Urban decision-making is not so much a matter of intelligence, artificial or otherwise. A discussion of AI starting from cost-benefit analysis

Cities 168 (2026) 106430

Contents lists available at ScienceDirect

Cities

journal homepage: www.elsevier.com/locate/cities

Urban decision-making is not so much a matter of intelligence, artificial or otherwise. A discussion of AI starting from cost-benefit analysis

Isabella M. Lami [a], Stefano Moroni [b,*]

[a] DIST, Politecnico di Torino, Viale Mattioli 39, 10125 Torino, Italy
[b] Department of Architecture and Urban Studies, Polytechnic University of Milan, Via Bonardi 3, 20133 Milano, Italy

ABSTRACT

It has long been assumed that effective decision-making presupposes the presence of a rational decision-maker and reliable information about alternatives, preferences and uncertainty. Unfortunately, the reality is quite different, particularly when one considers public decision-making in urban areas. In other words, and according to Herbert Simon's well-known formula, no decision-maker can operate without a form of "bounded rationality". This is one of the reasons why traditional Cost-Benefit Analysis received so many criticisms, and other decision-support techniques were developed with the intention of taking our limited rationality more directly into account (e.g. Multicriteria Decision Analysis and Problem Structuring Methods). However, now that rationality no longer seems inherently constrained thanks to the advent of Artificial Intelligence, it seems reasonable to assume that decision-making processes themselves may undergo significant changes. Specifically, the research question that this article addresses is this: "What contribution can AI make to overcoming the limitations of certain methodologies used to support public decision-making in urban contexts?". This question will be addressed by critically examining one of the main techniques of evaluation, Cost-Benefit Analysis, with particular regard to the pragmatic dimension of choice.

1. Introduction: A farewell to bounded rationality?

It has long been assumed that an effective decision-making process requires the presence of a rational decision-maker and reliable information about alternatives, preferences and consequences. Unfortunately, the reality has proved to be quite different. Although objective, data-driven information is usually preferred, there are times when we must rely solely on opinions, advice and speculation. Similarly, decision-makers are not always as rational as they are assumed to be (Moroni, 2019). Organisational goals are frequently unclear or conflicting, and decision-making is usually constrained by time pressures. Consequently, achieving the desired level of effective decision-making is often more difficult than presumed (Parnell et al., 2013).

A large number of approaches to support decision-making have been developed on the assumption that human beings possess "bounded rationality". As Vatn (2009: 2209) noted: "Choosing between appraisal methods, one needs to take into account how the aspect of bounded rationality can best be treated".

Consequently, the question became how a decision-maker, who certainly cannot consider all the information needed to make the best possible decision, could make a sufficiently good and defensible one (Simon, 1955). Thus, over time, decision-support tools have evolved. It was first assumed that everything is quantifiable (e.g. expressible in monetary terms) and summable. Then it was believed that certain aspects of decision-making problems should be expressed in other, more appropriate units of measurement (to be only subsequently aggregated with appropriate mathematical methods). Finally, it was realized that even the definition and structuring of the problem itself are fundamental, albeit qualitative, as long as they are expressed in formal terms.

Hence, after the widespread adoption of *Cost-Benefit Analysis* (CBA), techniques such as *Multicriteria Decision Analysis* (MCDA) and *Problem Structuring Methods* (PSMs) were introduced. In parallel, various optimisation methods developed within *Operations Research* (OR) have become a cornerstone of quantitative decision making (Bilir et al., 2020).

As well known, CBA is a systematic method used to assess the economic efficiency of a project or policy. It involves comparing the total expected costs with the total expected benefits in order to determine whether the benefits outweigh the costs, both of which are typically expressed in monetary terms. Not only are direct financial impacts quantified but so too are indirect social and environmental ones (e.g. Benis et al., 2018; Boardman et al., 2018; Chen & Jim, 2008). MCDA developed rapidly in the late 20th century. It encompasses methods to evaluate decisions involving multiple criteria by combining objective measurements with explicit value judgements (e.g. Belton & Stewart, 2002; Bouyssou et al., 2006; Greco et al., 2016; Keeney & Raiffa, 1993).

* Corresponding author.
E-mail addresses: isabella.lami@polito.it (I.M. Lami), stefano.moroni@polimi.it (S. Moroni).

https://doi.org/10.1016/j.cities.2025.106430
Received 23 February 2025; Received in revised form 23 July 2025; Accepted 29 August 2025
Available online 5 September 2025

Conversely, PSMs focus on participatory problem structuring rather than on direct problem-solving. They aim to identify feasible commitments and assess their compatibility with future scenarios, actively shaping social realities (e.g. Lami & Tavella, 2019; Lami & White, 2022; Mingers & Rosenhead, 2004; Rosenhead, 1996). While CBA, MCDA and PSMs focus on evaluating a predefined menu of alternatives, many OR techniques actively construct optimal portfolios. *Mixed-integer linear programming* (MILP) makes it possible to select discrete combinations of projects or land-use allocations that maximise efficiency while respecting budgetary or spatial constraints (Clautiaux & Ljubić, 2025; Kuhn et al., 2023; Kumar et al., 2016). *Portfolio decision analysis* (PDA) builds on the same logic by systematically generating bundles of projects that satisfy multiple objectives and resource limits (Hämäläinen et al., 2024; Liesiö et al., 2021). When decisions must be planned over long periods of time in the presence of uncertainty, *Multi-stage stochastic programming* (SP) enables analysts to embed scenario variability and adaptive learning within the optimisation process (Kayacık et al., 2024).

The interesting point is that certain methods (such as MCDA, PSMs, and MILP-based optimisation models) have been developed in the conviction that CBA neglects the limitations of our unavoidably "bounded" rationality[1] and that it is necessary to directly include this awareness in decision-supporting methods and their functioning.[2] However, now that rationality no longer seems inherently constrained thanks to the advent of Artificial Intelligence (AI) (on which, see e.g. Allam & Dhunny, 2019; Leal Filho et al., 2024; Yigitcanlar et al., 2024), it seems reasonable to assume that decision-making processes themselves may undergo significant changes. In particular, AI seems able to overcome bounded rationality (Shick et al., 2024). Accordingly, the research question that this article addresses is this: "What contribution can AI make to overcoming the limitations of certain methodologies used to support public decision-making in urban contexts?"

We focus mainly on CBA because it is precisely this traditional method of evaluation that has been most subject to criticism arising from acceptance of the idea that humans' rationality is severely "bounded". If it could be shown that AI can eliminate or at least significantly overcome the limits of human rationality, CBA would once again become the most viable decision support method. At the same time, other decision support methods that developed precisely as a consequence of the idea that CBA could not solve all problems because of humans' bounded rationality would lose relevance. Our focus on CBA has therefore both a narrow meaning (i.e. a meaning in itself, as a *direct* discussion of the role of AI in the case of this specific decision-support method) and a broader one (i.e. as an *indirect* discussion of the role of AI more in general for urban decision-making).

The article is mainly theoretical and conceptual; however, it is empirically informed.[3] It is based on an extensive multidisciplinary review of the literature (including economics, planning theory, urban studies, political philosophy).

After some preliminary specifications on fundamental background issues (Section 2), the focus will be on the shortcomings of traditional CBA and potential contributions of AI to remedying them (Section 3). The discussion and concluding part (Section 4) highlights the main critical findings, while underscoring some limitations of the study and further possible directions of research.

2. Preliminary specifications: Focus, context, conditions, types of support

A decision-making problem involves examining several possible courses of action in the presence of multiple stakeholders, different objectives, uncertainties and significant consequences in order to identify the one that is judged to be the most desirable on the basis of several factors (Greco et al., 2016).

Decision analysis was introduced with the intention of supporting decision-makers by means of a systematic and formalised procedure that made the different steps leading to the final choice more transparent (Howard, 1988). The benefit of decision analysis consists in its ability to formally express diverse judgements when evaluating alternatives and to create a clear framework that integrates the multidimensional elements of complex values. Real decision-making problems can be seen as sequences of several formal decision problems both because the set of possible solutions can be refined and because beliefs, information and values need to be updated or modified (Colorni & Tsoukias, 2024).

Decision support can be described as the process whereby elements that clarify decisions and enhance their consistency are gathered and structured (Roy, 1977). It consists of a set of theories, methodologies and models designed to guide action in complex systems, especially when there are conflicting points of view (Roy, 1996). It can be viewed as an approach based on a series of logical principles, together with a methodology and set of organised processes built on those principles, that seeks to responsibly address the complexities involved in decision-making (Keeney, 1982).

With the intention of focusing on *evaluation techniques* as particular cases of decision-support methods, in the next sub-sections we specify some preliminary questions concerning *focus*, *context*, *conditions*, and *types of support*.

2.1. Focus: Public decision-making

While decision-making in general is difficult, especially when important choices with major consequences are involved, *public* decision-making is even more complex (Chiffi & Moroni, 2025; Moroni & Chiffi, 2022). In the case of decisions made via political processes, the relationships between the parties are permanently asymmetrical because public institutions have the right to exercise their authority over citizens. This difference forms the basis of the idea that, in a democratic society, public decisions should be discussed and justified. Furthermore, if the decisions have considerable consequences on important resources, these effects should be assessed before the choices are made and become binding on all (Bobbio & Zeppetella, 1999).

Public decisions have several specific features. As stressed by Tsoukias et al. (2013), policymakers face five major complex issues when it comes to public decision-making:

(i) the use of public resources;
(ii) the presence of multiple stakeholders;
(iii) a long time horizon;
(iv) the need for legitimation and accountability;
(v) deliberation.

First, many of the resources – both tangible and intangible – used in the policy cycle are provided by public authorities. Moreover, public decisions involve largely irreversible resource allocations, which raises intergenerational and environmental concerns. Second, policymaking is inherently interactive, with various actors – citizens, groups or organisations – seeking involvement in the process. This requires consideration to be made of the diverse concerns, objectives, resources, languages, perceptions and expectations of stakeholders. Third, policy processes often take considerable time, which can conflict with stakeholders' varying agendas: from the short-term priorities of policymakers to the medium- and long-term concerns of experts, as well as the fluctuating

[1] See e.g. Shapiro (2011: 26): "Under conditions of bounded rationality, cost-benefit analysis is not the most effective way to make decisions". Compare with Harcourt (2018) and Adelman and Sinden (2023).

[2] See e.g. Vatn (2009: 2212) on MCDA: "Multicriteria analysis […] is a supporting tool not least in the context of bounded rationality to overcome restricted human abilities to treat complexity".

[3] It is based on long empirical investigation and experimentation, especially by one of the two authors, in the field of assessment and evaluation techniques (previous publications arising from this empirical investigation, which began more than 20 years ago, are cited throughout the article).

timescales of citizens. These different timelines, along with the unpredictability of social and economic developments, add structural complexity to the policy process. Fourth, policymakers seek to legitimise themselves, their actions, policy outcomes and the process itself. Participation is often considered a key element in achieving this. Fifth, and finally, for decision processes to be *public*, they must include formal deliberations where decisions are officially adopted, made public, legally enforceable, and result in authoritative distributions.[4]

2.2. Context: Cities

In discussing public decisions, we primarily focus on *urban decisions:* that is, decisions concerning the use of land and buildings in contexts of organised complexity and a high concentration of people and activities, as is the case in cities (Cozzolino & Moroni, 2021, 2022).[5] As well known, complex systems are composed of a very large number of components whose interaction is iterative and recursive (i.e. non-linear), with many direct and indirect feedback loops. They present unintentionally emergent forms of order and are self-organising. They are markedly dynamic and adaptive. In this case, the whole is not only more than the sum of its parts but also different from it (Coveney & Highfield, 1995; Holland, 1995).[6] The core feature of *complexity* understood in these terms is *uncertainty*.[7]

When discussing complex social-spatial system like cities, we should consider public decisions concerning two main undertakings (Moroni, 2023; Moroni & Chiffi, 2021):

(i) where and how to build new public infrastructure (e.g. public streets, bridges, hospitals, parks) and
(ii) whether and how to control, guide and channel the use and transformation of (private) land and buildings.

In the first case (i.e. infrastructural intervention), the public decision-maker is deciding how to allocate certain collective resources to the construction of certain urban artifacts.

In the second case (i.e. regulatory intervention) the public decision-maker is indirectly influencing the way in which other (private) actors can or cannot use and allocate their own resources to the use and transformation of artifacts.

In both cases, the final output mainly concerns immovable goods – that is, the outcome is a situation in which action reversibility is generally not easy.

In regard to the distinction among decisions in conditions of certainty, risk, parametric and radical uncertainty,[8] note that infrastructural decisions are usually taken in conditions of *parametric uncertainty* while regulatory interventions are generally taken in ones of *radical uncertainty* (Chiffi & Moroni, 2025).

2.3. Conditions: Internal and external limitations

Mainly as a consequence of the well-known works of Herbert Simon (1983, 1996), human rationality has been defined as "bounded" on the basis of two main aspects: first, the intrinsic complexity of the world – particularly the economic and social systems – with which we must deal; second, the limited cognitive and computational capacities of the human mind when dealing with the world. In the former case, there is a sort of "external" limitation on human rationality, while in the latter case the limitation is, so to speak, "internal". Therefore, bounded rationality depends on the relationship between these two aspects.[9]

As Bendor (2010: 2) emphasizes in this regard: "In Simon's pioneering formulation, the focus was always on a *comparison* between a decision-maker's mental abilities and the complexity of the problem he or she faces". In short, "for Simon […] the idea of bounded rationality is *not* a claim about the brilliance or stupidity of human beings, independent of their task environments" (Bendor, 2010: 2).[10]

Because of these two limitations – the internal and the external one – Simon (1961) suggested that it is not possible to make an *optimising* decision; we must content ourselves with *satisficing* ones. For instance, when discussing business firms Simon (1996: 28-29) wrote: "In the face of real-world complexity, the business firm turns to procedures that find good enough answers to questions whose best answers are unknowable. Because real-world optimisation […] is impossible, the real economic actor is in fact a satisficer, a person who accepts 'good enough' alternatives, not because less is preferred to more but because there is no choice". He continued: "One requirement of optimisation not shared by satisficing is that all alternatives must be measurable in terms of a common utility function. A large body of evidence shows that human choices are not consistent and transitive, as they would be if a utility function existed" (Simon, 1996: 29).

2.4. Types of support: Filtering, structuring, prioritising, involving

Forms of support for urban decision-making can be grouped into different categories according to the type of aid that the evaluation processes can provide to the decision-maker (Lami & Moroni, 2020).

The four main kinds of aid are the following:

(i) filtering information;
(ii) structuring the problem;
(iii) prioritising options;
(iv) involvement of the public.

[4] On these last aspects, see also Raz (1975) and Urfalino (2010).

[5] On cities as complex systems see the pioneering formulation by Jacobs (1961) and the developments in, especially, Portugali (1999) and Batty (2005).

[6] Note that, in the case of complex systems, only "explanations of the principle" and "pattern predictions" are possible (Buitelaar et al., 2021; Moroni, 2025).

[7] On this, see e.g. Loasby (2002), McDaniel and Driebe (2005), Batty and Marshall (2012), Giezen (2013), Osman (2017).

[8] In a situation of *certainty*, the possible events are listable, and the consequences of the choice made are clearly known to the decision-maker. In short, each decision is easily recognised as leading to a specific outcome. In a situation of *risk*, the possible outcomes are still clearly listable, and the decision-maker can specify the objective probability of each of them. In a situation of *parametric uncertainty*, the possible outcomes are still in some way listable, but the decision-maker lacks knowledge about the objective probability of each of them. In a situation of *radical uncertainty* – also known as deep or severe uncertainty – the decision-maker is unable to assign well-definable or computable probabilities and may even be ignorant about what states of affairs are possible (in other words, radical uncertainty implies the unlistability of all the potential outcomes of a decision) (Chiffi & Moroni, 2025).

[9] Compare with Rescher (1997, 2009), Todd and Gigerenzer (2003), Bendor (2010). As Rescher (2009: 101) notes: "In principle, there are both ontological and epistemological limits to predictive foreknowledge, and obstacles to successful prediction can reside either in the nature of things or in our own cognitive limitations. Ontological limits exist insofar as the future of the domain at issue is developmentally open – causally undetermined or underdetermined by the existing realities of the present and open to the development of wholly unprecedented patterns owing to the contingencies of choice, chance, and chaos. Epistemological limits on prediction exist insofar as the future is cognitively inaccessible – either because we cannot secure the needed data, or because it is impossible for us to discover the operative laws, or even possibly because the requisite inferences and/or calculations involve complexities that outrun the reach of our capabilities".

[10] To quote Simon (1990: 7) himself: "Human rational behaviour […] is shaped by a scissors whose two blades are the structure of task environments and the computational capabilities of the actor". On this crucial metaphor in Simon's thought, see Nickles (2018), Todd and Gigerenzer (2001), Marewski et al. (2024).

Filtering can be defined as the process of selecting information. It is related to the availability of data and to the input required by the method which will be applied (for an illustrative example, see Barbati et al., 2024).

Structuring concerns the definition and representation of the decision problem. Problems do not spontaneously arise and then wait to be "solved"; they are always the product of evaluations made collaboratively by the expert and the client. These inter-subjective decisions shape the nature of the problem that ultimately needs to be addressed (see, among others, Fregonese et al., 2020, Lami & Todella, 2023).

Prioritising, in general terms, is the activity of arranging items or activities in their order of relative importance. When evaluation techniques are applied, various scenarios may arise: they can range from producing a final ranking of alternatives to situations where the method must be repeatedly applied to different scenarios in order to compare and prioritise solutions (see e.g. Abastante et al., 2014, 2022; Costa et al., 2019, 2021).

The *involvement of* stakeholders can take different forms: some of the methods used are inclusive and participatory from the initial design and development stages onwards, while others include participation only after the results have been generated (see e.g. Lami et al., 2014; Pensa et al., 2013).

Different evaluation techniques assign different levels of importance to the various dimensions of assistance.

3. Cost-benefit analysis and AI

For the reasons explained in the "Introduction", and in order to examine the potential of AI to enhance decision-support techniques, the focus here is on CBA. The following analysis includes: (i) a general definition of CBA, and a brief description of the type of help it can provide to the decision-maker; (ii) its limitations; (iii) the potential contribution of AI to overcoming these limitations.

3.1. General features of cost-benefit analysis

As already highlighted, CBA is a systematic and analytical approach that compares the benefits and costs of a project or a policy, often one of a social nature, and serves as a formal method for making informed decisions about the allocation of society's limited resources (Mishan & Quah, 2020).

CBA is carried out to identify the solution that maximises overall the societal welfare ensuing from a certain choice. Quite surprisingly, according to the well-known work by Posner and Adler (1999), CBA is agnostic as to the correct conception of well-being (for a different, more critical view see Moroni, 2006).

A comprehensive CBA should account for all the benefits and costs related to an action, whether they are part of the market (with price tags) or are extraneous to normal market operations (such as air quality or climate change). CBA is commonly used to evaluate public projects, infrastructure and environmental policies, considering both direct and indirect impacts. The outcome of CBA is Net Present Value or a benefit-cost ratio which helps decision-makers to understand whether the benefits outweigh the costs.

The Contingent Valuation Method (CVM) is specifically designed to estimate the economic value of non-market goods by using stated preference methods such as willingness-to-pay and willingness-to-accept. CVM creates a hypothetical market for a non-priced good and asks individuals to specify the monetary value they assign to a proposed change in its quantity, quality or accessibility. It is a survey-based method designed to capture individual preferences and valuations under hypothetical scenarios (Loomis & Helfand, 2001). The result of CVM is typically a monetary value for a specific environmental or public good based on individuals' given preferences.

Regarding the type of help that CBA can provide (Section 2.4.), it gives moderate importance to *filtering* since it considers both monetary and non-monetary data. CBA tends to include a broad range of factors (e.g. economic, environmental and social impacts) in order not to omit anything significant. As a result, broad data inclusion may be prioritised over extensive data filtering, ensuring comprehensive coverage by the analysis. The focus is more on accurately calculating and presenting the selected data than on carefully filtering them to reduce complexity.

Problem structuring also has medium importance in CBA, reflecting the method's inherent balance between providing a structured approach and its focus on quantification and measurement. CBA relies on a relatively fixed and prescriptive framework, which reduces the need for deep or iterative problem structuring. Once the key elements have been identified, the focus shifts to applying established methods in order to monetise costs and benefits, making problem structuring important but not the central focus of the analysis.

CBA gives great importance to *prioritising options,* reflecting the core purpose and strength of this method: helping decision-makers to choose the best course of action by evaluating alternatives through a structured, quantitative lens. The method is designed to help decision-makers choose the option that offers the greatest net benefit, making prioritisation not just a feature but a fundamental purpose of the analysis. Whether CBA is used to make public policy decisions, it aims to provide clear rankings that should support efficient, justified and implementable decisions.

Finally, with regard to *involvement of the public*, CBA gives scant importance to this aspect, because the method is fundamentally expert-driven and focuses on quantitative, economic assessments rather than participatory processes. Participation typically occurs only after the experts have applied the technique: the *results* are used in public discussions.

3.2. Criticisms of cost-benefit analysis

In recent decades, the literature has emphasised several limitations associated with CBA (and CVM).

CBA experienced a surge in popularity during the 1960s, despite a lack of consensus on its theoretical foundation (Posner & Adler, 1999). By the 1970s, however, even applied economists and government agencies had begun to question its usefulness. The challenges of CBA were also technical/pragmatic. In practice, experts struggled to obtain relevant data, particularly when evaluating environmental resources, human life and other difficult-to-measure assets (Pearce & Nash, 1981). Claims that a project's benefits exceeded its costs were unconvincing when those values appeared to be based on arbitrary judgements. Ideologically, the technocratic and utilitarian nature of CBA was at odds with the political climate of the 1970s. While the 1980s and 1990s saw a revival of CBA, the original theoretical criticisms remained unresolved.

To summarise, two types of limitations attributed to CBA (and CVM) can be distinguished: *pragmatic* and *ethical*. As already stated, our focus here is mainly on the contribution AI can make to the "technical" dimension of choice, focusing on improving effectiveness and efficiency. Therefore, the attention will be primarily paid to pragmatic limitations.[11]

The three main pragmatic limitations that arise when applying the CBA method are the following:

(i) difficulty of *monetisation* (in particular in the case of benefits: Driesen, 2006), often accompanied by the omission of important information in CVM questionnaires (Fischhoff & Furby, 1988);

[11] For ethical issues related to CBA, see e.g. MacLean (1980), Hausman and McPherson (1984), Kelman (1985), MacIntyre (1985), Gillroy (1992), Glynn (1996) and Nussbaum (2000). As well known, the main criticism of CBA from an ethical point of view is the indifference of its choice criterion to how the advantages and disadvantages are *distributed* among individuals and groups.

(ii) tendency to capture *attitudinal intentions* rather than *actual behaviour* (Ajzen & Peterson, 1988);
(iii) susceptibility to *cognitive biases* (Brown & Slovic, 1988; Kahneman & Knetsch, 1992).

Concerning the first point, Driesen (2006) stressed that the monetisation of non-market benefits in CVM is fraught with difficulties due to the intangible nature of many of those benefits, the information limitations of respondents, and the hypothetical nature of the survey process. The typical result of a CBA provides a dollar estimate for expected costs and a broad range of dollar values for a few quantifiable benefits. However, this range is often so wide that it undermines CBA's ability to objectively inform decision-making. Additionally, many crucial environmental, health and safety impacts cannot be quantified, so that CBA in these areas is left with a long list of unquantified benefits, many of which are considered significant by experts in the field. Therefore, CBA cannot be neutral because of the inherent limitations of monetisation "and the impossibility of any neutral monetization methods" (Driesen, 2006: 67). Fischhoff and Furby (1988) criticised the use of CVM questionnaires, emphasising that they often omit crucial information that respondents need to make informed decisions. The omission of key details can lead to unreliable or inflated valuations because respondents may be forced to rely on incomplete or ambiguous information. Fischhoff and Furby (1988) pointed out that when essential aspects of the positive benefits or their broader implications are not adequately explained, respondents may make assumptions that do not align with the real-world scenario, giving rise to hypothetical bias. In their view, the failure to include comprehensive and relevant information undermines the validity of CVM as a tool for economic valuation.

With regard to the second point, Ajzen and Peterson (1988) discussed the gap between attitudes and actual behaviour. They emphasised that because the CVM method relies on hypothetical questions, it often captures attitudinal intentions rather than actual behaviour. They argued that when respondents express their *willingness to pay* for a good or service in a hypothetical scenario, this reflects their intentions or attitudes toward the good. This is due to several factors, such as social desirability bias, hypothetical bias or the lack of real economic constraints in the survey setting. Ajzen and Peterson (1988) thus highlighted the challenge of using CVM as a reliable measure of actual economic decisions because it primarily measures the intention to behave in a certain way, not the actual behaviour itself.

Finally, and concerning the third pragmatic limitation of this methodology, Brown and Slovic (1988) examined how CVM results are susceptible to various cognitive biases, arguing that individuals often rely on mental shortcuts or heuristics when making decisions in hypothetical valuation scenarios. They highlighted several specific cognitive biases that can affect CVM outcomes, such as anchoring bias, framing effects, scope insensitivity and hypothetical bias. They emphasised that these cognitive biases could undermine the reliability of CVM results, making it difficult to assess true preferences. As pointed out by Kahneman and Knetsch (1992), the challenge in interpreting CVM results arises when the value of a particular landmark is significantly higher when assessed independently, compared to its value when it is assessed as part of a broader package of public goods. It is unclear which of these values is correct. The literature on this issue offers no clear principles with which to determine the level of aggregation appropriate for evaluating a specific good. "In the absence of such principles, the results of CVM become arbitrary. This criticism could be fatal. No measuring instrument can be taken seriously if its permitted range of applications yields drastically different measures of the same object" (Kahneman & Knetsch, 1992: 60).

3.3. AI'S possible contribution to overcoming the traditional limitations of CBA

With respect to the main research question of this article – namely, what contributions AI can make to overcoming limitations of certain decision support methods – let us now discuss the above-mentioned technical difficulties of CBA.

Regarding the difficulty of monetising benefits, AI – particularly through machine learning and data analytics – could improve the accuracy and granularity of monetised non-market benefits. By processing vast amounts of data, AI systems could model complex relationships among environmental, social, and economic factors that are traditionally difficult to quantify. For example, *natural language processing* could analyse a large corpus of literature or public discourse to identify patterns in how people value intangible benefits like clean air, public health, or ecosystem services. Recent advances show that AI-powered systems, particularly those leveraging *large language models*, can also automate the extraction and structuring of such knowledge, generating ontologies and knowledge graphs that support more consistent and transparent decision-making across urban governance domains (Tupayachi et al., 2024). In addition to automating semantic structuring, these models can assist in constructing domain-specific conceptual frameworks from specialised bodies of literature, thus aligning technical outputs with institutional logics and policy needs. Moreover, large language models and generative AI models have demonstrated their ability to synthesise multimodal datasets – ranging from satellite imagery and sensor streams to social-media feeds – into interpretable urban simulations, while also supporting natural language querying and stakeholder engagement through conversational interfaces (Ye et al., 2025).

Data-driven valuation models based on real-world datasets (e.g. environmental, demographic and economic data) could estimate valuations more objectively by learning from previous behaviour and stated preferences. In this context, AI-based analytics applied to urban big data, from mobile phone records and GPS logs to participatory sensing results, enable planners to trace socio-spatial behaviours on fine-grained spatiotemporal scales, supporting more nuanced and adaptive urban policies (Kamrowska-Załuska, 2021). These tools can also reveal emergent patterns in land use, mobility, and service access, thus informing dynamic valuation frameworks responsive to shifting urban conditions.

Scenario simulation, which integrates scientific data such as climate or biodiversity data with socio-economic trends, could provide more comprehensive, evidence-based estimates of future benefits. Recent work has shown that deep generative models can be trained to simulate complex, uncertain urban futures so that planners can test the robustness of candidate policies under diverse and plausible trajectories (Hao et al., 2024). Xu et al. (2025) show that embedding context-aware generative agents into digital twins turns static simulations into autonomous decision-ready systems for urban logistics and transport planning. This ability to generate exploratory scenarios beyond expert-imagined futures could support more resilient and inclusive approaches to long-term urban planning.

Regarding the capturing of attitudinal intentions rather than actual behaviour, AI could help bridge the gap between them by using predictive analytics to model how people behave under different circumstances. For instance, by means of behaviour tracking – namely techniques such as real-time monitoring (e.g. via apps or digital platforms) – it could collect behavioural data over time in order to compare stated intentions with actual behaviour. This could produce improved CVM models that adjust according to discrepancies between intention and action. An interesting example in this regard is provided by Yang et al. (2021), who developed a deep neural network to predict pedestrian crossing intentions by combining spatiotemporal features with visual attention cues. Their work illustrated how AI can be trained to detect subtle indicators of intent, thus enhancing real-time behavioural prediction in complex urban environments.

Finally, AI offers promising ways to address persistent cognitive biases in the application of the CVM. Its role should be considered also with regard to methodological issues. For example, Lemieux et al. (2025) demonstrate how large language models can support real-time bias detection by dynamically adjusting question framing in order to mitigate anchoring and scope insensitivity. Similarly, Rastogi et al.

(2022) show that time-based de-anchoring strategies embedded in AI systems can improve the consistency of responses. These techniques could enhance the robustness of CVM by reducing the influence of context effects and cognitive overload.

Considering the points discussed, it is possible to envision an enhancement of the type of support provided with the help of AI, particularly in the area of filtering and, to some extent, in involving processes.

4. Discussion and conclusions: Not yet internally, but still externally bounded

While the potential of AI to support urban decision-making is widely acknowledged, the recent literature cautions against excessive optimism. As Ye et al. (2025) observe, the promise of AI as a neutral, scalable tool for improving urban governance often masks deeper epistemic and normative tensions – particularly in regard to what is measured, who defines value, and whose knowledge is represented. Lartey and Law (2025) similarly argue that, despite the rapid expansion of AI-related research, its actual integration into governance remains superficial, being constrained by data quality issues, and a persistent gap between technical innovation and institutional capacity.

Another element to consider is the disparity between the rapid pace of computational analyses and the comparatively slower procedural workflows within the public institutions responsible for territorial governance. The qualities that make AI models lightning-quick (opaque feature stacking, probabilistic shortcuts) also make their outputs vulnerable to bias and brittle generalization. Urban planners who act on such signals without reflection risk institutionalising error at machine speed. The literature flags this as the *black-box problem* and calls for step-by-step reasoning protocols and contextual prompts to keep AI "legible".

In this light, besides entailing computational enhancement, addressing the limitations of methods such as CBA through AI also requires critical scrutiny of the assumptions embedded in both the models and their implementation contexts.

This issue becomes particularly relevant when considering the *internal* and *external* constraints on decision-making discussed in Section 2.3: while AI could considerably reduce the former, it has little impact on the latter (Davidson, 2024; Karadimas, 2023; Martinelli, 2025). In other words, while certain *epistemic* limitations to decision-making (e.g. computational brain limits) can be largely overcome by AI, other *ontological* limitations – such as the intrinsic unpredictability of social-spatial systems, which mainly depend on the unintentional effects of innumerable human actions and interactions[12] – will remain.

Moreover, here the decision-making process has been analysed within a specific domain: namely, the urban context. In city-related decisions, the resources to be allocated or controlled are both tangible and intangible. They encompass land, finances, transportation, the environment, citizen behaviour, and more. As Italo Calvino emphasised in a lecture at Columbia University, "a city is a combination of many things: memory, desires, signs of a language; it is a place of exchange, as any text–book of economic history will tell you – only, these exchanges are not just trade in goods, they also involve words, desires, and memories" (Calvino, 1983: 41).

All of this seems to suggest that (public) decisions are not merely a matter of "intelligence". Therefore, improving "intelligence" is only a part of the story. Urban decisions based on AI will remain "composite" decisions; that is, the results of the combination of *heterogeneous* processes and elements (Santosuosso & Sartor, 2024). From this perspective, AI will not replace humans as much as it will increase *some* of their capacities (Mainardi, 2025).

To summarise: on the one hand, *only* some traditional *pragmatic* limitations of CBA can be overcome thanks to AI; on the other hand, certain decision support techniques introduced to overcome certain limitations of CBA continue to remain meaningful and useful, and so too does the direct involvement of stakeholders in decision-making processes and certain extended participatory procedures that some of them directly help to organize.

In conclusion, the two main limitations of our discussion should be expressly highlighted. First, we have not explicitly considered the *ethical* questions raised by using AI in (urban) decision-making processes. We have not addressed this topic because of the narrower focus of this study (mainly centred on revisiting the possibility of overcoming certain pragmatic limitations of traditional decision-supporting techniques thanks to AI). However, we cannot but recognise that this is an inescapable problem that we hope to directly address in further research. This will also involve reflecting on what institutional changes would be needed to ensure that AI is appropriately, legitimately and transparently integrated into urban decision-making.[13] Second, the predominantly theoretical perspective of this article has inevitably entailed simplifications and schematisations; a further limitation of the article is therefore the generality of its treatment of certain issues. This notwithstanding, we hope that our approach has nevertheless proved useful by highlighting certain significant general challenges of AI in the field of urban decision-making and evaluation techniques. Further research could empirically test *the extent* to which AI can help overcome certain limits of traditional decision-support techniques and *in which specific cases* other approaches will remain viable.

CRediT authorship contribution statement

Isabella M. Lami: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization. **Stefano Moroni:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

Abastante, F., Bottero, M., Greco, S., & Lami, I. M. (2014). Addressing the location of undesirable facilities through the dominance-based rough set approach. *Journal of Multi-Criteria Decision Analysis, 21*, 3–23.

Abastante, F., Corrente, S., Greco, S., Lami, I. M., & Mecca, B. (2022). The introduction of the SRF-II method to compare hypothesis of adaptive reuse for an iconic historical building. *Operational Research Inernational Journal, 22*, 2397–2436.

Adelman, D. E., & Sinden, A. (2023). The misleading successes of cost-benefit analysis in environmental policy. *Michigan Journal of Environmental and Administrative Law, 13*, 253–341.

Ajzen, I., & Peterson, G. L. (1988). Contingent value measurement: The price of everything and the value of nothing? In G. L. Peterson, B. L. Driver, & R. Gregory

[12] See on this, Batty (2024); Cozzolino and Moroni (2025).

[13] Among the many explorations of *ethical issues* connected with AI (as well as approaches, procedures and constraints required to deal with them), the works by Luciano Floridi and his co-authors are fundamental: see especially Mittelstadt et al. (2016), Cath et al. (2018), Floridi et al. (2018), Mökander and Floridi (2021), Morley et al. (2021), Tsamados et al. (2022). With a more specific focus on urban planning/policies (and ethical questions concerning bias, transparency, accountability, privacy, and misinformation, in this specific field) see e.g. Pastor-Escuredo et al. (2022), Rasoulzadeh Aghdam et al. (2025), Nizamani et al. (2025), Sanchez et al. (2025).

(Eds.), *Amenity resource valuation: Integrating economics with other disciplines* (pp. 5–76). Bath: Venture Publishing.

Allam, Z., & Dhunny, Z. A. (2019). On big data, artificial intelligence and smart cities. *Cities, 89*, 80–91.

Barbati, M., Greco, S., & Lami, I. M. (2024). The deck-of-cards-based ordinal regression method and its application for the development of an ecovillage. *European Journal of Operational Research, 319*(3), 845–861.

Batty, M. (2005). *Cities and complexity*. Cambridge, MA: The MIT Press.

Batty, M. (2024). *The Computable City. Histories, technologies, stories, predictions*. Cambridge (Mass.): MIT Press.

Batty, M., & Marshall, S. (2012). The origins of complexity theory in cities and planning. In J. Portugali, H. Meyer, & E. Stolk (Eds.), *Complexity theories of cities have come of age* (pp. 21–46). Berlin: Springer.

Belton, V., & Stewart, T. J. (2002). *Multiple criteria decision analysis: An integrated approach*. New York, NY: Springer.

Bendor, J. (2010). *Bounded rationality and politics*. Berkeley: University of California Press.

Benis, K., Turan, I., Reinhart, C., & Ferrão, P. (2018). Putting rooftops to use. A cost-benefit analysis of food production vs. energy generation under Mediterranean climates. *Cities, 78*, 166–179.

Bilir, C., Güngör, C., & Kökalan, Ö. (2020). Operations research/management science research in Europe: A bibliometric overview. *Advances in Operations Research, 2020*(1), 1–14.

Boardman, A. E., Greenberg, D. H., Vining, A. R., & Weimer, D. (2018). *Cost-benefit analysis: Concepts and practice*. Upper Saddle River (NJ): Pearson.

Bobbio, L., & Zeppetella, A. (1999). *Perché proprio qui? Grandi opere e opposizioni locali*. Milano: Franco Angeli.

Bouyssou, D., Marchant, T., Pirlot, M., Tsoukias, A., & Vincke, P. (2006). *Evaluation and decision models with multiple criteria: Stepping stones for the analyst*. New York (NY): Springer.

Brown, T. C., & Slovic, P. (1988). Effects of context on economic measures of value. In G. L. Peterson, B. L. Driver, & R. Gregory (Eds.), *Integrating economic and psychological knowledge in valuations of public amenity resources* (pp. 23–30). State College (PA): Venture.

Buitelaar, E., Moroni, S., & De Franco, A. (2021). Building obsolescence in the evolving city. Reframing property vacancy and abandonment in the light of urban dynamics and complexity. *Cities, 108*, 1–7.

Calvino, I. (1983). Italo Calvino on "invisible cities". *Columbia: A Journal of Literature and Art, 8*, 37–42.

Cath, C., Wachter, S., Mittelstadt, B., Taddeo, M., & Floridi, L. (2018). Artificial intelligence and the "good society": The US, EU, and UK approach. *Science and Engineering Ethics, 24*, 505–528.

Chen, W. Y., & Jim, C. Y. (2008). Cost-benefit analysis of the leisure value of urban greening in the new Chinese city of Zhuhai. *Cities, 25*(5), 298–309.

Chiffi, D., & Moroni, S. (2025). *Uncertainty, innovation and the City. Philosophical explorations*. Edward Elgar: Cheltenham.

Clautiaux, F., & Ljubić, I. (2025). Last fifty years of integer linear programming: A focus on recent practical advances. *European Journal of Operational Research, 324*(3), 707–731.

Colorni, A., & Tsoukias, A. (2024). What is a decision problem? *European Journal of Operational Research, 314*, 255–267.

Costa, A. S., Lami, I. M., Greco, S., Figueira, J. R., & Borbinha, J. (2019). A multiple criteria approach defining cultural adaptive reuse of abandoned buildings. In S. Huber, M. J. Geiger, & A. Teixeira de Almedia (Eds.), *Multiple criteria decision making and aiding* (pp. 193–220). Stanford: Springer.

Costa, A. S., Lami, I. M., Greco, S., Figueira, J. R., & Borbinha, J. (2021). Assigning a house for refugees: An application of a multiple criteria nominal classification method. *Operational Research, 21*(4), 2651–2687.

Coveney, P., & Highfield, R. (1995). *Frontiers of complexity*. New York: Faber and Faber.

Cozzolino, S., & Moroni, S. (2021). Multiple agents and self-organisation in complex cities: The crucial role of several property. *Land Use Policy, 103*, 1–7.

Cozzolino, S., & Moroni, S. (2022). Structural preconditions for adaptive urban areas: Framework rules, several property and the range of possible actions. *Cities, 130*, 1–7.

Cozzolino, S., & Moroni, S. (2025). *Action, property and beauty: Planning with and for emergent urban complexity*. London: Taylor & Francis.

Davidson, S. (2024). The economic institutions of artificial intelligence. *Journal of Institutional Economics, 20*, 1–16.

Driesen, D. M. (2006). Is cost-benefit analysis neutral? *University of Colorado Law Review, 77*, 335–402.

Fischhoff, B., & Furby, L. (1988). Measuring values: A conceptual framework for interpreting transactions with special reference to contingent valuation of visibility. *Journal of Risk and Uncertainty, 1*, 147–184.

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., … Vayena, E. (2018). AI4People. An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines, 28*, 689–707.

Fregonese, E., Lami, I. M., & Todella, E. (2020). Aesthetic perspectives in group decision and negotiation practice. *Group Decision and Negotiation, 29*(6), 993–1019.

Giezen, M. (2013). Adaptive and strategic capacity: Navigating megaprojects through uncertainty and complexity. *Environment and Planning. B, Planning & Design, 40*(4), 723–741.

Gillroy, J. M. (1992). The ethical poverty of cost-benefit methods: Autonomy, efficiency and public policy choice. *Policy Sciences, 25*(2), 83–102.

Glynn, S. (1996). Ethical issues in environmental decisionm and the limitations of cost/benefit analysis (CBA). *Ethics & the Environment, 1*(1), 27–39.

Greco, S., Ehrgott, M., & Figueira, J. R. (Eds.). (2016). *Multiple criteria decision analysis: State of the art surveys II*. New York (NY): Springer.

Hämäläinen, R. P., Lahtinen, T. J., & Virtanen, K. (2024). Generating policy alternatives for decision making: A process model, behavioural issues, and an experiment. *EURO Journal on Decision Processes, 12*, Article 100050.

Hao, H., Wang, Y., & Chen, J. (2024). Empowering scenario planning with artificial intelligence: A perspective on building smart and resilient cities. *Engineering, 43*, 272–283.

Harcourt, B. E. (2018). The systems fallacy: A genealogy and critique of public policy and cost-benefit analysis. *The Journal of Legal Studies, 47*(2), 419–447.

Hausman, D. M., & McPherson, M. S. (1984). The philosophical foundations of mainstream normative economics. In D. M. Hausman (Ed.), *The philosophy of economics: An anthology* (pp. 226–247). Cambridge: Cambridge University Press.

Holland, J. H. (1995). *Hidden order. How adaptation builds complexity*. New York: Basic Books.

Howard, R. A. (1988). Decision analysis: Practice and promise. *Management Science, 34*(6), 679–695.

Jacobs, J. (1961). *The death and life of great American cities*. New York: Vintage.

Kahneman, D., & Knetsch, J. L. (1992). Valuing public goods: The purchase of moral satisfaction. *Journal of Environmental Economics and Management, 22*(1), 57–70.

Kamrowska-Załuska, D. (2021). Impact of AI-based tools and urban big data analytics on the design and planning of cities. *Land, 10*(11), Article 1209.

Karadimas, P. (2023). The epistemic impossibility of economic calculation. *Synthese, 202*(6), 1–22.

Kayacık, S. E., Basciftci, B., Schrotenboer, A., & Ursavas, E. (2024). *Adaptive Multistage Stochastic Programming*. arXiv.org (pp. 1–39) https://arxiv.org/abs/2401.07701.

Keeney, R. L. (1982). *Value-focused thinking: A path to creative decision-making*. Cambridge (Mass.): Harvard University Press.

Keeney, R. L., & Raiffa, H. (1993). *Decisions with multiple objectives: Preferences and value trade-offs*. Cambridge: Cambridge University Press.

Kelman, S. (1985). Cost-benefit analysis and environmental, safety, and health regulation: Ethical and philosophical considerations. In M. Wachs (Ed.), *Ethics in planning* (pp. 233–245). New Brunswick (N.J.): The Center for Urban Policy Research.

Kuhn, C. C. N., Calbert, G., Garanovich, I., & Weir, T. (2023). Integer linear programming supporting portfolio design. arXiv.org. https://arXiv:2303.14364

Kumar, P., Rosenberger, J. M., & Iqbal, G. M. D. (2016). Mixed integer linear programming approaches for land use planning that limit urban sprawl. *Computers & Industrial Engineering, 102*, 33–43.

Lami, I. M., Abastante, F., Bottero, M., Masala, E., & Pensa, S. (2014). Integrating multicriteria evaluation and data visualization as a problem structuring approach to support territorial transformation projects. *EURO Journal on Decision Processes, 2*(3/4), 281–312.

Lami, I. M., & Moroni, S. (2020). How can i help you? Questioning the role of evaluation techniques in democratic decision-making processes. *Sustainability, 12*(20), 1–17.

Lami, I. M., & Tavella, E. (2019). On the usefulness of soft OR models in decision making: A comparison of problem structuring methods supported and self-organized workshops. *European Journal of Operational Research, 275*(3), 1020–1036.

Lami, I. M., & Todella, E. (2023). A multi-methodological combination of the strategic choice approach and the analytic network process: From facts to values and vice versa. *European Journal of Operational Research, 307*(2), 802–812.

Lami, I. M., & White, L. (2022). Are PSMs relevant in a digital age? Towards an ethical dimension. In S. Salhi, & J. Boylan (Eds.), *The Palgrave handbook of operations research* (pp. 781–801). Cham: Springer.

Lartey, D., & Law, K. M. Y. (2025). Artificial intelligence adoption in urban planning governance: A systematic review of advancement in decision-making, and policy making. *Landscape and Urban Planning, 58*, 1–15.

Leal Filho, W., Mbah, M. F., Dinis, M. A. P., Trevisan, L. V., de Lange, D., Mishra, A., … Aina, Y. A. (2024). The role of artificial intelligence in the implementation of the UN sustainable development goal 11: Fostering sustainable cities and communities. *Cities, 150*, 1–16.

Lemieux, F., Behr, A., Kellermann-Bryant, C., & Mohammed, Z. (2025). *Cognitive Bias Detection Using Advanced Prompt Engineering*. arXiv preprint (pp. 1–17). arXiv: 2503.05516.

Liesiö, J., Salo, A., Keisler, J. M., & Morton, A. (2021). Portfolio decision analysis: Recent developments and future prospects. *European Journal of Operational Research, 293*(3), 811–825.

Loasby, B. J. (2002). Evolution and institutions: A cognitive perspective. *East-West Journal of Economics and Business, 5*(1/2), 27–45.

Loomis, J., & Helfand, G. (2001). *Environmental policy analysis for decision making*. Dordrecht: Springer.

MacIntyre, A. (1985). Utilitarianism and the presuppositions of cost-benefit analysis: An rssay on the relevance of moral philosophy to the theory of bureaucracy. In M. Wachs (Ed.), *Ethics in planning* (pp. 216–232). New Brunswick (N.J.): The Center for Urban Policy Research.

MacLean, D. (1980). Benefit-cost analysis, future generations and energy policy: A survey of the moral issues. *Science, Technology & Human Values, 5*(2), 3–10.

Mainardi, I. (2025). Change management: Artificial intelligence (AI) at the service of public administrations. *AI & Society, 40*, 3953–3981. https://doi.org/10.1007/s00146-024-02136-2

Marewski, J. N., Katsikopoulos, K. V., & Guercini, S. (2024). Simon's scissors: meta-heuristics for decision-makers. *Management Decision, 62*(13), 283–308.

Martinelli, E. (2025). An agent-based approach to the limits of economic planning. *AI & Society, 40*, 3391–3403.

McDaniel, R. R., & Driebe, D. J. (2005). Uncertainty and surprise: An introduction. In R. R. McDaniel, & D. J. Driebe (Eds.), *Uncertainty and surprise in complex systems. Questions on working with the unexpected* (pp. 3–11). Berlin: Springer.
Mingers, J., & Rosenhead, J. (2004). Problem structuring methods in action. *European Journal of Operational Reseearch, 152*(3), 530–554.
Mishan, E. J., & Quah, E. (2020). *Cost-benefit analysis*. London: Routledge.
Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. *Big Data & Society, 3*(2), 1–21.
Mökander, J., & Floridi, L. (2021). Ethics-based auditing to develop trustworthy AI. *Minds and Machines, 31*(2), 323–327.
Morley, J., Elhalal, A., Garcia, F., Kinsey, L., Mökander, J., & Floridi, L. (2021). Ethics as a service: A pragmatic operationalisation of AI ethics. *Minds and Machines, 31*(2), 239–256.
Moroni, S. (2006). The ethics behind evaluation. In E. R. Alexander (Ed.), *Evaluation in Planning. Evolution and Prospects* (pp. 21–38). Aldershot: Ashgate.
Moroni, S. (2019). Critically reconsidering orthodox ideas: Planning as teleocratic intervention and planning as a rational decision method. *Planning Theory & Practice, 20*(3), 323–338.
Moroni, S. (2023). Distinguishing “planning” from the “plan”. Institutional and professional implications of taking urban complexity seriously. *European Planning Studies, 31*(11), 2327–2341.
Moroni, S. (2025). Insurmountable limitations of city-scale digital twins? On urban knowledge and planning. *Computational Urban Science, 5*(1), 1–12.
Moroni, S., & Chiffi, D. (2021). Complexity and uncertainty: Implications for urban planning. In J. Portugali (Ed.), *Handbook on cities and complexity* (pp. 319–330). Cheltenham: Edward Elgar.
Moroni, S., & Chiffi, D. (2022). Uncertainty and planning: Cities, technologies and public decision-making. *Perspectives on Science, 30*(2), 237–259.
Nickles, T. (2018). Bounded rationality, scissors, crowbars, and pragmatism: Reflections on Herbert Simon. *Mind & Society, 17*, 85–96.
Nizamani, M. M., Qureshi, S., Tarashkar, M., Zhang, H. L., Zhou, Q., & Lai, Z. (2025). Ethical AI: Human-centered approaches for adaptive and sustainable urban planning and policy. *Land Use Policy, 157*, 1–14.
Nussbaum, M. C. (2000). The costs of tragedy: Some moral limits of cost-benefit analysis. *The Journal of Legal Studies, 29*, 1005–1036.
Osman, M. (2017). Problem solving: Understanding complexity as uncertainty. In B. Csapó, & J. Funke (Eds.), *The nature of problem solving* (pp. 47–57). Paris: OECD Publishing.
Parnell, G. S., Driscoll, P. J., & Henderson, D. L. (Eds.). (2013). *Handbook of Decision Analysis*. Hoboken (N.J.): Wiley.
Pastor-Escuredo, D., Treleaven, P., & Vinuesa, R. (2022). An ethical framework for artificial intelligence and sustainable cities. *AI, 3*(4), 961–974.
Pearce, D. W., & Nash, C. A. (1981). *The social appraisal of projects: A text in cost-benefit analysis*. London: Macmillan.
Pensa, S., Masala, E., & Lami, I. M. (2013). Supporting planning processes by the use of dynamic visualisation. In S. Geertman, F. Toppen, & J. Stillwell (Eds.), *Lecture notes in Geoinformation and cartographyPlanning support Systems for Sustainable Urban Development* (pp. 451–467). Berlin: Springer.
Portugali, J. (1999). *Self-organization and the City*. Berlin: Springer.
Posner, R. A., & Adler, M. D. (1999). Rethinking cost-benefit analysis. *The Yale Law Journal, 109*, 165–247.
Rasoulzadeh Aghdam, S., Bababei Morad, B., Ghasemzadeh, B., Irani, M., & Huovila, A. (2025). Social smart city research: Interconnections between participatory governance, data privacy, artificial intelligence and ethical sustainable development. *Frontiers in Sustainable Cities, 6*, 1–15.
Rastogi, C., Zhang, Y., Wei, D., Varshney, K. R., Dhurandhar, A., & Tomsett, R. (2022). Deciding fast and slow: The role of cognitive biases in AI-assisted decision-making. *Proceedings of the ACM on Human-Computer Interaction, 6*, 1–22.
Raz, J. (1975). Reasons for action, decisions and norms. *Mind, 84*(336), 481–499.
Rescher, N. (1997). *Predicting the future: An introduction to the theory of forecasting*. New York: State University of New York Press.
Rescher, N. (2009). *Ignorance*. Pittsburgh: University of Pittsburgh Press.
Rosenhead, J. (1996). What’s the problem? An introduction to problem structuring methods. *Interfaces, 26*(6), 117–131.
Roy, B. (1977). *Optimisation et aide à la decision*. Paris: Cahier du Lamsade.
Roy, B. (1996). *Multicriteria methodology for decision aiding*. Dordrecht: Kluwer.
Sanchez, T. W., Brenman, M., & Ye, X. (2025). The ethical concerns of artificial intelligence in urban planning. *Journal of the American Planning Association, 91*(2), 294–307.
Santosuosso, A., & Sartor, G. (2024). *Decidere con l’AI. Intelligenze artificiali e naturali nel diritto*. Bologna: Il Mulino.
Shapiro, S. A. (2011). Cost-benefit analysis: An organizational design perspective. *NYU Environmental Law Journal, 19*, 1–126.
Shick, M., Johnson, N., & Fan, Y. (2024). Artificial intelligence and the end of bounded rationality: A new era in organizational decision making. *Development and Learning in Organizations: An International Journal, 38*(4), 1–3.
Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics, 69*(1), 99–118.
Simon, H. A. (1961). *Administrative behaviour. A study of decision-making processes in administrative organization*. New York: The Free Press.
Simon, H. A. (1983). *Reason in human affairs*. Stanford: Stanford University Press.
Simon, H. A. (1990). Invariants of human behavior. *Annual Review of Psychology, 41*(1), 1–20.
Simon, H. A. (1996). *The sciences of the artificial*. Cambridge (Mass): The MIT Press.
Todd, P. M., & Gigerenzer, G. (2001). Shepard’s mirrors or Simon’s scissors? *Behavioral and Brain Sciences, 24*(4), 704–705.
Todd, P. M., & Gigerenzer, G. (2003). Bounding rationality to the world. *Journal of Economic Psychology, 24*(2), 143–165.
Tsamados, A., Aggarwal, N., Cowls, J., Morley, J., Roberts, H., Taddeo, M., & Floridi, L. (2022). The ethics of algorithms: Key problems and solutions. *AI & Society, 37*, 215–230.
Tsoukias, A., Montibeller, G., Lucertini, G., & Belton, V. (2013). Policy analytics: An agenda for research and practice. *EURO Journal on Decision Processes, 1*, 115–134.
Tupayachi, J., Xu, H., Omitaomu, O. A., Camur, M. C., Sharmin, A., & Li, X. (2024). Towards next-generation urban decision support systems through AI-powered construction of scientific ontology using large language models. A case in optimizing intermodal freight transportation. *Smart Cities, 7*(5), 2392–2421.
Urfalino, P. (2010). Deciding as bringing deliberation to a close. *Social Science Information, 49*(1), 111–140.
Vatn, A. (2009). An institutional analysis of methods for environmental appraisal. *Ecological Economics, 68*(8/9), 2207–2215.
Xu, H., Sun, Y., Tupayachi, J., Omitaomu, O., Zlatanov, S., & Li, X. (2025). *Towards the autonomous optimization of urban logistics: Training generative AI with scientific tools via agentic digital twins and model context protocol*. arXiv preprint (pp. 1–29) arxiv.org/abs/2506.13068.
Yang, B., Zhan, W., Wang, P., Chan, C., Cai, Y., & Wang, N. (2021). Crossing or not? Context-based recognition of pedestrian crossing intention in the urban environment. *IEEE Transactions on Intelligent Transportation Systems, 23*(6), 5338–5349.
Ye, X., Yigitcanlar, T., Goodchild, M., Huang, X., Li, W., Shaw, S. L., … Newman, G. (2025). Artificial intelligence in urban science: Why does it matter? *Annals of GIS*, 1–9. https://doi.org/10.1080/19475683.2025.2469110
Yigitcanlar, T., Senadheera, S., Marasinghe, R., Bibri, S. E., Sanchez, T., Cugurullo, F., & Sieber, R. (2024). Artificial intelligence and the local government: A five-decade scientometric analysis on the evolution, state-of-the-art, and emerging trends. *Cities, 152*, 1–21.