Aalto University
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A Systemic Perspective on Bias Mitigation in Decision Analysis

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Systems Analysis Laboratory

Human behavior drives the Decision Analysis process

Behavioral effects are present in all the steps

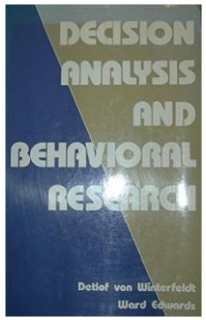
- Problem framing
- Choice of criteria
- …

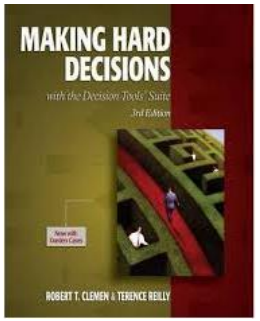
Biases influence elicitation of subjective values and parameter estimates

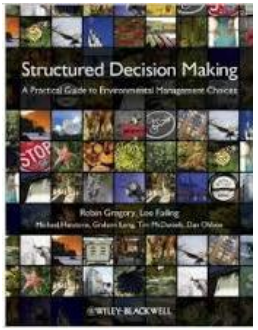
- Weighting
- Estimation of consequences and probabilities

Biases in multi-criteria decision analysis

Biases are widely covered in the decision analysis literature and textbooks

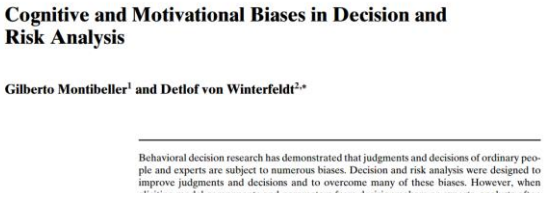






Montibeller and von Winterfeldt (2015) review:

- 175 references to papers related to biases in DA
- 30 biases and ideas for debiasing



Cognitive and Motivational Biases in Decision and Risk Analysis

Gilberto Montibeller[1] and Detlof von Winterfeldt[2,*]

Behavioral decision research has demonstrated that judgments and decisions of ordinary people and experts are subject to numerous biases. Decision and risk analysis were designed to improve judgments and decisions and to overcome many of these biases. However, when

Very little work on bias mitigation and debiasing in practice

Debiasing and bias mitigation approaches in multi-criteria preference elicitation

Consistency checks and feedback

Keeney and Raiffa 1976

Use different starting points in interactive multi-criteria optimization

Korhonen et al. 1990

Improvement of a preference elicitation method

Delquié 1997

Averaging responses

Anderson and Hobbs 2002

Adjusting numerical judgments with estimated bias coefficients

Bleichrodt et al. 2001, Anderson and Hobbs 2002

Training

Hämäläinen and Alaja 2008, Anderson and Clemen 2013

A systemic perspective is needed

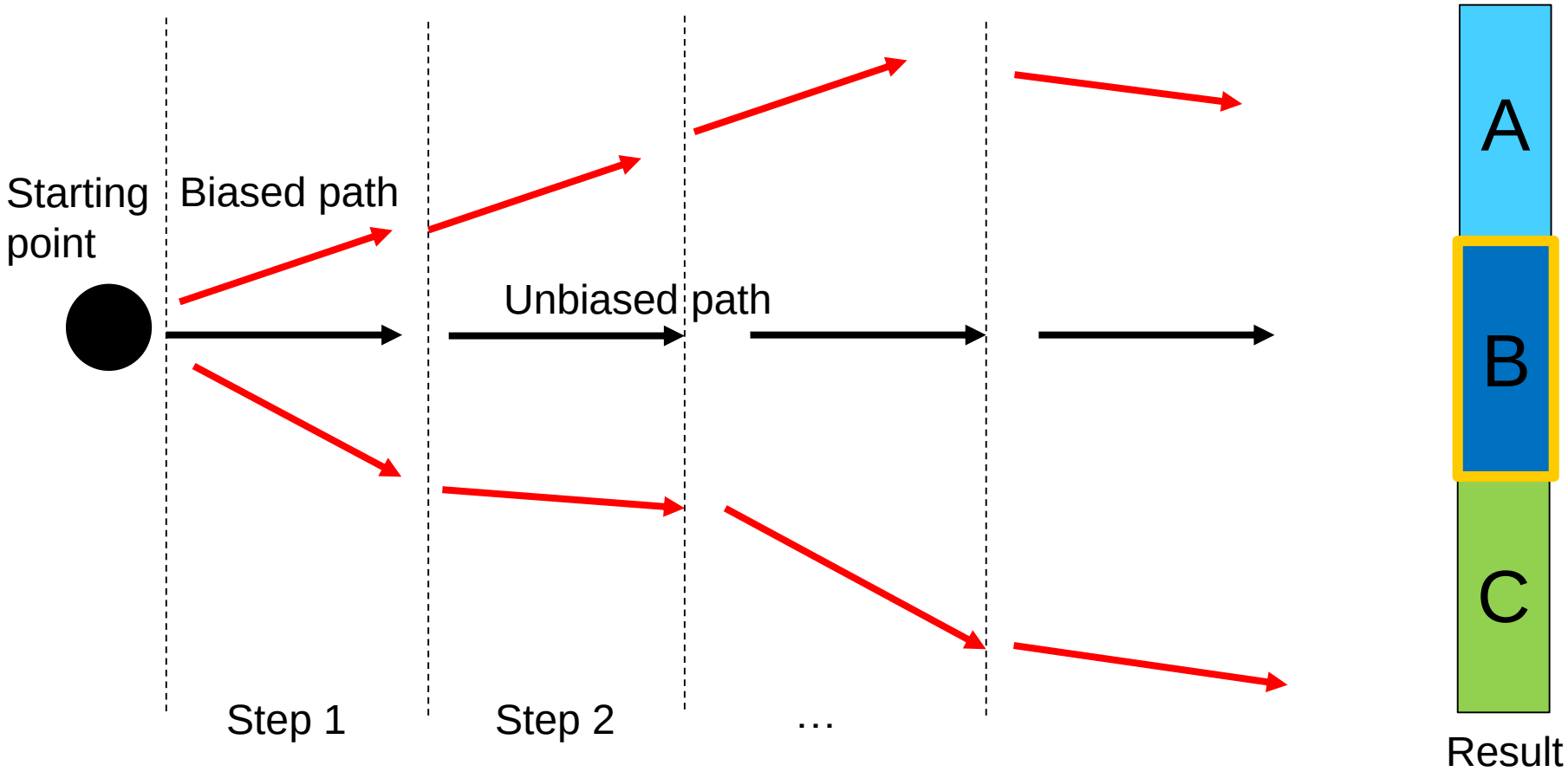
Not enough to understand and avoid biases in individual steps of the decision analysis process

The overall effects of biases depends on the path followed

Path: the sequence of steps in the decision support process

Biases are critical when they accumulate along the path

Accumulation of biases may create path dependence

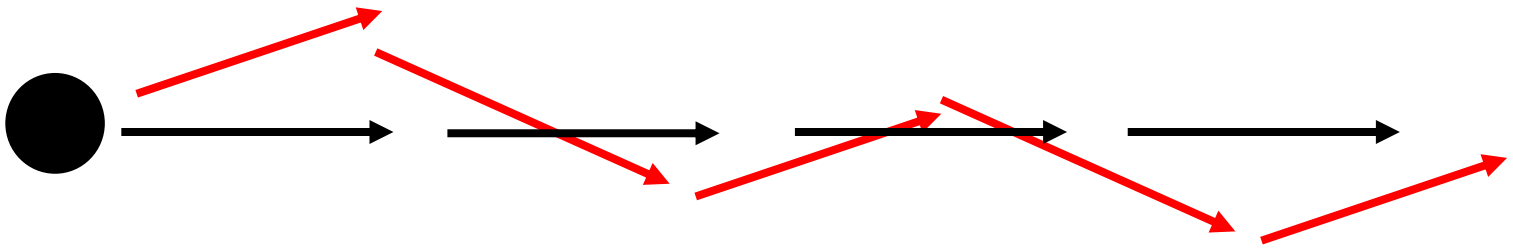


Path perspective in debiasing

Try to find paths where the effects of biases cancel out

(Examples: Anderson and Hobbs 2002, Lahtinen and Hämäläinen 2016)

Avoid paths where the effects of biases build up



Not always necessary to reduce biases in individual steps

Debiasing techniques need to be evaluated taking into account the complete process

So far, narrow focus in behavioral experiments: Behavioral phenomena occurring at isolated steps

Process evaluations:

We cannot use real decision makers in testing

Even with students it can be very cumbersome to go through all different techniques repeatedly

Computational analysis provides a new approach

Computational evaluation of debiasing methods

Based on models and estimates of the relevant biases

(Bleichrodt et al. 2001, Anderson and Hobbs 2002, Delquié 2003, Jacobi and Hobbs 2008, Lahtinen and Hämäläinen 2016)

- Assume biases and debiasing methods
- Compute the overall impact of biases in different settings

Enables testing of multiple techniques and helps to identify promising ones

New techniques to help create paths with reduced overall bias

1. **Introduce a virtual reference alternative**
2. **Introduce an auxiliary measuring stick attribute**
3. **Repeatedly rotate the reference point**
4. **Intermediate restarting of the elicitation process with a reduced set of alternatives**

Introduce a virtual reference alternative

- Can mitigate the loss aversion bias (Tversky and Kahneman 1991)

Apartment selection	Alternatives			
Attributes	A	B	C	**Virtual**
Rent (euros per month)	700	900	800	**800**
Size (square meters)	30	40	35	**35**
Condition (constructed scale)	1	2	3	**2**

- Different virtual or hypothethical reference points can be used, e.g. trade-off and swing methods, interactive MCO

Introduce an auxiliary measuring stick attribute

Irrelevant attribute can be the measuring stick

- Can mitigate the measuring stick bias (Delquié 1993) in trade-off judgments

	Alternatives		
Attributes	A	B	C
Rent (euros per month)	700	900	800
Size (square meters)	30	40	35
Condition (constructed scale)	1	2	3
Commute time (minutes)	**60**	**60**	**60**

- Trade-offs are widely used: estimation of attribute weights, pricing out, Even Swaps method

Repeatedly rotate the reference point

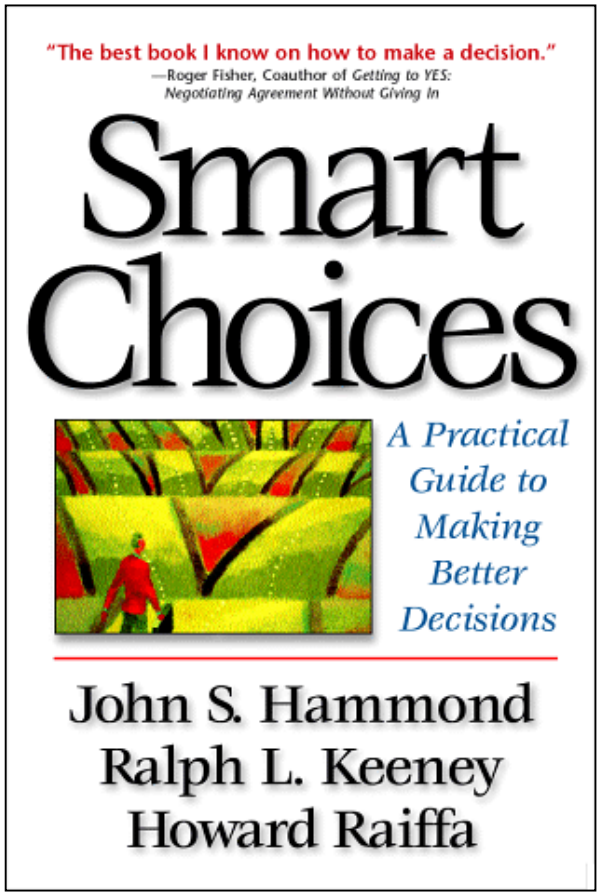
- Loss aversion bias can build up if the same original alternative defines the reference point in every attribute

Intermediate restarting of the elicitation process with a reduced set of alternatives

- Can eliminate the bias that has built up over earlier steps
- Swing method: Attribute swings depend on alternatives
- Intermediate restarting can help to cope with range insensitivity (Fischer 1995)

1. Assess attribute weights and score alternatives
2. Eliminate low scoring alternatives so that attribute swings are reduced
3. Repeat steps 1 and 2 until range of swings cannot be reduced

A demonstration with the Even Swaps process



1999

Office selection problem

(Hammond, Keeney, Raiffa 1999)

	Lombard	Baranov	Montana	Pierpoint
Commute Time	25	~~20~~ 25	25	30
Client Access	80	~~70~~ ~~78~~ 72	~~85~~ 88	75
Office Services	B	~~C~~ B	~~A~~ B	C
Office Size (m2)	700	500	950	700
Monthly Cost ($)	1700	1500	1900	1750

An even swap

Commute time irrelevant

Office services irrelevant

Dominated by Lombard

Reference method (attribute elimination method)

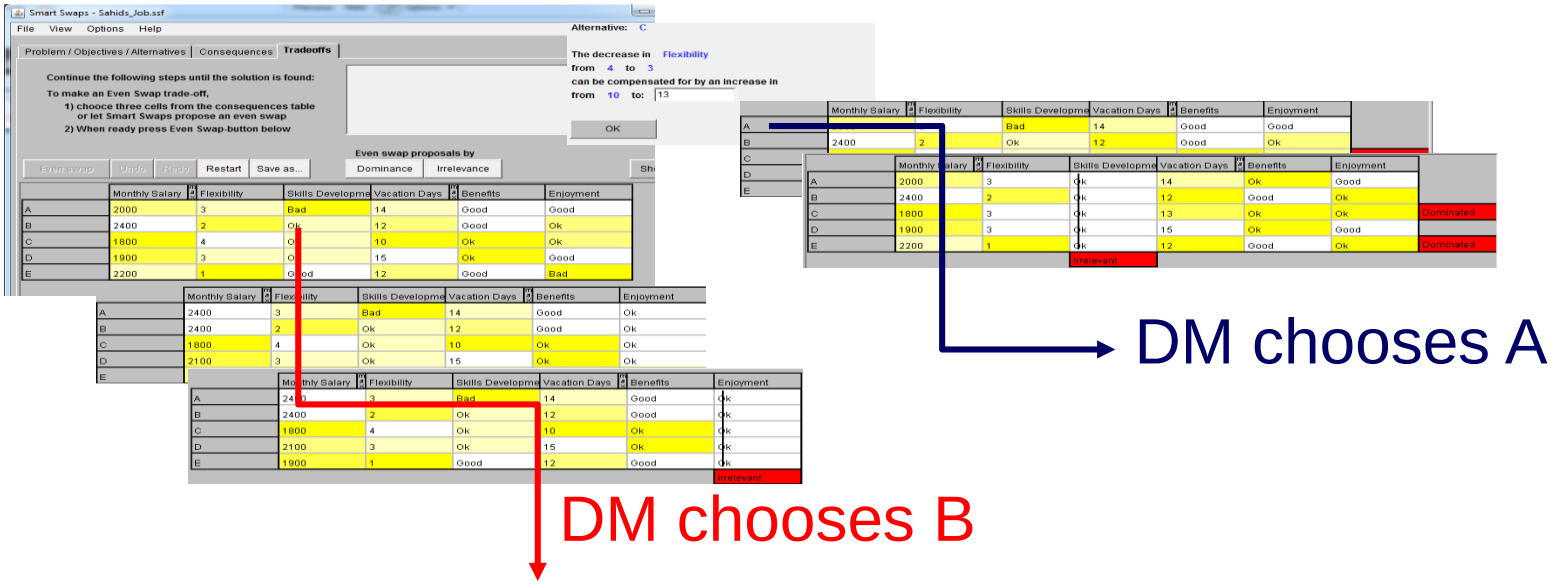
- Eliminate dominated alternatives
- Select a reference alternative (Lombard)
- Select a measuring stick attribute (Client Access)
- Make attributes irrelevant: Make all alternatives equal to reference alternative in all attributes besides the measuring stick attribute.

Biases can create path dependence in Even Swaps

Measuring stick bias: Extra weight for the measuring stick

Loss aversion: Extra weight for the loss attribute

What is the equally valuable loss in money if commuting time is decreased by 30 minutes?



Bias mitigation methods for Even Swaps

Reference method: Attribute elimination method with a fixed reference alternative

Method A: Attribute elimination method with a virtual reference alternative

Method B: Attribute elimination method with a virtual reference alternative and an auxiliary measuring stick

Method C: Pairwise attribute elimination method with an auxiliary measuring stick, rotating reference point and intermediate restarting

Method D: Pairwise attribute elimination method with an auxiliary measuring stick, virtual reference alternative, and intermediate restarting

Method D requires about twice as many swaps as the other methods

Computational analysis

Biased decision makers:

- Weight of measuring stick attribute increased by a factor S (1.1, 1.3 or 1.5)
- Weight of loss attribute increased by a factor L (1, 1.2 or 1.4)
- Non-systematic response error included in half of the settings

Sizes of the consequences tables varied

- Number of attributes: 3, 5 or 8 Number of alternatives: 2, 5 or 8
- 5000 randomly generated sets of alternatives per each case

Attribute weights varied

- 100 randomly generated weight profiles for each number of attributes

Performance criterion: Share of cases where method gives the same result as a bias free process

Overall results

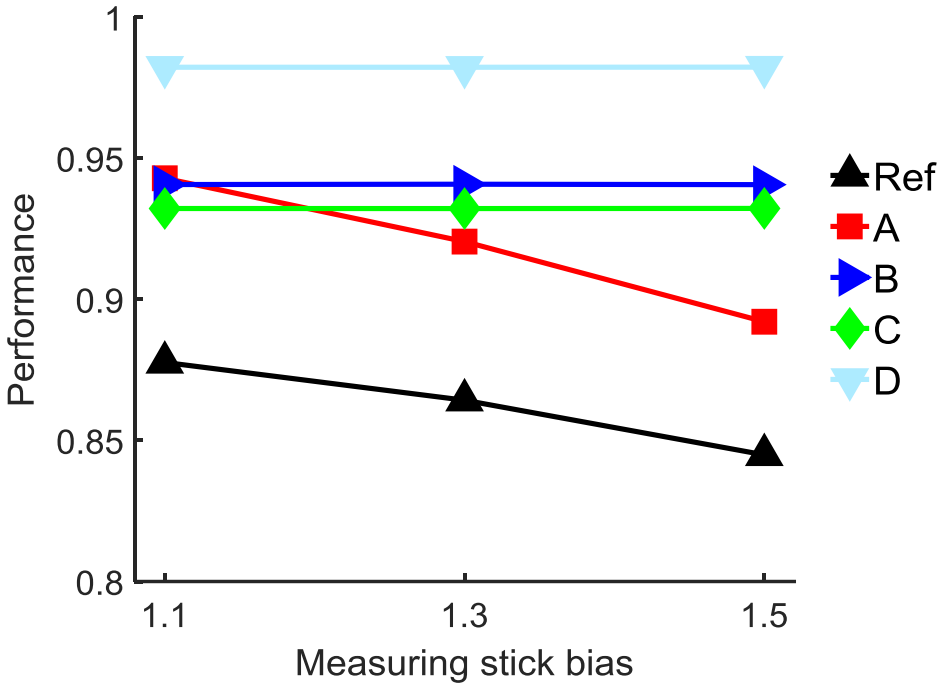
- All bias reduction methods A-D perform better than the reference method

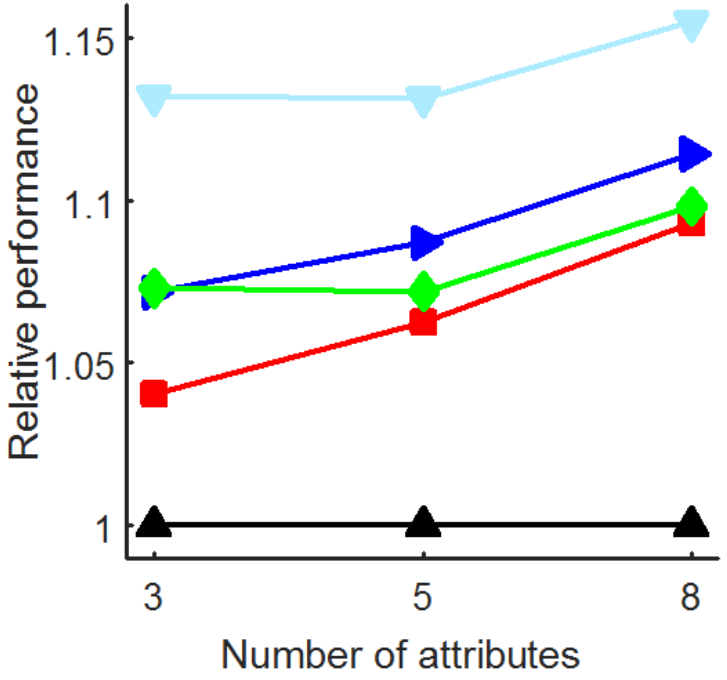
	Percentage of cases where a method gives the same result as a bias free process
Reference method	86
Method A	92
Method B	94
Method C	93
Method D	98

- Method D always finds the correct result if response error is zero

- When the value difference of top two alternatives is up to 0.3, the correct solution is not always found with all methods

Performance of the methods in different settings





- Performance of the reference method and Method A decreases with increasing magnitude of measuring stick bias
- Methods A-D increasingly better than the reference method with higher number of attributes

Discussion of results

All of the proposed new techniques help to mitigate the overall effects of biases in the Even Swaps process.

We evaluated methods based on these techniques across a number of different computational settings.

In a real-life case, the method to be used can be chosen based on more specific information

- e.g., the number of alternatives, the number of attributes, the consequences of the alternatives, as well as estimates of the magnitudes of the biases of the person using the Even Swaps process.

Conclusions

A systemic perspective helps to find effective debiasing methods

It is possible to find paths along which the effects of biases counteract each other leading to low overall bias.

New bias reduction techniques can easily be taken into use in Even Swaps, Trade-off weighting, Swing weighting

New techniques are potentially interesting in interactive multi-criteria optimization procedures too

Computational analysis helps to evaluate the effectiveness of different bias mitigation techniques

References

Anderson, R. M., Clemen, R. 2013. Toward an Improved Methodology to Construct and Reconcile Decision Analytic Preference Judgments, Decision Analysis, 10(2), 121-134.

Anderson, R. M., Hobbs, B. F. 2002. Using a Bayesian Approach to Quantify Scale Compatibility Bias. Management Science, 48(12), 1555-1568.

Bleichrodt, H. J., Pinto, J. L., Wakker, P. 2001. Making descriptive use of prospect theory to improve the prescriptive use of expected utility. Management Science, 47(11), 1498-1514.

Delquié, P. (1993) Inconsistent trade-offs between attributes: New evidence in preference assessment biases. *Management Science* 39(11):1382-1395

Delquié, P. 1997. “Bi-matching”: A new preference assessment method to reduce compatibility effects. *Management Science* 43(5), 640-658

Delquié, P. (2003). Optimal conflict in preference assessment. *Management Science* 49(1):102-115.

Fischer, G.W. 1995. Range sensitivity of attribute weights in multiattribute value models. *Organizational Behavior and Human Decision Processes* 62(3), 252-266.

Hammond, J.S., Keeney, R.L., Raiffa, H., 1999. Smart Choices: A practical guide to making better decisions. Harvard Business School Press, Boston, MA.

Hammond, J.S., Keeney, R.L., Raiffa, H., 1999. Smart Choices: A practical guide to making better decisions. Harvard Business School Press, Boston, MA.

Hämäläinen, R. P., Alaja, S. 2008. The threat of weighting biases in environmental decision analysis. *Ecological Economics* 68(1), 556-569.

Hämäläinen, R. P., and Lahtinen, T. J. (2016). Path dependence in Operational Research – How the modeling process can influence the results. *Operations Research Perspectives*, 3:14-20.

Jacobi, S. K., Hobbs, B. F. 2007. Quantifying and mitigating the splitting bias and other value tree-induced weighting biases, Decision Analysis, 4(4), 194-210.

Keeney, R. L., & Raiffa, H. 1976. Decisions with Multiple objectives: Preferences and value trade-offs. New York: John Wiley & Sons.

Korhonen, P., Moskowitz, H., & Wallenius, J. 1990. Choice behavior in interactive multiple-criteria decision making. Annals of Operations Research, 23(1), 161– 179.

Lahtinen, T. J., and Hämäläinen, R. P. 2016. Path dependence and biases in the even swaps decision analysis method. *European Journal of Operational Research*, 249(3): 890-898.

Lahtinen, T. J., Guillaume, J. H., and Hämäläinen, R. P. 2017. Why pay attention to paths in the practice of environmental modelling? *Environmental Modelling & Software*, 92:74-81.

Montibeller, G., and D. Winterfeldt. Cognitive and Motivational Biases in Decision and Risk Analysis. Risk Analysis, 2015

Tversky, A., Kahneman, D. 1991. Loss Aversion in Riskless Choice: A Reference-Dependent Model. Quarterly Journal of Economics, 106(4), 1039-1061.