multiverses—(*i*) environmental, (*ii*) social, and (*iii*) economic—AI proceeds to rule the urban landscape across numerous multiverses in accordance with the multidimensional decision-making philosophy of urban dynamism.

(*i*) By organizing methods to support land use and management decision-making, the AI-assessment seeks to improve the relationship between sustainable science from an environmental standpoint and urban policy. The evidence-based ecosystem services assessment can be directed towards the deployment of knowledge-shared forms about natural landscapes and stimulates the acquisition of nature-positive benefits through the use of AI operational approaches.

(*ii*) In terms of social factors, the goal is to create a collection of unique tools and techniques that consider, adjust, and enhance urban community participation and capture their viewpoint through firsthand experience by offering alternative multiverses among to select.

(*iii*) A family of algorithms specifically designed for situations requiring the precise modelling of the spatial representation of data. When making judgements on the sale of a property, for example, explainable artificial intelligence may be used to improve interpretability and explainability by providing information about the economic characteristics of the targeted area.

Based on the examples found in the literature and the domains in which Multi Criteria Decision Analysis (MCDA) techniques and tools are applied, a hierarchical information organization and decision-making process that resembles the workflow shown in Figure 2 below may be identified.

The following steps are included:

a. identifying the evaluation case that needs to be resolved, such as organizing alternatives in a preferred order or identifying the "ideal" solution among them;
b. figuring out the criteria and specification of relevant indicators to express the performance of the alternatives of interest;
c. allocating relevance weights to the performance indicators found in the preceding point;
d. building the decision support model to resolve the evaluative case under examination;
e. analyzing of the outcomes and potential model recalibration in accordance with the choices made by the decision-makers in the multi-criteria decision procedure.

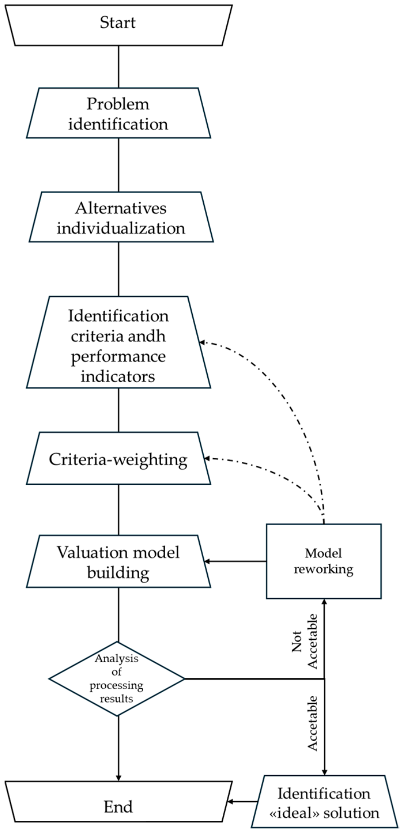

Figure 2. Flow-chart of an MCDA-based decision-making process. *Source*: authors' elaboration.

2.3. Scoping Review on AI for Multidimensional Analysis in Urban-Decision Environment

When integrating artificial intelligence into multidimensional decision-making processes in urbanized contexts, it becomes necessary to find the best tools and techniques for artificial intelligence analysis that have been used in evaluations of these environments thus far, and to compare them with multidimensional analyses that may be a component of the same decision-making process. It entails being able to take use of artificial intelligence's operational potential in terms of speed, quality, and originality in support of assessment techniques that are increasingly commonly employed and already recognise the multifaceted nature of urban environments, including those that use a multicriteria matrix.

A scoping assessment of relevant scientific material is carried out to identify areas of semantic conflict between AI methods/tools and multidimensional analytic methods/tools based on evaluative practices in urban environments. Scoping review techniques, also known as intelligent text analytics, text data mining, or knowledge development text, carry out a process of looking for meaningful information by finding key phrases that summarize the document being analysed. These strategies seek patterns that represent the underlying relationships in data, attempting to derive association and clustering principles. It has lately been employed in literature analysis [30] and is regarded as a method that enhances search strategy by grouping publications that deal with extremely comparable subjects. The approach uses association logic to group papers with related terms. As a consequence, the research will provide a map illustrating clusters of documents categorized by key phrases based on textual content analysis.

In order to determine the theme clusters of interest in this research, a methodological approach was followed that is made up of two stages: (*i*) a scoping review based on three sub-stages (identification, screening, inclusion); (*ii*) Text data clustering.

(*i*) In the current research, the initial collection of contributions of interest (*identification*) was discovered by consulting the Scopus database on 31 August 2024, and formulating two independent research questions, one on AI and one on MCDA in relation to assessments in urban contexts. Scopus allows studies to be confined to a certain time range and/or a defined subject of inquiry.

The *screening* process that followed took into consideration a number of exclusion/inclusion criteria, as:

- the publication period of the last five years (2019–2024);
- the identified works' relevance to the analysis topics as determined by the Subject Area of Interest specification;
- and the availability of the identified articles' texts for free and unrestricted consultation.

Following the screening process, the final list of contributions with content examined is defined (*included*).

Incorporating literature review results into a PRISMA framework entails arranging the aforementioned three processes (identification, screening, and inclusion) [31], as illustrated in the following Section 3.

(*ii*) The VosViewer software 1.6.20 is used for the development, display, and investigation of bibliometric maps. It is applied to analyze various kinds of network data related to bibliometrics, such as citation relationships between articles or journals, researcher cooperation connections, and recurrence relationships between scientific words.

The outcomes of the scoping review that focused on the thematic cluster's portrayal of artificial intelligence and decision multidimensional analysis in urban settings are highlighted in the following Section 3.

3. Results

3.1. Scoping Review

The aim of this study is to explore the connections between the cooperative approaches of Artificial Intelligence (AI) in urban evaluations and the multi-dimensional analyses, specifically multi-criteria and multi-objective (MCDA). A scoping review of the relevant literature in this field is conducted. The outcomes of the three stages—identification, screening, and inclusion—that define the proposed scoping review are depicted in Figure 3 of the PRISMA. The Scopus codes used for review are listed in Table S1 of the Supplemental Materials so that the study may be repeated and this analysis can keep going.

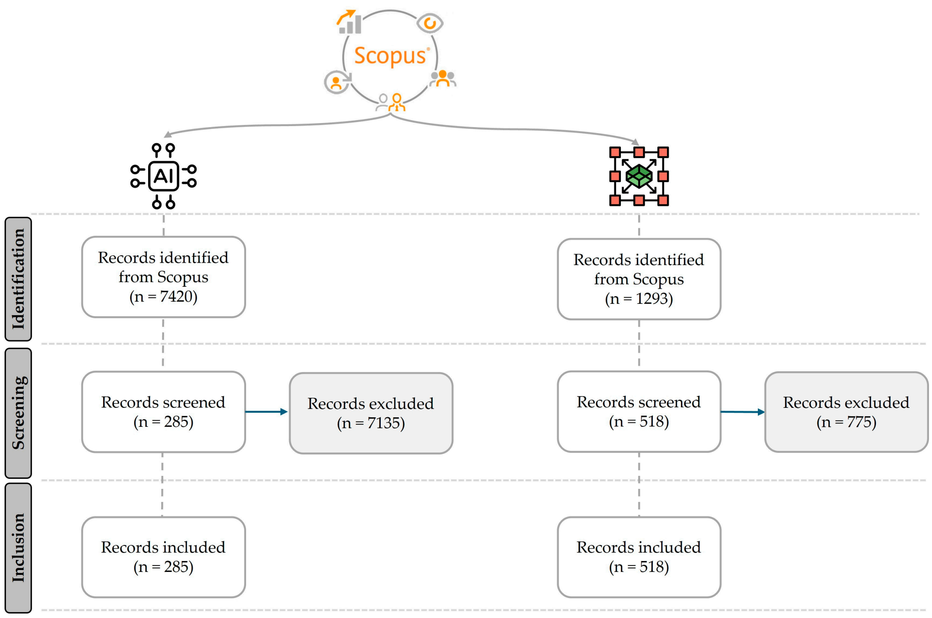

Figure 3. PRISMA flow diagram for literature screening. *Source*: authors' elaboration.

The titles, abstracts, and keywords of the 285 and 518 publications are then reviewed to find suitable and relevant "core-words" that describe the analytical windows for AI and MCDA in urban decision-making environments. The VosViewer program was used to identify the main words and thematic clusters to which they belong. The outcomes of its application are reported in Section 3.2.

3.2. Text-Data Clustering

The VosViewer analysis environment receives the 285 and 518 recognized articles that Scopus selected as the primary research references. This data is introduced as input data and fulfils two functions simultaneously: (*i*) it identifies the terms that appear the most frequently, and (*ii*) it connects the most frequently occurring words in survey articles.

Thematic clusters, in which linked words have a shared topic, are realized through the links between the essential keywords. Figures 4 and 5 depict the networks of keywords traced in the MCDA and AI domains, respectively. Clusters' key words become prominent when they provide clarification on a technique, instrument, application domain, or objective. A Multi-Criteria Decision Analysis (MCDA) and an Artificial Intelligence (AI) field heat map have been implemented to fulfil this interaction, as in Tables 1 and 2.

Table 1. MCDA Heat-map. *Source*: authors' elaboration.

	Method	Tool	Application Scale	Objective
Order preference				
Topsis				
Ideal solution				
Optimization				
Energy				
Feasibility				
Gap				
Scenario				
Project				
Performance				
Framework				
Time				
Application				
Cost				
Ranking				
Maintenance				
Benefit				
Solution				
Effectiveness				
Environmental impact				
Alternative				
Urban environment				
Policy				
Decision				
Perspective				
Sustainability				
Economy				
Stakeholder				
Safety				
Challenge				
Citizen				
Interaction				
Opportunity				
Transportation				
User				
Mobility				
Complexity				
Quality				
Decision making process				
Criteria-weight				

Table 1. *Cont.*

	Method	Tool	Application Scale	Objective
Exposure				
Risk assessment				
Resilience				
Risk				
Urban flooding				
Urbanization				
Damage				
Vulnerability				
Flooding				
Earthquake				
Flood				
Natural hazard				
Natural disaster				
Rural area				
Region				
Area				
Mapping				
Map				
Soil type				
Drainage density				
Rainfall				
Study area				
Soil				
Slope				
Zone				
Land cover				
Land use				
Spatial distribution				
Increase				
AHP				
Fuzzy logic				
Policymaker				

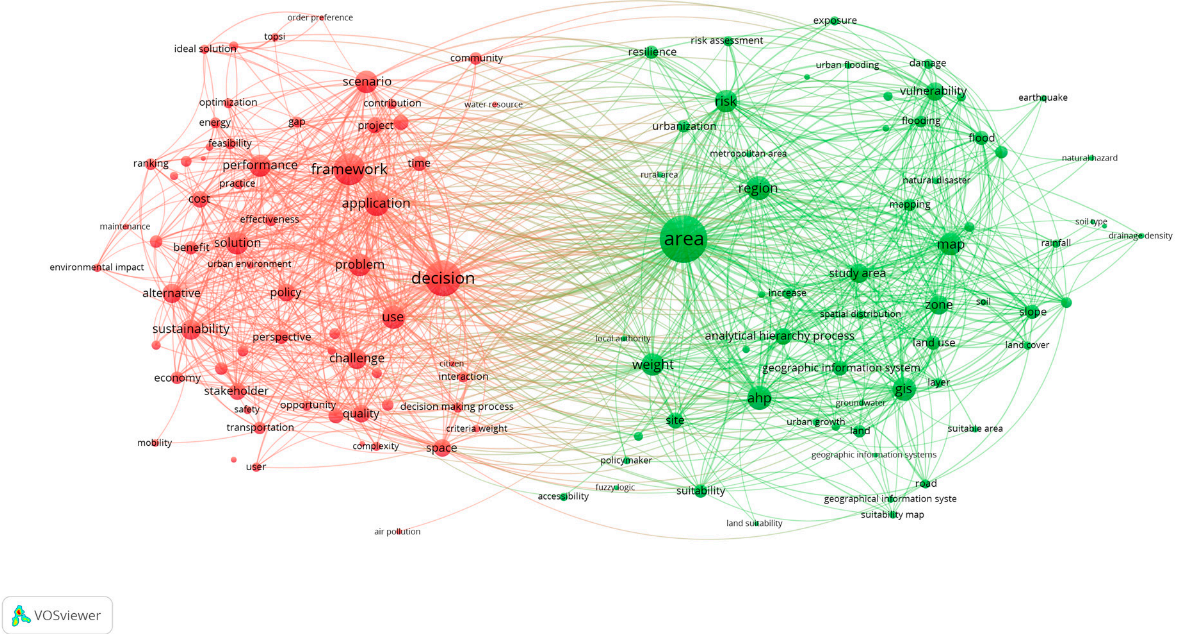

Figure 4. MCDA network map. *Source*: authors' elaboration.

Table 2. AI Heat-map. *Source*: authors' elaboration.

	Method	Tool	Application field	Objective
Accuracy				
Artificial neural network				
Location				
Machine learning				
Classification				
Image				
Improvement				
Comparison				
Road				
Vehicle				
Prediction				
Training				
Deep learning				
Sensor				
Opportunity				
Country				
Urban development				
Factor				
Relantionship				
Influence				
Internet				
Security				
Perspective				
Communication				
Human				
Citizen				
Perception				
Effect				
User				
Society				
Practice				
Innovation				
Autonomy				
Transportation				
Stakeholder				
Building				
Performance				
Urban area				
Place				
Urban environment				
Methodology				
Decision				
Insight				
Case study				
Policymaker				
Decision making				

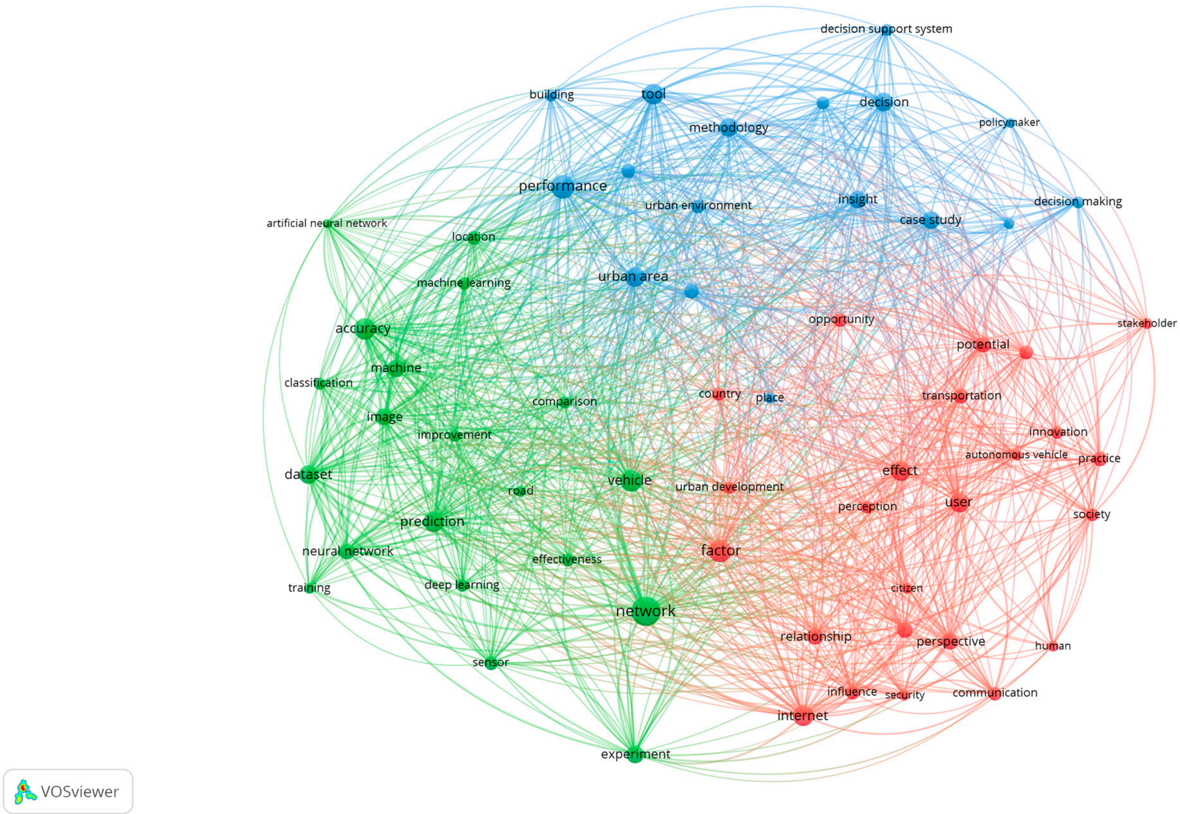

Figure 5. AI network map. *Source*: authors' elaboration.

Figure 4's network shows two distinctly different clusters: the first, represented by red, is more focused on decision-making systems, their objectives, and the optimization logics that are typically employed in the search for ideal solutions; the second, represented by green, is more concerned with characterising the urban area using operational and instrumental methodologies of a multi-criteria matrix, such as risk analysis, fuzzy philosophy, AHP, and the use of geo-referenced systems to foster decision-making in urban areas.

On the other hand, Figure 5's network illustrates the ambiguity surrounding AI in relation to urban decision-making environments by identifying three theme groupings that are not unduly distinct and antagonistic. Based on the examination of AI-related publications for urban decision-making systems, three theme groupings may be distinguished. The first, green-coloured group, which is arranged from left to right, is primarily concerned with the infrastructure of artificial intelligence (AI), both in terms of the functional relationships between various semantic domains and in managing vast amounts of data so that they are appropriately related to one another for the creation of composite indicators or assessment indices. The second, highlighted in red, demonstrates how artificial intelligence (AI) is connected to users' participatory dimension through technologies of perception and information usage in the data environment. The smaller one in blue, on the other hand, is related to AI in line with the methodological problem and how it is structured for measuring the performance level of urban settings at various study sizes (building, urban space, and others).

4. Discussion

In the context of the decision-making process involving AI, it is possible to identify a horizontally rigid structure; yet, a more hierarchical vertical organization is apparent when it comes to MCDA. The two analysis domains were integrated in an attempt to extract comparison components from a methodological and instrumental point of view, with the goal of creating AI+MCDA-based valuative structures.

Figure 6 depicts the results of combining MCDA and AI. The network, which was created by taking into consideration both AI and MCDA simultaneously, suggests putting the two primary clusters—AI and urban area analysis—side by side while taking into account the tools and techniques of multi-criteria analysis. In tiny blue letters, phrases related to the methodological and instrumental tools that may be used for preference judgement expression in sensitivity analysis and the creation of ranking lists of alternatives to be ranked in the quest for the optimal solution are highlighted.

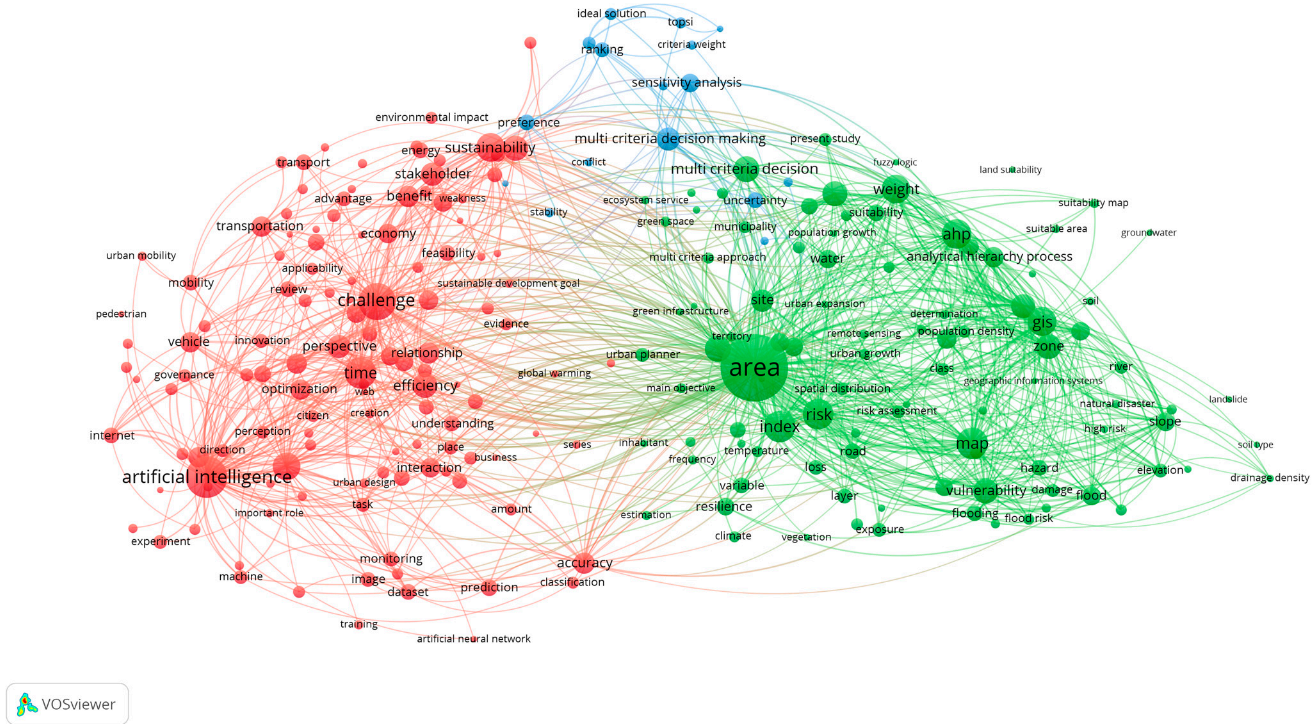

Figure 6. AI–MCDA network map. *Source*: authors' elaboration.

It is feasible to discover methodological–instrumental routes based on the integration of studies conducted using artificial intelligence and those of a multi-criteria matrix in the details of sensitivity analysis through an in-depth study of the scientific material gathered by the scoping review activity. Specifically, the use of evaluation procedures based on:

- **Rule-based inference**, the most widely used and straightforward method because it relies on explicit and static models of a domain. By representing and encoding knowledge through if-then-else instructions, it actually tends to mimic human intelligence. The system's mechanism consists of an inference engine, a working memory, a user interface for sending and receiving signals, and a rule set [32,33].
- **Natural language processing** [34], which aims to extract knowledge and intentions from the analysis of text and language structures, semantic linguistic analysis studies words and phrases in order to arrive at an interpretation and explication of the meaning of lemmas from the context of information extraction. Analysis techniques are used by intelligent systems in medical diagnosis [35] or in the analysis of financial data [36].
- **Bayesian networks**, which are graphical structures that, using Bayesian inference, represent the probabilistic relationships between a large number of variables [37]. They provide a model for the probability distributions between several variables, defining the randomness relationships between the nodes in the network. They adapt in light of new data and learn by adapting the output based on the new information provided [38].

- **Similarity measure**, which evaluates the degree of relationship between two data elements. The concept of similarity refers to the most fundamental rule of thumb employed by humans for problem solving: humans approach a new problem using approaches used to handle comparable issues (*similarity*) [39]
- **Neural networks**, or more specifically artificial neural networks (ANNs), strive to replicate the way the human brain operates and are at the forefront of approaches that contribute to the present growth of AI. They provide answers to a variety of issues, including image recognition, audio recognition, natural language processing, and prediction [40]. Networks generate an output that describes the answer to a given issue based on data observation.

These AI techniques follow the conceptual framework of Figure 1, but differ in terms of accuracy and reaction time. Figure 7 ranks the primary AI-based analysis methodologies in terms of both result Accuracy and Reaction time (AR) to input data. The rating is determined by examining case studies from the scoping review activity. The neural network methodology allows the operator to acquire correct findings in virtually real time, as does the usage of the Bayesian network; however, the accuracy is lowered owing to the type of probabilistic approach on which the analytic method is built. The rule-based inference technique of analysis is in an intermediate position, allowing conclusions to be derived that are only relevant to the analysis case of interest under the specific restrictions that must be satisfied depending on the nature of the decision issue to be resolved. Methodologies that use similarity metrics and extrapolations from textual sources often provide less accurate results and frequently take longer to respond than earlier approaches. This is related to the search for data sources and the uniformity of input information, particularly in terms of output extrapolation processes based on literary fonts. The AR curves that may be formed when AI approaches are combined grow or decrease depending on the kind of algorithm, polynomial and/or exponential, which solves the AI-based analysis method.

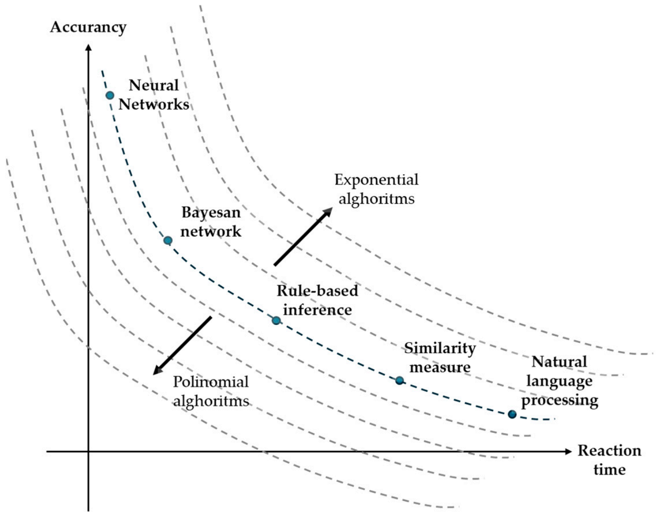

Figure 7. Reaction–Accuracy diagram of the main AI-based analysis approaches. *Source*: authors' elaboration.

Based on the assessment of MCDA publications, methodological and procedural properties enable the main multidimensional evaluation tools and methods (optimization algorithm, Topsis, AHP, and Fuzzy Logic) to approach AI-based analytical methodologies in terms of output turnaround time and accuracy of results. Through consideration of the logical-functional links discernible in the VOSviewer analysis environment, the association between multi-criteria analysis methods-tools and AI is realized. An example is shown in relation to AHP in Figure 8, whose hierarchical network design exhibits similarities and integrations with the neural networks' horizontal graph topology. This was completed for every MCDA strategy that was documented in the literature. Finding the paths of admixture between MCDA analysis approaches and artificial intelligence (AI) techniques enables us to follow domains of applicability and proximity between the tools and methods of interest in the AR diagram, revealing integrability domains between multi-criteria and AI methodologies that are relatively wide in terms of the kind of accuracy and response time required, as in Figure 9.

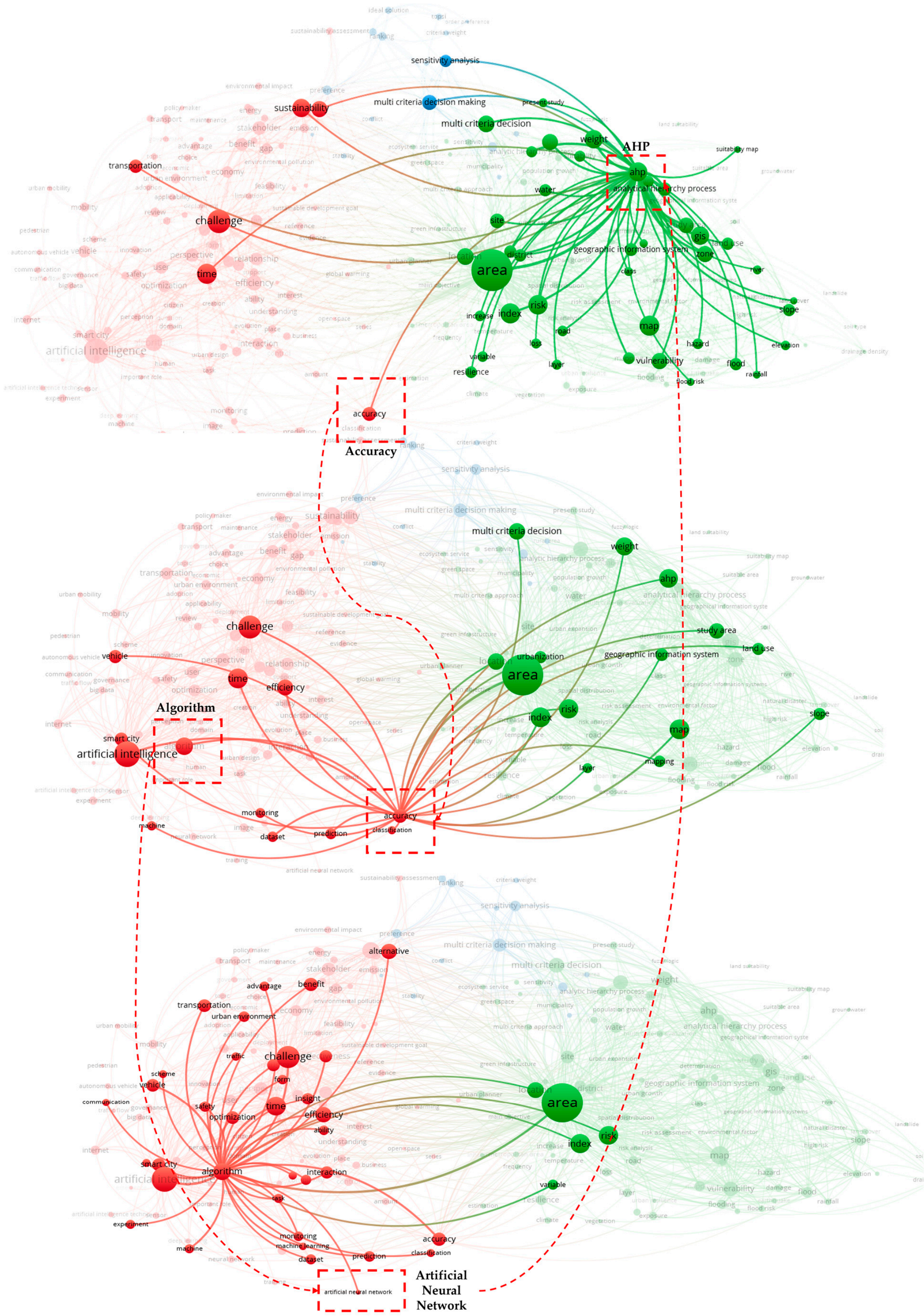

Figure 8. Example of an integrated AI–MCDA pathway for advanced analytical AHP. Source: authors' elaboration.

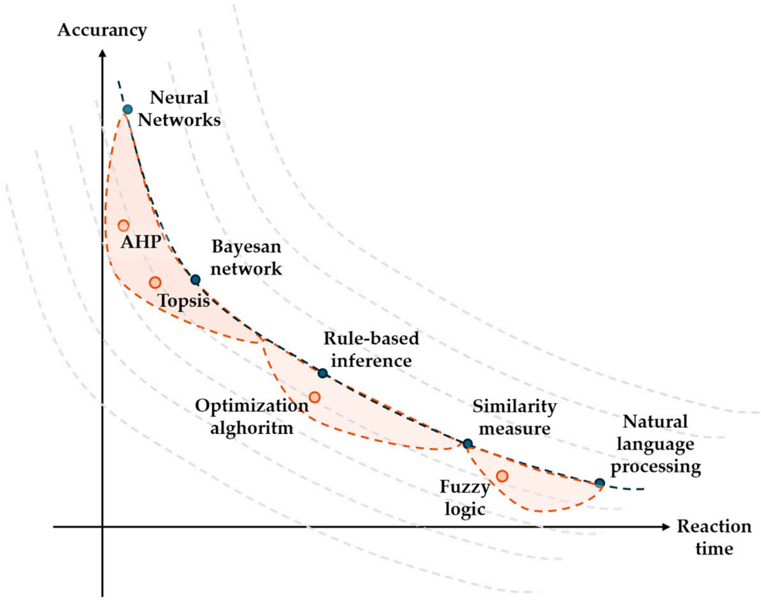

Figure 9. Interoperability domains between MCDA–AI approaches in the AR system. *Source*: authors' elaboration.

5. Conclusions

The study aims to assess the suite of artificial intelligence (AI)-based methods and tools for assessment in the urban landscape from an interdisciplinary perspective through an integrated approach that lowers uncertainty and promotes better informed decision-making. The multi-criteria matrix's nature and the broad range of decision-support approaches with varying implications set the context of this analysis. How can the most often used multi-dimensional evaluation tools be improved to produce more efficient and accurate results compatible AI systems?

With the scope of minimizing challenges and anticipating decision-frames without uncertainty and resilience to change, the interoperability between MCDA and the principal AI-based operative approaches will enable the evaluation of issues pertaining to urban interventions, allowing for more accurate judgements. Depending on the required degree of accuracy and reaction time, the framework, as shown in Figure 9, opens up windows for realistic, real-world study between multi-dimensional evaluation tools most commonly used in urban settings and AI-based analytic methodologies. The interplay between these two assessment domains (MCDA + AI) may prove beneficial for assessing investments made in the face of uncertainty and their consequences for the urban environment, society, and economy. The proposed alignment of MCDA and AI interoperability will facilitate the: (*i*) identification of initiatives that can most quickly and effectively pursue specific goals in line with community needs; (*ii*) improvement of the coherence and transparency of the planning, implementation and monitoring of the initiatives that will be implemented; (*iii*) negotiation of interests between public and private operators by defining measures of the "balance" parameters of the transformation (i.e., mutual financial benefits) in light of the potential beneficial contribution to the context and in response to its unsaturated and rapidly changing environment.

The study plans to proceed by examining the boundaries and possibilities of integration in the various interoperability domains that have been defined and evaluating the application with reference to assessment cases pertinent to urban systems, such as a project portfolio selection problem.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/info15110678/s1, Table S1: Scopus codes.

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