



ScienceDirect

Contents lists available at sciencedirect.com
Journal homepage: www.elsevier.com/locate/jval

Systematic Literature Review

The Use of Multicriteria Decision Analysis to Support Decision Making in Healthcare: An Updated Systematic Literature Review



Pamela Gongora-Salazar, MSc, Stephen Rocks, MSc, Patrick Fahr, DPhil, Oliver Rivero-Arias, DPhil, Apostolos Tsiachristas, PhD

ABSTRACT

Objectives: Multicriteria decision analysis (MCDA) is increasingly used for decision making in healthcare. However, its application in different decision-making contexts is still unclear. This study aimed to provide a comprehensive review of MCDA studies performed to inform decisions in healthcare and to summarize its application in different decision contexts.

Methods: We updated a systematic review conducted in 2013 by searching Embase, MEDLINE, and Google Scholar for MCDA studies in healthcare, published in English between August 2013 and November 2020. We also expanded the search by reviewing grey literature found via Trip Medical Database and Google, published between January 1990 and November 2020. A comprehensive template was developed to extract information about the decision context, criteria, methods, stakeholders involved, and sensitivity analyses conducted.

Results: From the 4295 identified studies, 473 studies were eligible for full-text review after assessing titles and abstracts. Of those, 228 studies met the inclusion criteria and underwent data extraction. The use of MCDA continues to grow in healthcare literature, with most of the studies (49%) informing priority-setting decisions. Safety, cost, and quality of care delivery are the most frequently used criteria, although there are considerable differences across decision contexts. Almost half of the MCDA studies used the linear additive model whereas scales and the analytical hierarchy process were the most used techniques for scoring and weighting, respectively. Not all studies report on each one of the MCDA steps, consider axiomatic properties, or justify the methods used.

Conclusions: A guide on how to conduct and report MCDA that acknowledges the particularities of the different decision contexts and methods needs to be developed.

Keywords: multicriteria decision analysis, healthcare, decision-making, priority-setting, systematic literature review.

VALUE HEALTH. 2023; 26(5):780–790

Introduction

Multicriteria decision analysis (MCDA) is defined as a systematic and theory-based approach to perform a comparative analysis of several competing options (eg, healthcare interventions) based on their performance on multiple and often conflicting criteria.^{1,2} The development of a quantitative MCDA involves the following steps^{2,3}: (1) defining the decision problem, (2) selecting the evaluation criteria, (3) assessing the performance scores of each alternative on each criterion, (4) determining the criteria weights, (5) aggregating performance scores and criteria weights in an overall value, (6) dealing with uncertainty, and (7) examining findings and deliberate.

In healthcare, MCDA has emerged as an alternative or complementary framework to address limitations of traditional health technology assessment (HTA) approaches^{3,4} such as cost-utility

analysis.^{5,6} As documented previously, the growing need for MCDA in healthcare is reflected by the steep increase of empiric studies across different decision contexts.^{7–11}

Although the application of MCDA in healthcare has been summarized in several review studies, none of them has systematically detailed how MCDA has been applied within and across different healthcare decision contexts. The most comprehensive review of MCDA studies was published 8 years ago by Marsh et al (2014)⁷ and did not examine the methodological differences by decision context. In addition, all previous review studies did not include grey literature, such as technical documents from HTA agencies and policy reports from healthcare authorities or multi-lateral bodies, thereby increasing the risk of missing important applications of MCDA in healthcare. The aim of this updated systematic literature review was to provide a comprehensive overview of MCDA studies in different healthcare decision contexts. To

achieve this, we provided a detailed overview of (1) the different decision contexts in healthcare and then by decision context, (2) the criteria used, (3) the data sources and methods used to derive performance scores, (4) the applied scoring and weighting techniques, (5) the approaches used to obtain overall values and rank the compared alternatives, and (6) the type of sensitivity analysis conducted.

This is the first review that includes grey literature and summarizes key methodological information by decision context. Such information could guide researchers in designing MCDA studies by supporting the selection of appropriate methods and criteria relevant to their decision context. In light of the numerous MCDA methods available¹² and the criticism of lack of transparency,² findings from this review could also be used as a basis to start developing a detailed methodological and reporting guidance by decision context.

Methods

This review was registered in PROSPERO (CRD42020219093) in November 2020, and the results were reported following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020 statement,^{13,14} the guidance for updated systematic reviews,¹⁵ and recently published systematic literature reviews in *Value in Health* journal.

Search Strategy

To update the review by Marsh et al (2014),⁷ we conducted a database search of scientific literature published between August 2013 and November 2020. We decided to update this review because it seems to be the most comprehensive in terms of the number of included studies, extracted information, and data synthesis. As Marsh et al (2014)⁷ included studies up to 2013, we searched for more recent MCDA studies in the reviews of Adunlin et al (2015)⁸ and Frazão et al (2018),⁹ which also reviewed the application of MCDA in different decision contexts in healthcare. We also searched grey literature¹⁶ published between January 1990 and November 2020 to expand the scope of review of Marsh et al.⁷ All searches were conducted by P.G. under the guidance of a librarian who advised on the search strategy and selection of databases.

Variations in search terms were added and terms were searched as free-text keywords in the title and abstract fields.¹⁷ The search terms were based on Marsh et al (2014),⁷ Adunlin et al (2015),⁸ and Frazão et al (2018).⁹ Scientific studies were identified from the following databases: MEDLINE, Embase, and Google Scholar (100 first hits).

It is expected that all relevant academic studies are identified from MEDLINE and Embase, because they are high-level academic databases. Nevertheless, Google Scholar was used as an additional tool to locate potentially relevant studies that might not have been included in MEDLINE or Embase. Although for primary review searches Google Scholar is unsuitable, it is considered a suitable supplementary source of evidence when conducting systematic literature reviews.^{18,19} Due to the vast number of results displayed and the inability to directly export results in bulk as citations, systematic reviews typically screen the first 50 to 100 search records within Google Scholar.^{19,20}

To identify grey literature—online resources—searches were conducted in Trip Medical Database and Google. In Trip Medical Database, records classified as evidence-based synopses and guidelines were reviewed, using the title and short text underneath. Relevant titles were selected for further screening by a reviewer using the eligibility criteria. All previously defined search

terms were used. We used Google¹⁹ to search within 53 websites of governmental entities, networks, societies, and international bodies in health economics, using the “site” option in the search box (eg, site:nhs.uk) and all previously defined search terms. For Google, the search was limited to 4 search terms given that searches cannot be limited to abstract and title. See Appendices 1 and 2 in Supplemental Materials found at <https://doi.org/10.1016/j.jval.2022.11.007> for more in detail information about the search terms and websites used.

Selection Process and Eligibility Criteria

All study titles and abstracts were exported to EndNote X9 (Clarivate, Philadelphia, PA).²¹ Before the screening of titles and abstracts, all reviewers met to finalize the eligibility criteria. Titles and abstracts were doubled screened independently by 2 reviewers (P.G., anonymous reviewer (A.R.), and S.R.): P.G. screened titles and abstracts of all records, and the same studies were equally split and screened by A.R. and S.R. Disagreements between reviewers were resolved through discussion, and the fourth reviewer (A.T.) was consulted when necessary. All studies were assessed and included based on the following eligibility criteria:

Inclusion criteria

1. Full-text studies in English language
2. Studies that reported an empiric application of MCDA to inform decisions in healthcare and described the MCDA methods used
3. Studies that specified the MCDA method implemented

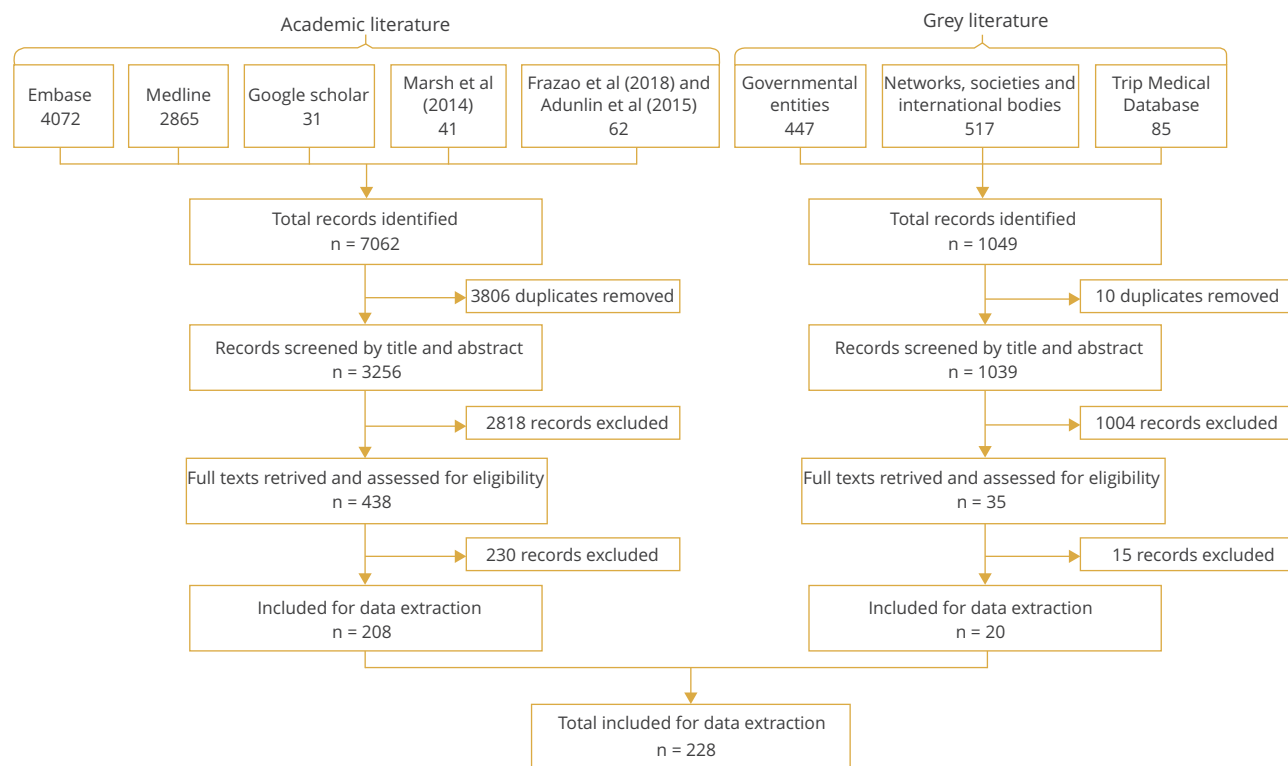
Exclusion criteria

1. Studies that did not apply MCDA
2. Studies that did not complete all the steps in the MCDA definition stated in the introduction (eg, relevant criteria were identified but weights were not elicited or defined)
3. Studies that did not aim to inform a decision in healthcare (eg, studies that used MCDA to derive health status utility values and with this calculate quality-adjusted life-years)

Similar to Marsh et al's study (2014),⁷ studies were not excluded on the basis of methodological quality. Nevertheless, we used a broader definition of healthcare by adopting a system perspective. Therefore, we included all studies that addressed decisions made within the healthcare sector or the entire healthcare system (ie, decisions made across the production, sourcing, organization, and delivery of healthcare) and exclude studies that inform interventions delivered outside the health sector (eg, social, occupational, or environmental interventions), despite their potential health impact.

Data Extraction and Analysis

A comprehensive template for data extraction was developed and piloted to ensure high level of consistency in extracting data between reviewers (P.G., A.R., and P.F.). The data were grouped in decision contexts, criteria, weighting and scoring techniques, sources of data, stakeholders involved, and methods to address uncertainty. The categorization of decision contexts was based on Marsh et al (2014),⁷ but we provided another layer of detail by providing subcategories in each decision context. Then, we allocated the selected studies to each subcategory using the reported (often in the study aim) information on what decision each MCDA study was aiming to inform. To define the different criteria categories, we used the taxonomies from Tsiachristas et al,²² and

Figure 1. PRISMA flowchart.

PRISMA indicates Preferred Reporting Items for Systematic Reviews and Meta-Analyses.

Marsh et al (2014)⁷ and used an explicit code book with definitions and examples for each category. To identify the type of uncertainty addressed by the MCDA studies, we used Broekhuizen et al's²³ classification and distinguish among heterogeneity, parameter uncertainty (ie, criterion weight or performance score), and structural uncertainty.

Descriptive statistics were used for analyzing data with regard to the decision context, the applied MCDA techniques, and the type of stakeholders that participated in each of the MCDA steps. We used Microsoft Excel²⁴ (Microsoft, Redmond, WA) for constructing all tables, figures, and descriptive statistics and summarized the results for each of the MCDA steps.^{3,4}

Reviewers' Consistency

For reducing potential biases during the assessment and data extraction process and following good practice guidelines,²⁵ a selection of papers was discussed between reviewers during the agreement meeting. P.G. reviewed and extracted data from a sample of 10% of the studies reviewed by A.R. and P.F., respectively. A.R. and P.F. did the same with 10% of the records reviewed by P.G. The extracted data were then compared and a strong consensus was achieved between reviewers for both the assessment and extraction process (> 95% and > 85% inter-reviewer agreement, respectively).

Results

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses flowchart of this review is presented in Figure 1. After removing duplicates, 4295 studies (3256 and 1039 studies from the database and grey literature search, respectively) were retained. After the screening of all records, 438 academic titles and

35 grey literature documents met the inclusion criteria. The full-text examination of the retrieved records excluded 230 academic studies and 15 grey literature documents. The analysis included in the end 228 eligible studies (219 MCDA studies). A summary of the results of all searches conducted, with the list of studies included in the review, can be found in Appendix 2 in Supplemental Materials found at <https://doi.org/10.1016/j.jval.2022.11.007>. Derived data supporting the findings of this study are available upon request.

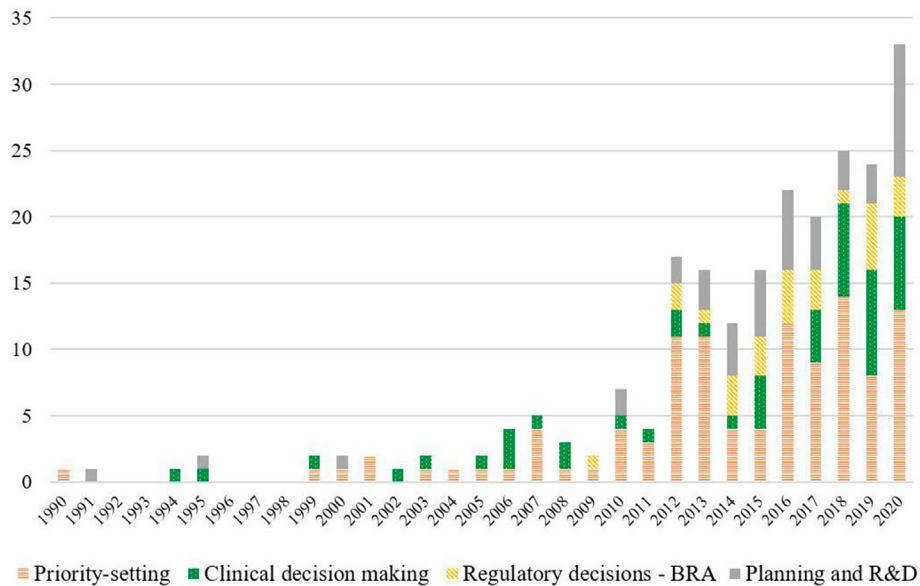
Study Characteristics

Figure 2 illustrates the number of MCDA studies (ie, 219 MCDA studies in total) in healthcare between 1990 and 2020. Although the first studies were conducted in the early 90s, it is since 2010 that a sharp upward trend can be observed, with no grey literature found before 2010. Studies informing priority-setting decisions were the first and have been the most predominant, although the share of studies informing other decision contexts has increased over the last 10 years. A definition of each one of the decision contexts identified is provided in Appendix 2 in Supplemental Materials found at <https://doi.org/10.1016/j.jval.2022.11.007>.

In almost 90% of the MCDA studies (n = 192), academia was involved either solely (62%, n = 135) or in conjunction with the public sector (18%, n = 39), the private sector (10%, n = 22), or international organizations (3%, n = 7).

Decision Context

As presented in Table 1, most studies have informed priority-setting decisions (48%, n = 107). Roughly 22% of MCDA studies (n = 48) were concerned with clinical decision making, and 11% (n = 25) with guiding regulatory decisions such as marketing authorizations. Although to a lesser extent, MCDA studies have

Figure 2. Publication trend of MCDA studies in healthcare by decision context.

BRA indicates benefit-risk assessment; MCDA, multicriteria decision analysis; R&D, research and development.

also informed hospitals or health systems when making capital investment decisions (4%, $n = 8$) or decisions on the location or reallocation of healthcare services or facilities (4%, $n = 8$). We also identified MCDA studies conducted to support manufacturers in the development of new medicines (4%, $n = 8$), to guide research decisions (2%, $n = 5$), to inform the regulation of addictive substances (1%, $n = 3$), and to support the selection of best healthcare wastes management method (1%, $n = 3$).

Most of the MCDA studies (63%, $n = 137$) have taken place in high-income countries, principally in Europe (37%, $n = 82$) and North America (19%, $n = 41$). With exception of regulatory decision contexts, where almost all studies have informed high-income countries (96%, $n = 22$), approximately a third of MCDA studies

applied in the other decision contexts have taken place in low- and middle-income countries.

More than a third of the MCDA studies (35%, $n = 76$) have been developed to inform decisions at national level, followed by studies conducted to inform decisions at local level (14%, $n = 31$). Nevertheless, 21% of the studies ($n = 47$) did not report the decision level. Regulators or budget holders are the most common users of MCDA in healthcare, with > 40% of the studies ($n = 90$) informing ministries of health, commissioners, public health institutes, or local authorities. Nevertheless, in clinical decision making, 56% of the MCDA studies ($n = 27$) aimed to inform physicians, 29% ($n = 14$) informed patients or carers, and only 10% ($n = 5$) informed regulators or budget holders.

Table 1. Decision contexts that MCDA studies have been applied in.

Decision context		n	% of 219*
Priority setting	Prioritization of interventions for coverage, reimbursement, funding or future developments	85	39
	Prioritization of diseases for coverage, reimbursement or funding	12	5
	Prioritization of patients to access healthcare	10	5
Clinical decision making	Treatments or Prescription	34	16
	Screening	14	6
Regulatory decisions	BRA to issue recommendations [†]	25	11
Planning and R&D	Capital investment decisions	8	4
	Location/reallocation decisions	8	4
	Guide pharmaceutical developments	8	4
	Research purposes	5	2
	Regulation of addictive substances	3	1
	Decisions on hospital wastes management decisions	3	1
	Other investing planning decisions [‡]	9	3

BRA indicates benefit-risk assessment; MCDA, multicriteria decision analysis; R&D, research and development.

*5 MCDA studies inform more than one type of decision.

[†]For example, market authorization.

[‡]For example, MCDA to guide the selection of healthcare providers or to choose best length of stay policy alternatives.

MCDA studies in healthcare have evaluated a diverse types of alternatives. More than 40% of the studies ($n = 93$) have assessed pharmaceuticals, followed by public health (14%, $n = 31$) and screening interventions (12%, $n = 27$). Pharmaceuticals are the most evaluated alternative (41%, $n = 90$) across all decision contexts, a frequency that goes up to 92% ($n = 23$) in the regulatory decision context. The second most frequent are public health interventions among priority-setting studies (26%, $n = 28$) and medical screening programs in the case of clinical decision making (25%, $n = 12$). Nearly 16% of the eligible studies ($n = 35$) evaluated more than one type of alternative.

In terms of the number of alternatives assessed, on average, MCDA studies have evaluated 15 alternatives (median = 5, SD = 39.8), with a minimum of one and a maximum of 500. Priority-setting studies evaluated on average 20 alternatives (median = 8, SD = 51, min = 1, max = 500). This contrasts with the lower number of alternatives assessed when informing diagnosis or prescription decisions (mean = 5.1, median = 4, SD = 4.6, min = 1, max = 22) and regulatory decision (mean = 4.9, median = 4, SD = 3.6, min = 1, max = 15) or planning and research and development (R&D) decisions (mean = 18.7, median = 6, SD = 39.8, min = 1, max = 194). See Appendix 3 in Supplemental Materials found at <https://doi.org/10.1016/j.jval.2022.11.007> for more detailed information about the decision contexts.

Criteria

Different sources have been used to identify and define the MCDA criteria. Almost half of the MCDA studies have chosen criteria based on literature ($n = 103$). From these, 50% ($n = 52$) have solely used literature as a source, whereas the rest ($n = 51$) have additionally used other sources (eg, specialists or experts in the field). A quarter of the studies ($n = 56$) have chosen the criteria based on expert opinion, of which 15% ($n = 32$) used literature as well. More than 20% ($n = 48$) have adopted an established set of criteria (published or not published), most frequently from the Evidence and Value: Impact on Decision Making framework (7%, $n = 16$).²⁶

Less than 35% ($n = 76$) have considered stakeholders' views in the process of defining the criteria set. This includes providers of medical care (13%, $n = 28$), health authorities (8%, $n = 18$), patients (6%, $n = 13$), the private sector (3%, $n = 7$), social care authorities (2%, $n = 5$), government entities for social care services (2%, $n = 4$), and nongovernmental organizations (0%, $n = 1$).

In terms of the ways to agree on the criteria, approximately 37% of the studies ($n = 80$) have resorted to group discussions, 18% ($n = 39$) have relied on experts' opinions, and 11% ($n = 23$) have based the final selection of criteria on related literature. Nevertheless, a considerable number of studies have failed to report the method adopted to agree on the criteria (39%, $n = 86$).

When structuring the criteria, 41% of the studies ($n = 89$) have adopted a hierarchical structure. On average, 4.8 criteria (SD = 2.1, min = 2.0, max = 18) and 13.7 subcriteria (SD = 8.5, min = 3, max = 45) have been included in MCDA studies in healthcare that used a hierarchical structure. Studies that adopt a nonhierarchical structure have used on average 7.1 criteria (SD = 3.2, min = 2, max = 18).

As presented in Figure 3, several criteria have been used to inform decisions in healthcare, with "safety" (54%, $n = 119$), "cost" (49%, $n = 107$), "quality of care delivery" (40%, $n = 88$), "intermediate health outcomes" (34%, $n = 74$), and "feasibility or acceptability" (30%, $n = 65$) as the 5 most frequently used. Although in regulatory decisions > 70% of the studies have used "safety" (100%, $n = 25$) and "intermediate health outcomes" criteria, in priority setting a wider variety of criteria have been used, with

"cost" (52%, $n = 56$) and "safety" (44%, $n = 47$) at the front. Studies informing clinical decisions have mainly used "safety" (75%, $n = 36$) and "quality or process of care delivery" (60%, $n = 29$), whereas in the context of planning and R&D, "cost" (66%, $n = 29$) and "other" (50%, $n = 22$) are the 2 most predominant criteria. If we aggregate the number of studies that have used intermediate, final, and unspecified health outcomes as criteria, "health outcomes" becomes the most common criterion in all decision contexts, but planning and R&D.

MCDA Approaches

As presented in Figure 4A, the vast majority of studies have adopted a value-measured approach²⁷ (86%, $n = 189$), with linear additive models (eg, multiattribute utility theory, weighted sum) and analytical hierarchy process (AHP)²⁸ as the most common approaches adopted. Only 21 studies (10%) have used outranking models,³ such as PROMETHEE,³⁰ and 15 studies (7%) adopted a goal programming approach,³ with TOPSIS³² being the most popular one. A similar pattern is observed across studies informing prioritization decisions and treatment or screening decisions. Almost all studies that inform regulatory decisions via benefit-risk assessment (BRA) have adopted the linear additive model (91%, $n = 21$). These approaches were frequently applied using Microsoft Excel (29%, $n = 37$) and Expert Choice (15%, $n = 19$), although just 58% of the studies ($n = 127$) have reported the software used.

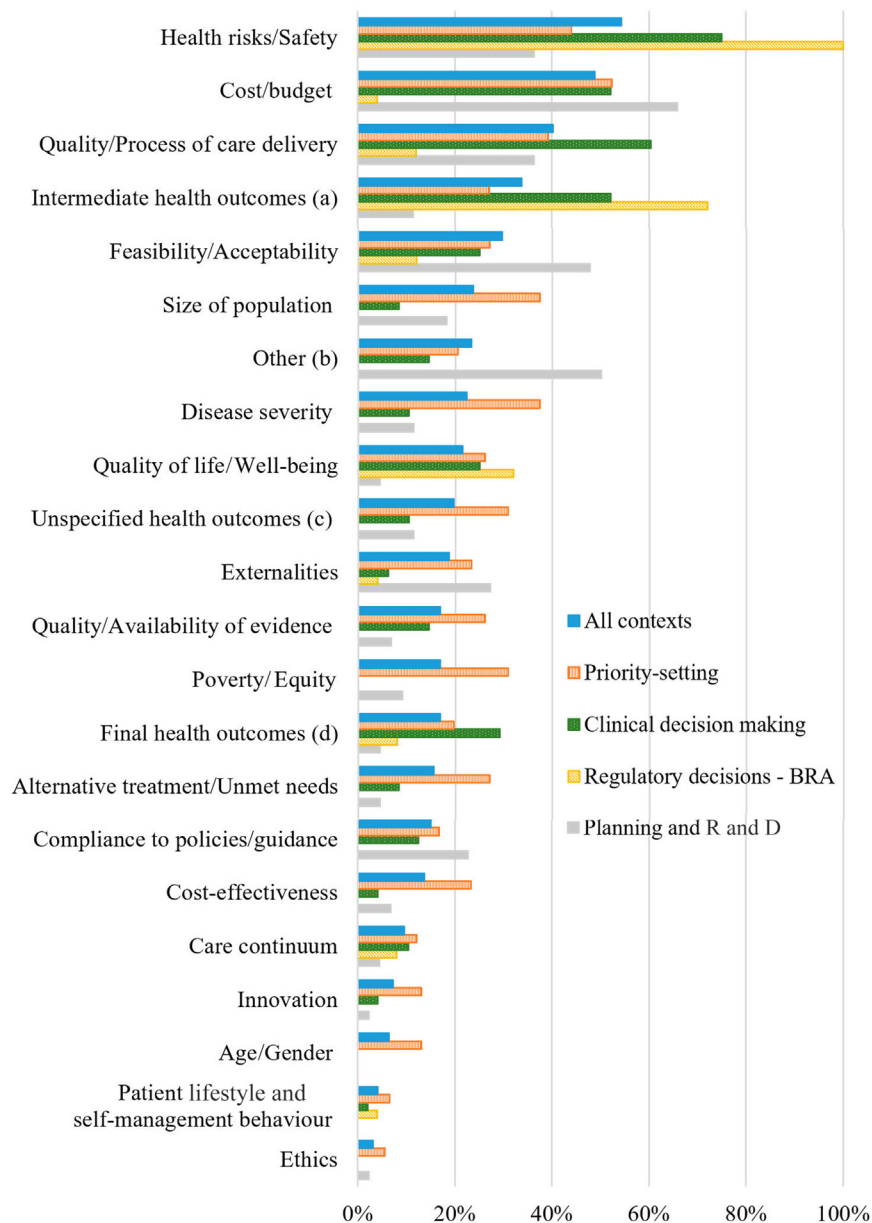
More than 70% of the studies retrieved ($n = 156$) have provided some justification for the MCDA approach applied, but few have justified the scoring and weighting technique adopted. Some of the reasons offered by these studies include the broad application of the method, the theoretical soundness, and the flexibility and relative ease to use.

Performance Scoring

Direct rating methods seem to be the preferred ones for scoring alternative's performance, with 30% of the studies ($n = 65$) using direct scales (eg, Likert scale) and 5% ($n = 12$) using a point allocation system (see Fig. 4B). AHP (26%, $n = 56$) and value function (13%, $n = 29$) are the second and the third most frequently used methods, respectively. Scales are the preferred technique (38%, $n = 41$) among prioritization-focused studies, whereas in clinical decision making and planning and R&D most studies have used AHP (35%, $n = 17$). Value function seems to be preferred when conducting BRA (60%, $n = 15$).

Regarding the sources to measure the performance of alternatives, 60% of the studies ($n = 131$) have used evidence from the literature. Approximately 32% of the MCDA studies ($n = 69$) have relied on experts' opinions, 16% ($n = 35$) have used trial data, and 14% ($n = 30$) have used routinely collected data. Approximately 20% of the studies ($n = 41$) have solely used research evidence, and 5% ($n = 12$) have relied only on expert opinions as a source. Almost half of the studies ($n = 104$) have used more than one source when measuring alternatives' performance, and more than a fifth ($n = 50$) have failed to report information on this MCDA stage. There are no considerable differences across decision contexts.

In terms of the stakeholders that participate in the scoring of alternatives, most of the studies have involved experts (41%, $n = 90$), healthcare providers (40%, $n = 88$), representatives from health authorities (23%, $n = 50$), and patients or carers (15%, $n = 32$). Few studies involved the private sector (7%, $n = 15$) or the general public (6%, $n = 14$). In 98 studies (45%), more than one actor has participated in this MCDA step, and on average 69 individuals (median = 12.5; SD = 346.7, min = 1, max = 3914) have been involved at this stage. Nevertheless, roughly 40% of the studies ($n = 87$) failed to report the number of stakeholders

Figure 3. Criteria used by decision context.

BRA indicates benefit-risk assessment; HbA1c, hemoglobin A1c; R&D, research and development. (A) Biomedical, physiological, and clinical health outcomes, for example, "reduction of HbA1c by 0.5%." (B) Other criteria that we did not classify (eg, "Total distance to the nearest hospital," "The type of medical insurance and its place of belonging," or criteria called as "Others" in the studies directly). (C) Unspecified health outcomes, such as "Improvement of efficacy/effectiveness." (D) Final health outcomes, such as mortality (eg, death from pulmonary tuberculosis) or life expectancy gains.

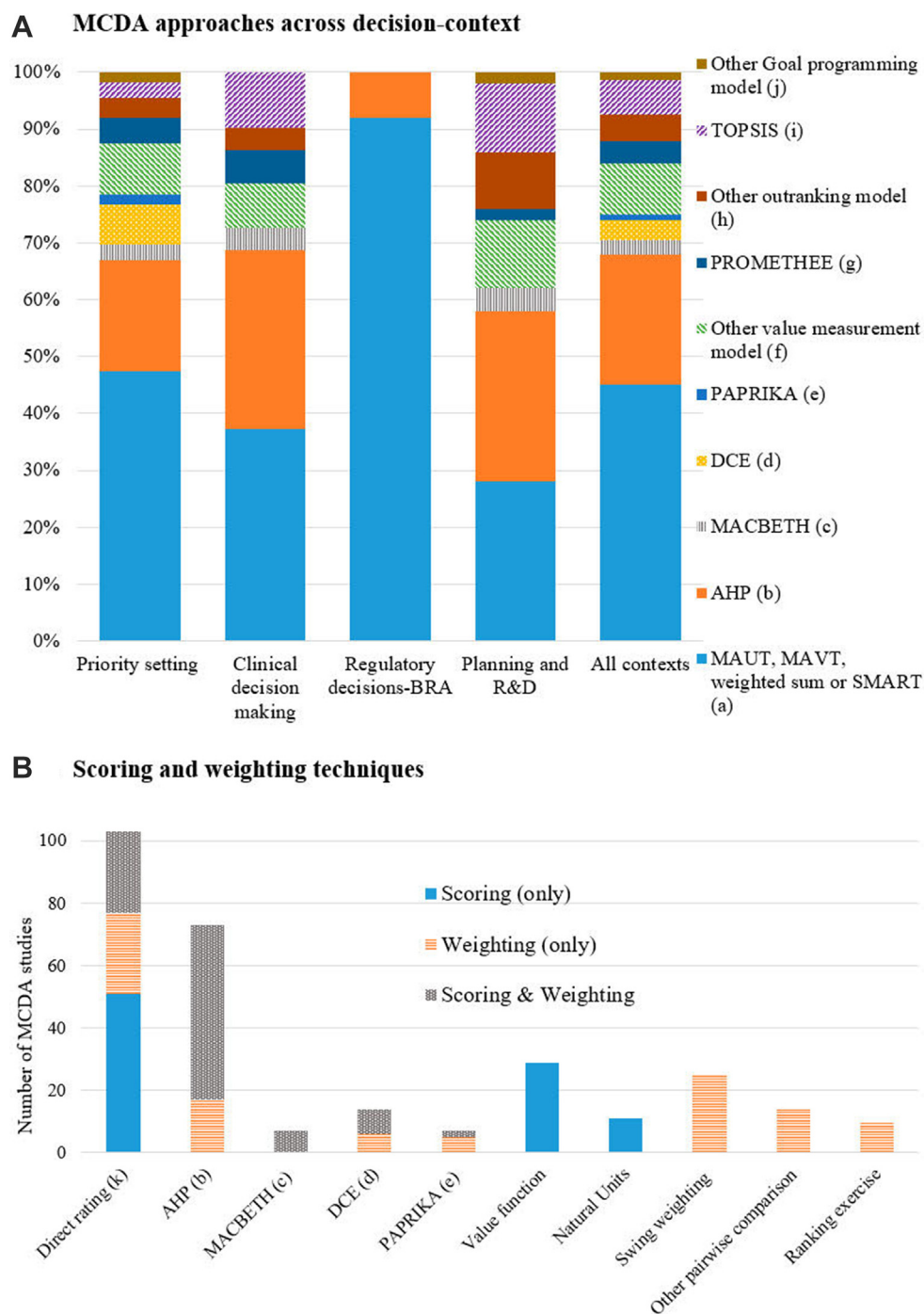
involved in the scoring of alternatives (see [Appendix 3](#) in [Supplemental Materials](#) found at <https://doi.org/10.1016/j.jval.2022.11.007>).

Criteria Weighting

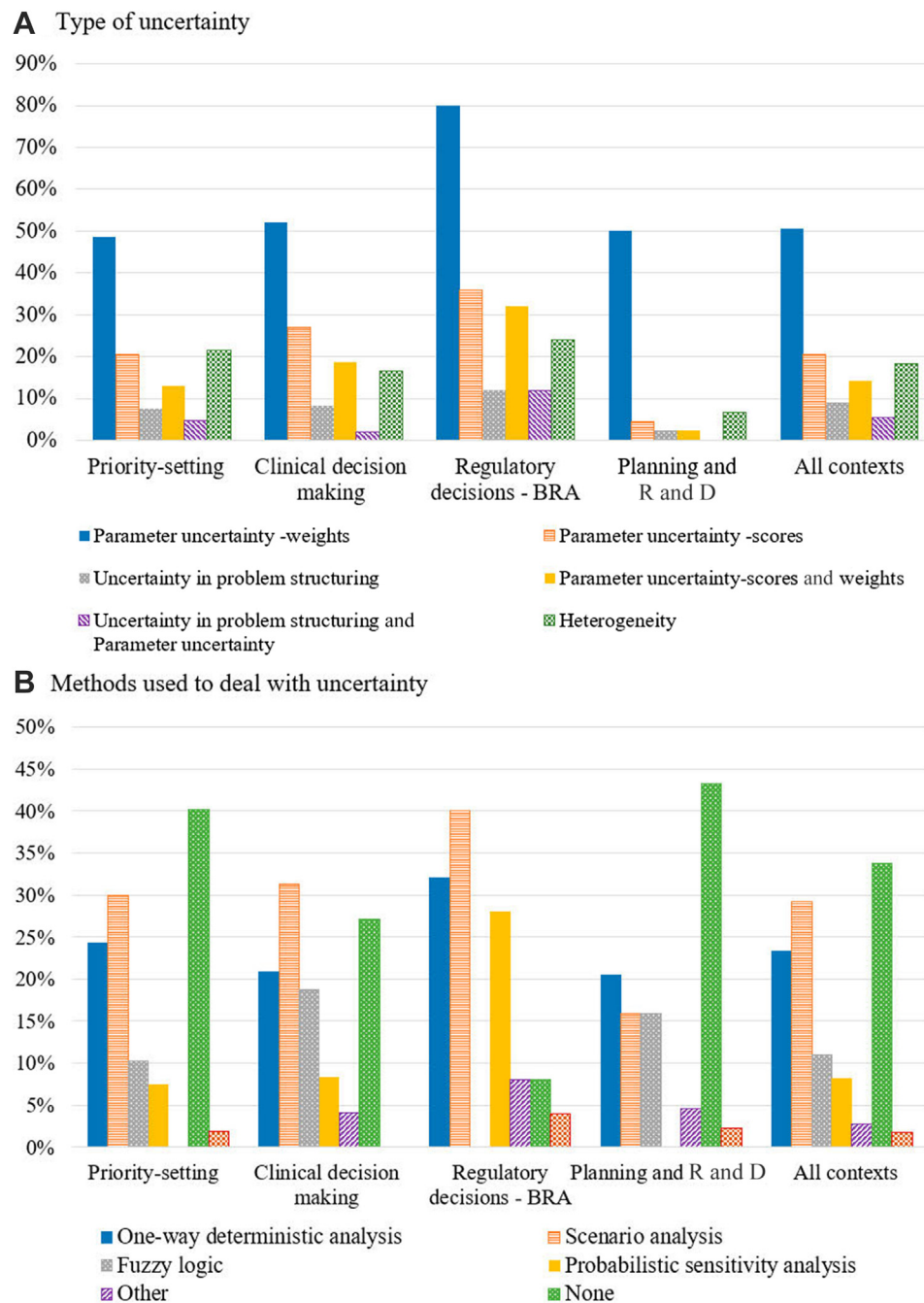
To elicit stakeholders' preferences between criteria, 33% of the studies ($n = 73$) have used AHP, with 76% of them ($n = 56$) using this technique also at the scoring stage (see [Fig. 4B](#)). Direct rating was also applied (24%, $n = 52$), followed by swing weighting (11%, $n = 25$), discrete choice experiment (6%, $n = 14$),³³ and other

pairwise comparison methods (6%, $n = 14$). A similar pattern is observed across decision contexts, except for studies informing "regulatory decisions" in which swing weighting has been used by most MCDA studies (56%, $n = 14$), with relatively few using AHP (16%, $n = 4$) (see [Appendix 3](#) in [Supplemental Materials](#) found at <https://doi.org/10.1016/j.jval.2022.11.007>).

Although virtually the same type of stakeholders are involved in the weighting and scoring steps (see [Appendix 3](#) in [Supplemental Materials](#) found at <https://doi.org/10.1016/j.jval.2022.11.007>), a relatively larger number of individuals is on average involved in the weighting of the criteria (mean = 118, median = 12.5, SD = 493.8, min = 1, max = 4288).

Figure 4. MCDA approaches and techniques applied.

Value-measurement models include: (A) MAUT, MAVT, weighted sum, and SMART methods²⁷; (B) AHP²⁸; (c) MACBETH²⁹; (d) DCE³⁰; (e) PAPRIKA³¹; and (f) other value-measurement models (eg, Socio-Technical Allocation of Resources). Outranking models include: (g) PROMETHEE³⁰; and (h) other outranking models (eg, elimination and choice expressing the reality). Goal programming models include: (i) TOPSIS³² and (j) other goal programming models (eg, VIKOR). (K) Direct rating includes scales and point allocation techniques.

Figure 5. Type of uncertainty and methods used to deal with it across decision context.

BRA indicates benefit-risk assessment; R&D, research and development.

Uncertainty Analyses

More than 65% of the MCDA studies ($n = 145$) in healthcare have addressed one or more types of uncertainty.²³ Half of the MCDA studies ($n = 111$) have addressed uncertainty in the weighting of the criteria, a fifth in the scoring step ($n = 45$), and nearly 15% ($n = 31$) have accounted for both types of parameter uncertainty (Fig. 5). Heterogeneity in criteria weights or performance scores (ie, variability attributed to a person's characteristics) was assessed in 18% of the MCDA studies ($n = 40$). Dealing with structural

uncertainty (eg, MCDA method used, criteria included) is less common, with only 9% of the studies ($n = 20$) reporting it.

Across decision contexts, the patterns are roughly similar. Nevertheless, studies informing planning and R&D decisions are the exception, with < 2% of these studies reporting structural uncertainty and only 5% reporting parameter uncertainty on the performance scores.

Most studies that assessed uncertainty have used scenario analysis (29%, $n = 64$) or a one-way deterministic analysis (23%, $n = 51$). Fuzzy logic and probabilistic sensitivity analysis are less

common, with only 11% ($n = 24$) and 8% of the studies ($n = 18$) using these methods, respectively.

Discussion

The application of MCDA continues growing in healthcare, with most of the studies being conducted in high-income countries to inform priority setting and regulatory decisions at national level. The fact that no MCDA has been conducted to inform regulatory decisions in low- and middle-income countries, despite the increasing use of MCDA in other decision contexts, possibly reflects the embryonic stage of HTA in these countries.³⁴

As identified by Khan et al (2021),¹⁰ it is just after 2010 that a rise in MCDA studies in healthcare took off. This upward trend might have been driven by the rise and consolidation of HTA agencies across Europe,³⁵ an increasing concern from national and local governments to justify investment and authorization decisions,^{36,37} and the use of MCDA in emerging decision contexts (eg, pharmaceutical R&D). MCDA studies informing regulatory decisions emerged between 2009 and 2012, which coincides with the publication of the first report from the European Medicines Agency in 2010, acknowledging MCDA as one of the quantitative approaches to conduct BRA for medicinal products.³⁸ In the United States and later on across Latin America, the industry might have played a role in promoting the use of MCDA when conducting BRA of medicines.³⁹⁻⁴¹

As expected, we found considerable differences across decision contexts on the criteria used and some noticeable preferences for specific criteria sets, particularly among studies that have informed regulatory decisions. Nevertheless, there is significant within-context variation in the type of criteria used, which does not facilitate study comparisons and can potentially affect the consistency of MCDA studies.² Defining a set of top-level criteria clusters for each one of the different decision contexts could contribute to the comparability of MCDA studies and help decision makers take into account all relevant aspects when agreeing on the criteria. This could reduce subjectivity and variation in criteria sets within decision contexts and improve the MCDA's credibility in informing healthcare decisions. An example of this is the advanced value tree with 5 key value domains proposed by Angelis and Kanavos⁴² for evaluating new medicines in HTA.

With regard to the number of criteria used, we found that more than a third of the studies have used > 5 criteria and in some cases > 10 criteria. Nevertheless, this appears to be not in line with good practice and MCDA guidelines that recommend the inclusion of only few criteria.⁴ This increases the risk of violating the non-overlap and preferential independence requirements of linear additive models undermining the usefulness of the most used MCDA method.^{43,44} A large number of criteria also increases data requirements, making the application of MCDA more complex and compromising the quality of the results. Although flexibility in the criteria selection step might be desirable in some settings,⁴ a uniform set of criteria by decision context that considers all axiomatic properties⁴⁵ could serve as a starting point for future applications of MCDA in healthcare. This could potentially improve the consistency and credibility of the resulting recommendations.^{2,22,46}

With regard to the structure of the criteria, we found that less than half of the studies have adopted a hierarchical structure. Exploring hierarchies, using for instance value trees, is a crucial step of the definition of criteria and should be reported by studies.⁴ Even if the subcriteria are not operationalized in the end, identifying them can help MCDA developers verify that the axiomatic requirements for linear additive models are not

violated. Identifying hierarchies could be an essential part of a detailed MCDA guidance.

This review is the first that summarizes the criteria used in MCDA studies in healthcare, and such findings could be used as a basis to start developing a uniform set of top-level criteria by decision context.

Our results highlight a preference of MCDA users in applying the additive model for calculating total scores (ie, MCDA approach) and hybrid techniques (ie, scales for scoring and AHP for weights elicitation) in the scoring and weighting steps. Nevertheless, not all studies made a clear distinction between the MCDA approach used and the scoring and weighting techniques applied, and very few justified the selection of the techniques used. Most of the studies have also favored scoring and weighting techniques that are relatively easier to apply (eg, direct rating approaches and AHP) but less theoretically sound.⁴⁷ This might partly reflect the little guidance on the choice and application of MCDA methods. As highlighted previously, the lack of standardization of the terms and classifications of MCDA methods may partially explain the flaws in reporting MCDA studies.^{10,11} Khan et al (2021)¹⁰ identified at least 4 different classifications of MCDA models or approaches. Different nomenclatures and categorizations have also been used to summarize the scoring and weighting techniques applied. For instance, the review conducted by Marsh et al (2014)⁷ reported scales, AHP, natural units, and discrete choice experiment as weighting techniques, whereas Oliveira et al (2019)¹¹ reported point systems, direct rating, measuring attractiveness through a categorical-based evaluation technique, AHP, and selecting functions. This lack of consensus affects the comparability, credibility, and policy usefulness of MCDA studies in healthcare.^{2,11}

Although many types of uncertainty might arise when conducting MCDA in healthcare^{23,48-50} and all guidelines recommend addressing them,^{3,4} uncertainty analysis is still not universally and consistently used across MCDA studies. This contrasts with studies using traditional type of economic evaluation, which tend to address uncertainty in a systematic way.^{51,52} Nevertheless, we found an increasing trend in the incorporation of uncertainty analysis in MCDA studies, suggesting that MCDA designers and analysts are responding to the voices calling to address uncertainty.^{3,4,23} In terms of the approaches adopted to deal with uncertainty, there seems to be a preference for one-way deterministic approach or scenario analysis, which is consistent with findings from Broekhuizen et al (2015).²³ Structural uncertainty is barely explored, which might be due to the lack of methodological approaches to systematically deal with it²³ or the cost of re-running analyses under different MCDA specifications (eg, another set of alternatives or criteria).

The possibility of involving all relevant parties in the decision-making process is one of the advantages that MCDA offers,^{12,37} and we found that different types of stakeholders have participated in the scoring and weighting steps. Nevertheless, $> 50\%$ of the studies were not explicit about the stakeholders involved in each one of the MCDA stages. Additionally, several studies have highlighted limitations in regard to stakeholders' involvement. This includes the small number of participants⁵³⁻⁵⁶ and the exclusion of relevant actors, such as patient representatives or caregivers.⁵⁷⁻⁵⁹ Given that big groups of participants might not be possible, some studies have suggested involving representatives of the relevant stakeholders when conducting an MCDA.⁶⁰ Other studies also emphasize the need to include all relevant stakeholders from the beginning to ensure the relevance and usefulness of the MCDA.^{61,62}

All flaws in the application and reporting across all MCDA steps described earlier compromise the transparency and legitimacy of

the MCDA-based recommendations.² The lack of standardization of MCDA methods and their classification jeopardizes the comparability, credibility, and policy usefulness of MCDA studies in healthcare.^{2,11} This reinforces the need to clearly report the methods applied in each MCDA step. Even though some reports have been published to guide the application of MCDA in healthcare,^{3,4} the lack of a detailed methodological and reporting guidance might partly explain the questionable methodological quality of MCDA studies in healthcare.¹¹ This guide could include (1) a universal classification of the MCDA methods; (2) a guidance on the application of each method, highlighting the particularities for each one of the different decision contexts in healthcare; (3) a common set of criteria or macro domains by decision context; and (4) a checklist with standards for reporting, similar to the Consolidated Health Economic Evaluation Reporting Standards statement⁶³ used in traditional economic evaluations. The development of this methodological and reporting guide should be based on empiric work and the experience accumulated by scholars and decision makers in healthcare.

Such a guidance could increase transparency and clarity in the application of MCDA and ultimately improve the credibility and systematic application of MCDA in different decision contexts in healthcare.

Limitations

First, we might have missed out non-English MCDA studies that have informed decisions in healthcare, particularly grey literature.⁷ Second, all searches were conducted by one reviewer, which might have affected the identification of relevant studies. Third, the inclusion criteria we adopted were less restrictive compared with the ones in Marsh et al (2014)⁷ with the risk of missing relevant scientific studies before 2013. To address this, we supplemented Marsh et al's^{8,9} studies with 2 other reviews with start review period as early as in the 90s and a similar scope to our study. Our time trend of MCDA studies published over the last years is similar to the one from Khan et al (2021),¹⁰ which suggests that the sharp increase observed from 2011 onward is not an artifact of our updating strategy (ie, starting academic searches in 2013).

Conclusions

Although the application of MCDA keeps increasing across different decision contexts in healthcare, the lack of quality and transparency is an obstacle to the adoption of MCDA widely in healthcare. Findings of this review could guide future MCDA applications in healthcare. Nevertheless, to support the usefulness and applicability of MCDA in healthcare, it is crucial to standardize the methods and reporting. A guide on how to conduct and report MCDA, which acknowledges the particularities of the different decision contexts and methods, needs to be developed.

Supplemental Material

Supplementary data associated with this article can be found in the online version at <https://doi.org/10.1016/j.jval.2022.11.007>.

Article and Author Information

Accepted for Publication: November 17, 2022

Published Online: January 24, 2023

doi: <https://doi.org/10.1016/j.jval.2022.11.007>

Author Affiliations: Health Economics Research Centre, Nuffield Department of Population Health, University of Oxford, Oxford, England, UK (Gongora-Salazar, Tsiachristas); National Perinatal Epidemiology Unit, Nuffield Department of Population Health, University of Oxford, Oxford, England, UK (Rivero-Arias); Nuffield Department of Primary Care Health Sciences, University of Oxford, Oxford, England, UK (Fahr); The Health Foundation, London, England, UK (Rocks).

Correspondence: Pamela Gongora-Salazar, MSc, Health Economics Research Centre, Nuffield Department of Population Health, University of Oxford, Richard Doll Building, Old Road Campus, Headington, Oxford, England OX3 7LF, United Kingdom. Email: pamela.gongora@ndph.ox.ac.uk

Author Contributions: *Concept and design:* Gongora-Salazar, Tsiachristas

Acquisition of data: Gongora-Salazar, Tsiachristas, Rocks

Analysis and interpretation of data: Gongora-Salazar, Rocks, Fahr, Rivero-Arias, Tsiachristas

Drafting of the manuscript: Gongora-Salazar, Fahr, Rivero-Arias, Tsiachristas

Critical revision of the paper for important intellectual content: Gongora-Salazar, Fahr, Rivero-Arias, Tsiachristas

Statistical analysis: Gongora-Salazar

Provision of study materials or patients: Tsiachristas

Administrative, technical, or logistic support: Gongora-Salazar, Rocks, Tsiachristas

Supervision: Tsiachristas

Conflict of Interest Disclosures: The authors reported no conflicts of interest.

Funding/Support: The study was funded by the Nuffield Department of Population Health of the University of Oxford as part of the corresponding author's doctorate scholarship. The authors are also grateful for the support from the National Institute for Health and Care Research Oxford & Thames Valley Applied Research Collaboration. AT also acknowledges support from the Oxford Biomedical Research Centre (BRC).

Role of the Funder/Sponsor: The funder had no role in the design and conduct of the study; collection, management, analysis, and interpretation of the data; preparation, review, or approval of the manuscript; and decision to submit the manuscript for publication.

Acknowledgment: The authors thank Ms Nia Wyn Roberts (Bodleian Health Care Libraries, University of Oxford, Oxford, United Kingdom) for her support in defining the literature search strategy. The authors would also like to thank A.R., the reviewer who wished to remain anonymous in this publication.

REFERENCES

1. Keeney RL, Raiffa H. *Decisions With Multiple Objectives: Preferences and Value Trade-Offs*. Cambridge, United Kingdom: Cambridge University Press; 1993.
2. Baltussen R, Marsh K, Thokala P, et al. Multicriteria decision analysis to support health technology assessment agencies: benefits, limitations, and the way forward. *Value Health*. 2019;22(11):1283–1288.
3. Thokala P, Devlin N, Marsh K, et al. Multiple criteria decision analysis for health care decision making - an introduction: Report 1 of the ISPOR MCDA Emerging Good Practices Task Force. *Value Health*. 2016;19(1):1–13.
4. Marsh K, Ijzerman M, Thokala P, et al. Multiple criteria decision analysis for health care decision making - emerging good practices: Report 2 of the ISPOR MCDA Emerging Good Practices Task Force. *Value Health*. 2016;19(2):125–137.
5. Baltussen R, Niessen L. Priority setting of health interventions: the need for multi-criteria decision analysis. *Cost Eff Resour Alloc*. 2006;4:1–9.
6. Tsiachristas A, Stein KV, Evers S, Rutten-van Mölken M. Performing economic evaluation of integrated care: highway to hell or stairway to heaven? *Int J Integr Care*. 2016;16(4):3.
7. Marsh K, Fau LT, Neasham D, et al. Assessing the value of healthcare interventions using multi-criteria decision analysis: a review of the literature. *Pharmacoecon*. 2014;32(4):345–365.
8. Adunlin G, Diaby V, Xiao H. Application of multicriteria decision analysis in health care: A systematic review and bibliometric analysis. *Health Expect*. 2015;18(6):1894–1905.
9. Frazão TDC, Camilo DGG, Cabral ELS, Souza RP. Multicriteria decision analysis (MCDA) in health care: a systematic review of the main characteristics and methodological steps. *BMC Med Inform Decis Making*. 2018;18(1):1–16.

10. Khan I, Pintelon L, Martin H. The application of multicriteria decision analysis methods in health care: a literature review. *Med Decis Making*. 2022;42(2):262–274.
11. Oliveira MD, Mataloto I, Kanavos P. Multi-criteria decision analysis for health technology assessment: addressing methodological challenges to improve the state of the art. *Eur J Health Econ*. 2019;20(6):891–918.
12. Marsh K, Goetghebuer M, Thokala P, Baltussen R. *Multi-criteria Decision Analysis to Support Healthcare Decisions*. 1st ed. Vol. VI. Cham, Switzerland: Springer; 2017:329.
13. Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ*. 2021;372:n71.
14. Rethlefsen ML, Kirtley S, Waffenschmidt S, et al. PRISMA-S: an extension to the PRISMA Statement for Reporting Literature Searches in Systematic Reviews. *Syst Rev*. 2021;10(1):39.
15. Garner P, Hopewell S, Chandler J, et al. When and how to update systematic reviews: consensus and checklist. *BMJ*. 2016;354:i3507.
16. Alberani V, De Castro Pietrangeli P, Mazza AM. The use of grey literature in health sciences: a preliminary survey. *Bull Med Libr Assoc*. 1990;78(4):358–363.
17. Bramer WM, de Jonge GB, Rethlefsen ML, Mast F, Kleijnen J. A systematic approach to searching: an efficient and complete method to develop literature searches. *J Med Libr Assoc*. 2018;106(4):531–541.
18. Gusenbauer M, Haddaway NR. Which academic search systems are suitable for systematic reviews or meta-analyses? Evaluating retrieval qualities of Google Scholar, PubMed, and 26 other resources. *Res Synth Methods*. 2020;11(2):181–217.
19. Haddaway NR, Collins AM, Coughlin D, Kirk S. The role of Google Scholar in evidence reviews and its applicability to grey literature searching. *PLoS One*. 2015;10(9):e0138237.
20. Boeker M, Vach W, Motschall E. Google Scholar as replacement for systematic literature searches: good relative recall and precision are not enough. *BMC Med Res Methodol*. 2013;13(1):131.
21. The EndNote Team. *EndNote*. Philadelphia, PA: Clarivate; 2013, 64 bit; vEnd-Note X9.
22. Tsiachristas A, Cramm JM, Nieboer A, Rutten-van Mölken M. Broader economic evaluation of disease management programs using multi-criteria decision analysis. *Int J Technol Assess Health Care*. 2013;29(3):301–308.
23. Broekhuizen H, Groothuis-Oudshoorn CG, van Til JA, Hummel JM, Ijzerman MJ. A review and classification of approaches for dealing with uncertainty in multi-criteria decision analysis for healthcare decisions. *Pharmacoecon*. 2015;33(5):445–455.
24. Microsoft Excel 16.0. Microsoft Corporation. <https://office.microsoft.com/excel>. Accessed October 26, 2020.
25. Taylor KS, Mahtani KR, Aronson JK. Summarising good practice guidelines for data extraction for systematic reviews and meta-analysis. *BMJ Evid-Based Med*. 2021;26(3):88.
26. Goetghebuer MM, Wagner M, Khoury H, Levitt RJ, Erickson LJ, Rindress D. Evidence and Value: impact on DEcisionMaking—the EVIDEM framework and potential applications. *BMC Health Serv Res*. 2008;8(1), 270–270.
27. Belton V, Theodor JS. *Multiple Criteria Decision Analysis: An Integrated Approach*. New York, NY: Springer; 2002.
28. Saaty TL. Axiomatic foundation of the analytic hierarchy process. *Manag Sci*. 1986;32(7):841–855.
29. Bana e Costa CA, Vansnick J-C. *The MACBETH approach: Basic ideas, software, and an application*. *Advances in Decision Analysis. Mathematical Modelling: Theory and Applications*. 4. Springer; 1999:131–157. https://doi.org/10.1007/978-94-017-0647-6_9.
30. Brans JP, Mareschal B. Promethee methods. In: Figueira J, Greco S, Ehrgott M, eds. *Multiple Criteria Decision Analysis: State of the Art Surveys*. New York, NY: Springer; 2005:163–186.
31. Hwang CL, Yoon K. *Multiple Attribute Decision Making: Methods and Applications*. New York, NY: Springer-Verlag; 1981.
32. Hansen P, Ombler F. A new method for scoring additive multi-attribute value models using pairwise rankings of alternatives. *J Multi-Criteria Decis Anal*. 2008;15(3–4):87–107.
33. Ryan M, Bate A, Eastmond CJ, Ludbrook A. Use of discrete choice experiments to elicit preferences. *Qual Health Care*. 2001;10(suppl 1):i55.
34. Babigumira JB, Jenny AM, Bartlein R, Stergachis A, Garrison LP. Health technology assessment in low- and middle-income countries: a landscape assessment. *J Pharm Health Serv Res*. 2016;7(1):37–42.
35. Löblová O. Three worlds of health technology assessment: explaining patterns of diffusion of HTA agencies in Europe. *Health Econ Policy Law*. 2016;11(3):253–273.
36. Benoit C, Gorry P. Health technology assessment: the scientific career of a policy concept. *Int J Technol Assess Health Care*. 2017;33(1):128–134.
37. Devlin N, Sussex J. Incorporating multiple criteria in HTA: methods and processes. Office of Health Economics. <https://www.ohe.org/publications/> incorporating-multiple-criteria-hta-methods-and-processes; 2011. Accessed November 13, 2020.
38. Benefit-risk methodology project. Work package 2 report. Applicability of current tools and processes for regulatory benefit-risk assessment. EMA. https://www.ema.europa.eu/en/documents/report/benefit-risk-methodology-project-work-package-2-report-applicability-current-tools-processes_en.pdf. Accessed February 10, 2022.
39. Drake JL, de Hart JCT, Monleón C, Toro W, Valentim J. Utilization of multiple-criteria decision analysis (MCDA) to support healthcare decision-making FIFARMA, 2016. *J Mark Access Health Policy*. 2017;5(1):1360545.
40. Liberti L, McAuslane JN, Walker S. Standardizing the benefit-risk assessment of new medicines. *Pharm Med*. 2011;25(3):139–146.
41. Angelis A, Phillips LD. Advancing structured decision-making in drug regulation at the FDA and EMA. *Br J Clin Pharmacol*. 2021;87(2):395–405.
42. Angelis A, Kanavos P. Multiple criteria decision analysis (MCDA) for evaluating new medicines in health technology assessment and beyond: the Advance Value Framework. *Soc Sci Med*. 2017;188:137–156.
43. Marttunen M, Lienert J, Belton V. Structuring problems for multi-criteria decision analysis in practice: a literature review of method combinations. *Eur J Oper Res*. 2017;263(1):1–17.
44. Marsh KD, Sculpher M, Caro JJ, Tervonen T. The use of MCDA in HTA: great potential, but more effort needed. *Value Health*. 2018;21(4):394–397.
45. Dodgson J, Spackman M, Pearman A. *Multi-criteria analysis: a manual*. Department for Communities and Local Government. https://eprints.lse.ac.uk/12761/1/Multi-criteria_Analysis.pdf. Accessed January 23, 2021.
46. Rutten-van Mölken M, Leijten F, Hoedemakers M, et al. Strengthening the evidence-base of integrated care for people with multi-morbidity in Europe using multi-criteria decision analysis (MCDA). *BMC Health Serv Res*. 2018;18(1):576.
47. Bana e Costa CA, Vansnick J-C. A critical analysis of the eigenvalue method used to derive priorities in AHP. *Eur J Oper Res*. 2008;187(3):1422–1428.
48. Briggs AH, Weinstein MC, Fenwick EA, et al. Model parameter estimation and uncertainty analysis: a report of the ISPOR-SMDM modeling good research practices task force working group. *Med Decis Mak*. 2012;32(5):722–732.
49. Durbach IN, Stewart TJ. Modeling uncertainty in multi-criteria decision analysis. *Eur J Oper Res*. 2012;223(1):1–14.
50. Groothuis-Oudshoorn CGM, Broekhuizen H, van Til J. Multi-Criteria Decision Analysis to Support Healthcare Decisions. In: Marsh K, Goetghebuer M, Thokala P, Baltussen R, eds. *Dealing with uncertainty in the analysis and reporting of MCDA*. Berlin, Germany: Springer International Publishing; 2017:67–85.
51. Gray A, Clarke PM, Wolstenholme JL, Wordsworth S. *Applied Methods of Cost-Effectiveness Analysis in Health Care*. Oxford, United Kingdom: Oxford University Press; 2011.
52. Drummond MF, Sculpher MJ, Claxton K, Stoddart GL, Torrance GW. *Methods for the Economic Evaluation of Health Care Programmes*. Oxford, United Kingdom: Oxford University Press; 2015.
53. Dolan JG. Patient priorities in colorectal cancer screening decisions. *Health Expect*. 2005;8(4):334–344.
54. Wagner M, Khoury H, Bennetts L, et al. Appraising the holistic value of lenvatinib for radio-iodine refractory differentiated thyroid cancer: a multi-country study applying pragmatic MCDA. *BMC Cancer*. 2017;17(1):272.
55. Hongoh V, Gosselin P, Michel P, et al. Criteria for the prioritization of public health interventions for climate-sensitive vector-borne diseases in Quebec. *PLoS One*. 2017;12(12):e0190049.
56. Angelis A, Linch M, Montibeller G, et al. Multiple criteria decision analysis for HTA across four EU Member States: piloting the Advance Value Framework. *Soc Sci Med*. 2020;246:112595.
57. Agapova M, Bresnahan BW, Linnau KF, et al. Using the analytic hierarchy process for prioritizing imaging tests in diagnosis of suspected appendicitis. *Acad Radiol*. 2017;24(5):530–537.
58. Guarga L, Badia X, Obach M, et al. Implementing reflective multicriteria decision analysis (MCDA) to assess orphan drugs value in the Catalan Health Service (CatSalut). *Orphanet J Rare Dis*. 2019;14(1):157.
59. Howard S, Scott IA, Ju H, McQueen L, Scuffham PA. Multicriteria decision analysis (MCDA) for health technology assessment: the Queensland Health experience. *Aust Health Rev*. 2019;43(5):591–599.
60. Sussex J, Rollet P, Garau M, Schmitt C, Kent A, Hutchings A. A pilot study of multicriteria decision analysis for valuing orphan medicines. *Value Health*. 2013;16(8):1163–1169.
61. Pieter WGB, Josee AMH. Designing multi-criteria decision analysis processes for priority setting in health policy. *J Multi-Cri Decis Anal*. 2000;9(1–3):56–75.
62. Youngkong S, Teerawattananon Y, Tantivess S, Baltussen R. Multi-criteria decision analysis for setting priorities on HIV/AIDS interventions in Thailand. *Health Res Policy Syst*. 2012;10(1):6.
63. Husereau D, Drummond M, Petrou S, et al. Consolidated Health Economic Evaluation Reporting Standards (CHEERS) statement. *BMJ*. 2013;346:f1049.