# Chapter 15
# Beyond Value Function Methods in MCDA for Health Care

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**Abstract** In health-care decision-making, the predominance of some value function multi-criteria decision analysis (MCDA) methods may obscure the existence and potential usefulness of alternative MCDA methods. The current chapter provides an introduction to alternative value function and non-value function methods. The alternative value function methods presented are approaches based on multi-attribute value theory (MAVT): measuring attractiveness by a categorical-based evaluation technique (MACBETH), Variable Interdependent Parameters (VIP) analysis, and stochastic multi-criteria acceptability analysis (SMAA). Non-value function methods described include goal programming models, dominance-based rough set approach, and outranking models. The chapter also reviews their use in health to date and ends with concluding remarks.

## 15.1 Introduction

MCDA, used as an umbrella term, is a decision-making framework that encompasses a large set of methods or approaches that simultaneously and explicitly take account of multiple and conflicting criteria (Baltussen and Niessen 2006). These methods can roughly be classified into five main families: elementary methods (Yoon and Hwang 1995), value function methods (Belton and Stewart 2002), goal and reference methods (Belton and Stewart 2002), outranking models, (Belton and Stewart 2002) and dominance-based approaches (Pawlak and Sowinski 1994; Greco et al. 2001; Moshkovich and Mechitov 2013). MCDA consists of three steps (Belton and Stewart 2002). The first step, referred to as problem identification and

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structuring, deals with identifying the decision-makers and setting their goals. At this step, the relevant competing options and their evaluation criteria are defined. The second step, called multi-criteria evaluation model development and use, requires the selection of the relevant aggregation model and the elicitation of the model's parameters, which defines the role played by each evaluation criterion when synthesizing the performance of the alternatives in multiple attributes. The last step, called the development of action plans, consists of making recommendations to decision-makers. Additionally, the presentation of sensitivity analyses informs the decision-makers regarding their level of confidence about the plans.

Even though analysts and researchers have access to a wide range of evaluation models in MCDA to respond to multifaceted problems in health care, the use has been confined to the application of only a few value function methods. Adunlin et al. conducted a systematic review to identify applications of MCDA in health care (Adunlin et al. 2015). The time horizon for the search spanned the years 1980–2013 and encompassed a wide range of bibliographic sources (electronic databases, gray literature). Of the 66 studies that met the inclusion criteria of the review, 91 % used a value function method, a method that computes a single value to summarize the performance of an alternative on multiple criteria (Adunlin et al. 2015).

Value function methods are techniques that compute an overall value for each competing alternative representing the global performance of each alternative on their attributes. As a result, these methods are referred to as full aggregation or compensatory methods. Other MCDA methods that do not compute an overall value and/or are not compensatory are available but have been applied less in health care.

The objective of this chapter is to highlight alternative MCDA methods that can be used to address health-care decision-making problems. The chapter is structured as follows. Sections 15.2 and 15.3 describe alternative value function methods and non-value function methods, respectively. Both sections review the use of these methods in health to date. The chapter ends with concluding remarks.

## 15.2 Alternative Value Function Methods

Multi-attribute utility theory (MAUT) and multi-attribute value theory (MAVT) (Keeney and Raiffa 1993) are well-known approaches in MCDA to obtain an overall score for an alternative being evaluated on multiple criteria. The main difference between these approaches is that MAUT makes use of utility functions that account for decision-makers' attitudes toward risk, utilizing the concept of lotteries, as opposed to MAVT where a global value function is constructed for each alternative to represent the global performance of the alternatives on the decision criteria, using the concept of preference intensity. This section briefly reviews how MAVT can be used to obtain an overall valuation for an alternative and suggests related approaches that can constitute an alternative to the traditional way of applying MAVT.

The implementation of the MAVT traditionally involves two main steps. The first step deals with the construction of a partial value function for each criterion.

A partial value function reflects how the value of an attribute varies along the measurement scale for the decision-maker. It can be an increasing function for an attribute such as quality of life or a decreasing function for an attribute such as cost. The second step aggregates the partial value functions to obtain a global value function. The most common aggregation model is the additive value function where the partial value of the alternative on each decision criterion is weighted by a scaling coefficient assigned to the respective value function, and these weighted values are then added yielding a global value. This requires the determination of scaling coefficients, which indicate the weight of each value function. Scaling coefficients can be elicited using a number of techniques including swing weighting (Diaby and Goeree 2014). The alternative with the highest global value is the preferred one. Construction of value functions needs to satisfy the transitivity of preference and indifference rule, while the additive aggregation model used in MAVT needs to satisfy the additive independence condition (namely, that trade-offs between two criteria do not depend on the level of the remaining criteria) (Belton and Stewart 2002).

There are only a few published applications of MAVT in health care. To our knowledge, there is only one study that applied the MAVT to patient-bed assignment in hospital admission management (Tsai and Lin 2014) in addition to a tutorial that illustrated the way to use MAVT to support reimbursement decision-making in health care (Diaby and Goeree 2014). Nevertheless, a recent project of the European Medicines Agency suggests using MAVT as the framework to support regulatory decisions about medicinal products (Phillips et al. 2012).

It is the authors' opinion that MAVT is an intuitive and easy-to-understand MCDA method, since it uses a way of aggregating scores that individuals are familiar with (e.g., computing GPA scores in academia, building composite indices such as United Nation's Human Development Index, etc.). It thus reflects the way data are aggregated in the above and many other examples. Like MAUT, MAVT defines an axiomatically based process for the construction of commensurable value scales and the definition of scaling coefficients.

A potential obstacle to using MAVT is the potential difficulty of eliciting precise values for the scaling coefficients that reflect the decision-maker's trade-offs (Dias and Clímaco 2000). However, to cope with this concern, it is possible to assess the robustness of conclusions through the use of software such as the Variable Interdependent Parameters (VIP) analysis (Dias and Clímaco 2000). VIP analysis suggests an alternative process to conduct an MAVT-based analysis consisting of eliciting only information that is easier to obtain, such as a ranking of the scaling coefficients, rather than precise numerical values. To the authors' best knowledge, there are no applications of VIP analysis in the health domain.

Another alternative approach to conduct an MAVT-based analysis is stochastic multi-criteria (or multiobjective) acceptability analysis (SMAA) (Lahdelma and Salminen 2001). Similar to the VIP analysis, this method does not require decision-makers to specify a vector of scaling coefficients. The space of all admissible scaling coefficients is sampled using Monte Carlo simulations in order to produce statistics about the ranking of each alternative. SMAA can also provide information about what scaling coefficients, if any, make each alternative a winner. The potential for SMAA has been advocated for health economic evaluation of medical interventions and was illustrated on a case of infertility treatment selection (Postmus et al. 2014).

A third alternative process to conduct an MAVT-based analysis is MACBETH (Ishizaka and Nemery 2013; Bana et al. 2012). MACBETH is distinguished from other MCDA methods by the fact that only qualitative judgments about the difference of attractiveness (desirability) between pairs of alternatives are needed. The decision-maker can state the difference of attractiveness between two alternatives using an ordinal qualitative scale composed of six levels, from "very weak" to "extreme." A consistency check is conducted to ensure the responses obtained from such pairwise comparisons do not conflict. The MACBETH procedure allows for the computation of numerical scores on an interval scale (0–100) for the alternatives on each criterion by the means of linear programming. A similar process is used to weight the criteria. A global score is estimated for each alternative using an additive aggregation, taking into account the scores of the alternative on the multiple criteria and the respective criteria weights. The alternative with the highest global score is considered the most attractive. The implementation of this method is supported by a software called M-MACBETH.

In health care, MACBETH has been applied to diagnosis and treat Alzheimer's and diabetes (de Castro et al. 2009a, b; de Moraes et al. 2010; Nunes et al. 2011). MACBETH shares similar features with the AHP. They both use pairwise comparisons to derive criteria and alternatives priorities, except that the MACBETH derives value functions based on linear programming, whereas AHP derives priorities using the eigenvalue method (Ishizaka and Nemery 2013; Dodgson et al. 2009). As a result, MACBETH may be of interest for decision-makers that would like to explore the use of other methods that convert verbal preferences into numerical scores. Recent works have demonstrated the feasibility of using MACBETH for group decision-making (Belton and Pictet 1997; Bana e Costa et al. 2014).

## 15.3 Non-value Function Methods for Health-Care Decision-Making

Using value function methods entails accepting that a very poor performance on one criterion can always be compensated by a very good performance on some other criterion. Therefore, these methods may not be the most appropriate when such compensatory effects are not considered to be adequate in the decision-making process. For instance, this type of compensability may be inadequate if criteria refer to impacts on different stakeholders (e.g., patients versus hospital managers or medical staff) or when criteria refer to rather different dimensions (economic, versus social or environmental risks, for instance) (Munda and Nardo 2005).

The following families of non-value function methods are presented in this section: (1) goal and reference point methods, (2) dominance-based approaches, and (3) outranking methods.

### 15.3.1 Goal and Reference Point Methods

There are several MCDA methods that evaluate alternatives by comparing them to some reference(s). The references can be internal (i.e., defined exclusively based on the set of alternatives) or can be external to the set of alternatives. The evaluation of each alternative does not depend only on its characteristics as in value-based approaches but also on the chosen references.

A popular MCDA method based on comparisons with internal references is TOPSIS (Yoon and Hwang 1995). In this case, there are two references defined with regard to the set of alternatives being evaluated. The first reference is the so-called ideal point, a fictitious alternative defined by selecting, for each criterion, the best observed performance in the set of the alternatives. The second reference is referred to as the anti-ideal point, a fictitious alternative defined by selecting, for each criterion, the worst observed performance in the set of the alternatives. The idea is to select an alternative that is near the ideal point and far from the anti-ideal point.

In TOPSIS, the evaluation score for an alternative is the distance to the anti-ideal solution divided by the sum of the same distance and the distance to the ideal solution. This yields a score between 0 and 1, like value function methods do. However, this value is not an evaluation of the alternative on its own merits but an evaluation of how the alternative compares to the chosen references. The chosen distance metric is the weighted euclidean distance, which allows placing different importances on different criteria. In order to make the distances comparable, a normalization operation is needed to transform the criteria scales into a common scale. The most common normalization in TOPSIS, performed separately for each criterion, consists of dividing each performance of an alternative by the square root of the sum of the squares of the performances of all alternatives on that criterion. An important concern about this method is that depending on the normalization method, the resulting scores can be different (Ishizaka and Nemery 2013). Another major concern is that introducing a poor and possibly irrelevant alternative that changes the anti-ideal point can reverse the relative positions of the remaining alternatives.

Upon reviewing the literature, one example framework was found using TOPSIS for health technology assessment (HTA) by Liang et al. (2014). This framework was built to appraise different medicines based on economic and health-related criteria. The method suggested by these authors was a variant of TOPSIS using judgment from different stakeholders, combined with the use of AHP to derive criteria weights. A similar combination of AHP, to derive weights, and TOPSIS, to rank alternatives, was used by Akdag et al. to evaluate the service quality of some hospitals in Turkey (Akdag et al. 2014). This study constitutes one of the several examples of TOPSIS applications to problems other than HTA in the health sector (Beheshtifar and Alimoahmmadi 2015; Sang et al. 2014; Bahadori et al. 2014).

There are many other methods based on distances to references (Ehrgott 2006), which include goal programming (Jones and Tamiz 2010). Such methods are used to set the value of decision variables subject to constraints, but the same principles can be used to rank a finite list of alternatives in order of their distance to a given reference point. Distances may or may not be weighted, attaching importance weights to the criteria. The reference alternative is usually an external reference indicating goals or aspiration levels.

In the health sector, goal programming has been mainly used for scheduling beds, staff, and/or patients (Thomas et al. 2013). No application of goal programming for HTA was identified in the literature, except for an illustration of how this approach could be used to support reimbursement decision-making in health care (Diaby and Goeree 2014).

Methods based on references may potentially be interesting for health-care decision-makers as they are often able to verbalize their aspirations by setting goals to be attained on each criterion. Then, a logical consequence is to seek which of the alternatives is closer to satisfying such goals, according to some metric, and possibly assigning a different weight to each goal. For instance, if a manager has a set of targets that he or she would like to attain (possibly including targets set by external entities), then it may be helpful to evaluate different decision alternatives considering their contribution to these targets. If the set of targets is very large and therefore they cannot all be met at the same time, then a reference-based approach will indicate which alternatives are most interesting with regard to those targets.

As a separate note, we might also mention data envelopment analysis (DEA) Cook and Seiford 2009; Thomas et al. 2013; Liu et al. 2013) as a close relative of MCDA (Ishizaka and Nemery 2013; Bouyssou 1999; Gouveia et al. 2008; Cooper 2005) that uses references. Indeed, DEA evaluates the performance of each alternative (decision-making unit in DEA terminology) considering the entire set of alternatives as potential references, rather than asking decision-makers to indicate aspiration levels. DEA could potentially be used to support decisions about whether or not to approve a new health technology, based on how it compares with the set of technologies already in operation.

### *15.3.2 Dominance-Based Approaches*

A different way to perform a comparison of alternatives based on MCDA is to compare them directly, rather than computing an overall value (value-based approach) or comparing them with a reference. The simplest way to compare alternatives is to perform a pairwise comparison, i.e., a comparison of two alternatives, to check whether one of them is clearly superior to the other. An alternative $x$ is said to dominate another alternative $y$ if it is better on some criteria and is not worse in any other criterion. The resulting dominance relation does not require any subjective parameters such as criteria weights. If the purpose of the analysis is to identify a single best alternative, dominated alternatives can be discarded. However, the dominance relation typically applies to a few pairs of alternatives, and there are usually several non-dominated alternatives (especially if the number of criteria is large).

One of the most recent methods in MCDA, the dominance-based rough set approach (DRSA), is based on exploiting the idea of dominance using rough sets theory (RST) (Greco et al. 2005). This approach can be used in sorting problems (assigning alternatives to categories) or in problems where a ranking of the alternatives is sought. RST does not require setting any preference-related parameters (such as importance weights) but requires the decision-makers to provide examples of comparisons, e.g., stating that alternative *x* is better than alternative *y*. The method is able to extract *if-then* rules from such examples of preferences by an induction process. As an illustration, a rule might state "if alternative *x* is much better than alternative *y* on criterion 1 and it is not much worse on criterion 2, then *x* is better than *y*." Another approach that uses induction rules based on qualitative assessments is verbal decision analysis (VDA) (Moshkovich et al. 2002, 2005), which can also be used for sorting or ranking problems based on statements provided by a decision-maker.

In the health field, DRSA has been mainly used as a tool to discover knowledge from data, e.g., to identify metabolites involved in disease pathogenesis (Blasco et al. 2015) or to identify which factors predispose patients to return to intensive care units after cardiac surgery (Jarzabek et al. 2014). VDA has been mainly used as a diagnostic tool in the neuropsychology and neurologic disease domains (e.g., (Tamanini et al. 2011; Yevseyeva et al. 2008)).

Dominance-based approaches, particularly DRSA, are appealing for the modest information they require from decision-makers and for conveying results in the form of rules that are easy to understand. The method is particularly interesting when the set of alternatives is very large and when the decision-maker wishes to have a set of rules in natural language (*if… then…*) to sort alternatives. However, the requirement of comparing a few alternatives as examples can be difficult unless they differ only in a couple of criteria, and the resulting set of rules may be insufficient to provide a crisp sorting or a complete ranking of the alternatives as an output.

### *15.3.3 Outranking Approaches*

As described in the previous section, the establishment of dominance relations does not require any subjective parameters such as criteria weights. That being said, the relation is usually poor, i.e., it applies to a few pairs of alternatives, not allowing to distinguish between alternatives which are not dominated. Outranking methods use additional inputs to enrich this relation such that even if an alternative *x* is not better than (or possibly equal to) an alternative *y* on every criterion, a decision-maker can conclude that *x* outranks *y* if a majority of the criteria support this assertion contingent upon the fact that there is no criterion on which *x* is too much worse than *y* (in which case this criterion might "veto" the outranking assertion). This is the basic principle of ELECTRE (Elimination Et Choix Traduisant la Réalité, in French or ELimination and Choice Expressing REality, when translated into English) methods, the first methods of this kind (Roy 1991; Greco et al. 2016).

In ELECTRE methods, each alternative is compared to every other alternative, one at a time (as in a round-robin tournament) to assert whether an alternative outranks (i.e., is as good as) another one. The outranking relations are established by taking into account the weights of the criteria in favor of the outranking relation (i.e., concordance) and also the possibility that an opposing criterion vetoes that outranking relation (i.e., discordance). These outranking relations obtained are then exploited using an appropriate method from the ELECTRE family. There are methods to select a winner (ELECTRE I and IS), to rank the alternatives (ELECTRE II, III, and IV), or to sort them into predefined categories (ELECTRE TRI). The outranking relation is not transitive (if $x$ outranks $y$ and $y$ outranks $z$, then it does not necessarily hold that $x$ outranks $z$), and it is not complete (it may happen that $x$ does not outrank $y$ and $y$ does not outrank $x$, in which case they are said to be incomparable). In other words, the ELECTRE methods do not always yield a single winner or a complete ranking. This can be seen as a shortcoming of these methods (the method may not distinguish between some alternatives), or it can be seen as a plus in the sense that the method highlights situations where alternatives are incomparable and does not force a conclusion that is not supported by sufficiently strong arguments.

Another popular outranking method is PROMETHEE (Behzadian et al. 2010; Brans et al. 1986). Contrary to ELECTRE, PROMETHEE does not require a majority threshold and does include the possibility of one criterion vetoing an outranking assertion. PROMETHEE is able to provide a partial or a complete ranking of the alternatives by considering, on average, how much an alternative outranks or is outranked by its competitors. Other outranking methods that deserve consideration, but less known, are NAIADE (Munda 1995) and methods that use qualitative information such as ORESTE, QUALIFLEX, and REGIME (Martel and Matarazzo 2005).

There are numerous examples of application of outranking methods to support health-care decision-making. ELECTRE IS has been used in France to select strategies for screening hemoglobinopathies taking into account cost-effectiveness and five other qualitative criteria (Gales and Moatti 1990). More recently, Diaby and Goeree illustrated how ELECTRE IS could be used for a hypothetical HTA problem. ELECTRE TRI has been used in several applications (Diaby and Goeree 2014). Figueira et al. (2011) used this method to assign couples seeking assisted reproduction to embryo transfer categories defining the number of embryos to be implanted (Figueira et al. 2011). The use of PROMETHEE for health-care decision-making includes, but is not limited to, the ranking of alternative strategies to deal with an overcrowded emergency room in Brazil (Amaral and Costa 2014) and the ranking of regional hospitals assessing their degree of specialization (D'Avignon and Mareschal 1989). Chen et al. used a variant of QUALIFLEX to select the best treatment to a patient with a diagnosis of acute inflammatory demyelinating disease, evaluating three therapies against eight health-related criteria and a cost criterion (Chen et al. 2013).

Outranking methods were devised to avoid one of the main characteristics of value function models, full compensation. As a result, it is the authors' opinion that outranking methods may be appealing to decision-makers who wish to avoid making trade-offs or those who deem that an alternative's poor performances on some decision criteria should not be compensated by its high performances on other criteria.

## 15.4 Concluding Remarks

MCDA was developed outside health care but has been increasingly applied in this field. It provides a unique opportunity to align decision-makers' preferences with their choices and provide a systematic and transparent way of making health-care decisions. Even though value functions are largely used in health care, MCDA users should be aware of the existence of alternative families of MCDA methods. Within value function methods, which synthesize the merits of each alternative into a global value figure, there are methods that have been applied less in health care, such as MACBETH, which were presented in this chapter. However, value function methods have certain key characteristics. First, these methods allow compensation, i.e., an alternative can make up for its poor performance on some criteria by compensating with higher performance on other criteria. Second, the weights represent the trade-offs between criteria, which need to satisfy conditions such as the preferential independence of criteria. Third, there is a requirement to elicit precise numerical weights for all criteria and scores for each alternative on all criteria. These characteristics may be too restrictive for some decision problems, where alternative methods to function methods may be more appropriate.

This chapter reviewed these other methods besides value function methods. A different way of evaluating alternatives is to compare these with given references, which can be based on the best observations (e.g., TOPSIS) or be externally provided. This type of approach may best suit situations in which decision-makers have a clear idea of the goals they wish to achieve. However, if the reference is derived from the actual performances of the alternatives, adding or removing an alternative may alter the conclusions pertaining the remaining alternatives.

Dominance-based approaches may be particularly interesting if the decision-makers prefer to reason in terms of examples rather than weights. DRSA, in particular, only requires modest information from end users (parsimonious models). This allows decision-makers to avoid dealing with the parameters of a mathematical model, provided that they have a set of exemplary decisions (e.g., from past experience) that can be provided as an input to the method. Although decision-makers may be quite unfamiliar with RST (hindering transparency), the results it produces are in the form of decision rules that can be easily understood.

Finally, outranking methods are particularly suited to decision-makers that are not willing to define substitution trade-offs between criteria. Outranking methods may also be useful if the goal is to identify a small subset of alternatives that fulfill a minimum requirement from a large set of alternatives as developing a total value score for each alternative using value function methods might be impractical. However, outranking methods do not always provide a clear-cut result, i.e., these approaches might lead to incomparability between two alternatives; that being said, one could argue that this is appropriate as further deliberation might be needed to choose between them.

By offering this large set of methods, MCDA proves to be flexible enough to accommodate the needs of decision-makers. However, as presented in this chapter, there are a diverse set of MCDA techniques each with different features and advantages/disadvantages. There is a long way to go before the potential of MCDA is used to its fullest extent. To that end, we call for further research with the decision-makers to identify which of these alternative methods in health care are suitable in different decision contexts.

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## References

Adunlin G, Diaby V, Xiao H (2015) Application of multicriteria decision analysis in health care: a systematic review and bibliometric analysis. Health Expect 18:1894–1905

Akdag H, Kalaycı T, Karagöz S, Zülfikar H, Giz D (2014) The evaluation of hospital service quality by fuzzy MCDM. Appl Soft Comput 23:239–248

Amaral TM, Costa AP (2014) Improving decision-making and management of hospital resources: an application of the PROMETHEE II method in an Emergency Department. Oper Res Health Care 3(1):1–6

Bahadori M, Izadi M, Karamali M, Teymourzadeh E, Yaghoubi M (2014) Research priorities in a military health organization using multi criteria decision making techniques. J Mil Med 16(1):37–44

Baltussen R, Niessen L (2006) Priority setting of health interventions: the need for multi-criteria decision analysis. Cost Eff Resour Alloc 4:14

Bana e Costa CA, Lourenço JC, Oliveira MD, Bana e Costa JC (2014) A socio-technical approach for group decision support in public strategic planning: the pernambuco PPA case. Group Decis Negot 23(1):5–29

Bana e Costa CA, De Corte JM, Vansnick J (2012) Macbeth. Int J Info Tech Dec Mak 11(02):359–387

Beheshtifar S, Alimoahmmadi A (2015) A multiobjective optimization approach for location-allocation of clinics. Int Trans Oper Res. 22(2):313–28.

Behzadian M, Kazemzadeh RB, Albadvi A, Aghdasi M (2010) PROMETHEE: a comprehensive literature review on methodologies and applications. Eur J Oper Res 200(1):198–215

Belton V, Pictet J (1997) A framework for group decision using a MCDA model: sharing, aggregating or comparing individual information? J Decis Sys 6(3):283–303

Belton V, Stewart T (2002) Multiple criteria decision analysis: an integrated approach. Springer Science & Business Media. Norwell, Massachussets, US and Dordrecht, The Netherlands
Blasco H, Błaszczyński J, Billaut J et al (2015) Comparative analysis of targeted metabolomics: dominance-based rough set approach versus orthogonal partial least square-discriminant analysis. J Biomed Inform 53:291–299
Bouyssou D (1999) Using DEA, as a tool for MCDM: some remarks. J Oper Res Soc 50(9):974–978
Brans J, Vincke P, Mareschal B (1986) How to select and how to rank projects: the PROMETHEE method. Eur J Oper Res 24(2):228–238
Chen T, Chang C, Lu JR (2013) The extended QUALIFLEX method for multiple criteria decision analysis based on interval type-2 fuzzy sets and applications to medical decision making. Eur J Oper Res 226(3):615–625
Cook WD, Seiford LM (2009) Data envelopment analysis (DEA)–thirty years on. Eur J Oper Res 192(1):1–17
Cooper W (2005) Origins, uses of, and relations between goal programming and data envelopment analysis. J Multi-Criteria Decis Anal 13(1):3–11
D'Avignon G, Mareschal B (1989) Specialization of hospital services in Québec: an application of the PROMETHEE and GAIA methods. Math Comput Model 12(10):1393–1400
de Castro AKA, Pinheiro PR, Pinheiro MCD (2009a) An approach for the neuropsychological diagnosis of Alzheimer's disease: a hybrid model in decision making. In: Rough sets and knowledge technology. Springer, Berlin, pp 216–223
de Castro AKA, Pinheiro PR, Pinheiro MCD (2009b) Towards the neuropsychological diagnosis of Alzheimer's disease: a hybrid model in decision making. In: Best practices for the knowledge society. Knowledge, learning, development and technology for all. Springer, Berlin, pp 522–531
de Moraes L, Garcia R, Ensslin L, da Conceição MJ, de Carvalho SM (2010) The multicriteria analysis for construction of benchmarkers to support the Clinical Engineering in the Healthcare Technology Management. Eur J Oper Res 200(2):607–615
Diaby V, Goeree R (2014) How to use multi-criteria decision analysis methods for reimbursement decision-making in healthcare: a step-by-step guide. Expert Rev Pharmacoecon Outcomes Res 14(1):81–99
Dias L, Clímaco J (2000) Additive aggregation with variable interdependent parameters: the VIP analysis software. J Oper Res Soc 51(9):1070–1082
Dodgson J, Spackman M, Pearman A, Phillips L (2009) Multi-criteria analysis: a manual. Department for Communities and Local Government, London
Ehrgott M (2006) Multicriteria optimization. Springer Science & Business Media. New York (original version)
Figueira JR, Almeida-Dias J, Matias S, Roy B, Carvalho MJ, Plancha CE (2011) Electre Tri-C, a multiple criteria decision aiding sorting model applied to assisted reproduction. Int J Med Inform 80(4):262–273
Gales CL, Moatti J (1990) Searching for consensus through multicriteria decision analysis. Int J Technol Assess Health Care 6(03):430–449
Gouveia M, Dias L, Antunes C (2008) Additive DEA based on MCDA with imprecise information. J Oper Res Soc 59(1):54–63
Greco S, Matarazzo B, Slowinski R (2001) Rough sets theory for multicriteria decision analysis. Eur J Oper Res 129(1):1–47
Greco S, Matarazzo B, Słowiński R (2005) Rough membership and bayesian confirmation measures for parameterized rough sets. In: Rough sets, fuzzy sets, data mining, and granular computing. Springer, Berlin, pp 314–324
Greco S, Ehrgott M, Figueira J (2016) Multiple criteria decision analysis: state of the art surveys, 2nd edn. Springer, New York
Ishizaka A, Nemery P (2013) Multi-criteria decision analysis: methods and software. John Wiley & Sons, Chichester

Jarzabek R, Bugajski P, Greberski K, Blaszczynski J, Slowinska-Jarzabek B, Kalawski R (2014) Readmission to an intensive care unit after cardiac surgery: reasons and outcomes. Kardiol Pol 72(8):740–747

Jones D, Tamiz M (2010) History and philosophy of goal programming. In: Practical goal programming. Springer, New York, pp 1–9

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

Lahdelma R, Salminen P (2001) SMAA-2: stochastic multicriteria acceptability analysis for group decision making. Oper Res 49:444–454

Liang L, Liu Z, Wang H (2014) Appling the EVIDEM framework with fuzzy multicriteria group decision making method to medicines appraisal⋆. J Comput Inf Syst 10(4):1659–1667

Liu JS, Lu LY, Lu W, Lin BJ (2013) A survey of DEA applications. Omega 41(5):893–902

Martel J, Matarazzo B (2005) Other outranking approaches. In: Multiple criteria decision analysis: state of the art surveys. Springer, New York, pp 197–259

Moshkovich HM, Mechitov AI (2013) Verbal decision analysis: foundations and trends. Adv Decis Sci 2013:9

Moshkovich HM, Mechitov AI, Olson DL (2002) Ordinal judgments in multiattribute decision analysis. Eur J Oper Res 137(3):625–641

Moshkovich H, Mechitov A, Olson D (2005) Verbal decision analysis. In: Multiple criteria decision analysis: state of the art surveys. Springer, New York, pp 609–633

Munda G (1995) Multicriteria evaluation in a fuzzy environment: theory and applications in ecological economics. Physica-Verlag, Heidelberg

Munda G, Nardo M (2005) Constructing consistent composite indicators: the issue of weights. European Commission – Joint Research Center, Office for Official Publications of the European Communities, Luxembourg [EUR 21834 EN]

Nunes LC, Pinheiro PR, Pequeno TC, Pinheiro MCD (2011) Toward an application to psychological disorders diagnosis. In: Software tools and algorithms for biological systems. Springer, New York, pp 573–580

Pawlak Z, Sowinski R (1994) Rough set approach to multi-attribute decision analysis. Eur J Oper Res 72(3):443–459

Phillips LD, et al (2012) Benefit-risk methodology project: work package 4 report: benefit-risk tools and processes. European Medicines Agency, London. Available at: http://www.ema.europa.eu/docs/en_GB/document_library/Report/2012/03/WC500123819.pdf

Postmus D, Tervonen T, van Valkenhoef G, Hillege HL, Buskens E (2014) A multi-criteria decision analysis perspective on the health economic evaluation of medical interventions. Eur J Health Econ 15(7):709–716

Roy B (1991) The outranking approach and the foundations of ELECTRE methods. Theor Decis 31(1):49–73

Sang S, Wang Z, Yu C (2014) Evaluation of health care system reform in Hubei Province, China. Int J Environ Res Public Health 11(2):2262–2277

Tamanini I, de Castro AK, Pinheiro PR, Pinheiro MCD (2011) Verbal decision analysis applied on the optimization of alzheimer's disease diagnosis: a case study based on neuroimaging. In: Software tools and algorithms for biological systems. Springer, New York, pp 555–564

Thomas BG, Bollapragada S, Akbay K et al (2013) Automated bed assignments in a complex and dynamic hospital environment. Interfaces 43(5):435–448

Tsai P, Lin F (2014) An application of multi-attribute value theory to patient-bed assignment in hospital admission management: an empirical study. J Healthc Eng 5(4):439–456

Yevseyeva I, Miettinen K, Räsänen P (2008) Verbal ordinal classification with multicriteria decision aiding. Eur J Oper Res 185(3):964–983

Yoon KP, Hwang C (1995) Multiple attribute decision making: an introduction, vol 104. Sage Publications, Thousand Oaks