Operations Research Forum (2024) 5:92
https://doi.org/10.1007/s43069-024-00371-3

ORIGINAL RESEARCH

Incomplete Objectives in Decision Making: How Omitting Objectives Affects Identifying the Most Promising Alternative

Sara J. M. Abdeen[1] · **Florian Methling**[1] · **Rüdiger von Nitzsch**[1]

Received: 9 March 2022 / Accepted: 27 September 2022
© The Author(s) 2024

Abstract
Research has shown that decision-makers omit a significant number of their objectives when making a decision. This study examines the consequences of incomplete objectives on decision making, i.e., how does omitting objectives affect identifying the most promising alternative? We investigate this question using a dataset of 945 observed decisions. These decisions were developed by students using the decision-skills and training tool entscheidungsnavi.com. The tool guides students in a step-by-step process based on value-focused thinking, multi-attribute utility theory, and debiasing methods. Results show that omitting objectives significantly reduces the chances of identifying the most promising alternative. Hence, neglecting only 20% of the objectives is sufficient to mislead more than one in four decisions. We have found three factors that influence this risk of misidentifying the most promising alternative: (1) the weight of the omitted objectives; (2) the consensus on the best alternative across all objectives; and (3) the consensus on the ranking of all alternatives across all objectives.

Keyword Decision analysis; Decision support systems; Value-focused thinking; Multi-attribute utility theory

1 Introduction

The role of objectives in decision making has long been given special importance [1]. Researchers have described "structuring," i.e., "the process of generating objectives and identifying attributes" [2], as the "art" of decision making [2–4]. Ralph Keeney proposed value-focused thinking, which emphasizes the importance of identifying and articulating objectives for sound decision making [5–7].

✉ Florian Methling
methling@efi.rwth-aachen.de

[1] Chair of Decision Theory and Financial Services, RWTH Aachen University, Aachen, Germany

Published online: 02 October 2024

Despite the importance of identifying objectives, investigation shows that decision-makers fail to identify about half of their objectives [8]. When presented with the omitted objectives, decision-makers evaluate those objectives just as important as the objectives they have identified. The reason for this shortcoming in identifying objectives is considering only a narrow range of objectives and/or not giving enough thought into articulating each identified objective [1].

Identifying only a subset of objectives is described as an omission bias [9]. It belongs to the group of association-based errors, which are difficult to correct by logic or decomposition. Nevertheless, multiple procedures and techniques can be used to reduce the omission bias by stimulating the generation of a more complete set of objectives. For example, researchers have found that providing decision-makers with broad categories for the objectives facilitates generating a more comprehensive set of objectives [1, 10]. Another effective technique to expand the depth and breadth of thought is direct challenges to generate a specific number of overlooked objectives [1, 10]. Keeney [11] suggests prescriptive methods such as creating wish lists, using generic objectives and structuring objectives. Literature provides a wide range of other techniques to support decision-makers in generating more objectives [7, 12–14].

Ultimately, the goal of any decision-making procedure is to identify or rank the most promising alternative. Thus, the importance of reducing this omission bias depends on its influence on identifying the most promising alternative.

Findings in literature can be divided into two categories. The first category views the omission of objectives as an opportunity to reduce effort or simplify decision situations. Thus, the focus is on identifying conditions under which omitting objectives can still lead to good decisions. For example, Barron and Barrett [15] have found that when the subset of attributes contains the most important attributes, the value loss is less than that when all attributes were evaluated as equally important. Albar and Kocaoglu [16] provide more specific findings by classifying cases based on the correlation between the attributes and whether weights are distributed equally. Attributes are positively correlated when they agree on the ranking of alternatives. Negatively correlated attributes require trade-offs, because each attribute highlights a different alternative [17]. Negatively correlated attributes with equal weights require at least 80% of the attributes to identify an alternative that is at most 10% lower in value than the highest value possible (i.e., most promising alternative) [17]. In comparison, negatively correlated attributes with unequal weights require only the most important attribute to identify an alternative within 10% value loss. In the case of positively correlated attributes with different weights, one or two attributes are sufficient to choose an alternative within the 10% mark.

The dominating view of the second category of findings is that omitting objectives is an error that reduces the quality of the decision. Thus, efforts are focused on demonstrating the decrease in quality because of an incomplete set of objectives. For example, Barron [2] compared the ranking of alternatives in a complete and an incomplete set of objectives and measured the value loss and correlation. Previous research argues that if the correlation coefficient between the values of the alternatives in the two models (complete and incomplete attributes) is high, then the multi-attribute additive value is robust against an incomplete set of attributes. However,

Barron argues that this criterion is insufficient. Results show that high value losses at a high frequency can occur simultaneously with high correlation values. Thus, an incomplete set of objectives can mislead the decision-maker from choosing the most promising alternative even when high correlations are evident. Fry et al. [18] adopt a broader perspective and show how omitted objectives and response error can have more severe effects depending on the elicitation procedure used (simple multi-attribute rating technique (SMART), holistic orthogonal parameter estimation (HOPE), and Keeney-Raiffa).

These findings illustrate different scenarios and conditions of decision structures in which the omission of attributes leads to certain deviations. However, when decision-makers fail to identify certain objectives in personal decisions, these conditions and scenarios might be very different. Hence, this paper adds to the literature a different perspective. It focuses on the practical consequences of incomplete objectives for individual decision-makers in personal decisions. This study's goal is to investigate how the omission of objectives in personal decisions affects identifying the most promising alternative.

The analysis is based on a dataset consisting of 945 exclusively personal decisions generated by students. We have found that the higher the proportion of omitted objectives, the lower the chances of identifying the most promising alternative. This effect becomes stronger with increasing importance of the omitted objectives, i.e., the higher the weight of the omitted objectives the higher the average relative value loss and the lower the likelihood of identifying the most promising alternative. In addition to the weights of the omitted objectives, two other influencing factors are considered, consensus between objectives on the ranking of alternatives (correlation) and consensus on the best alternative.

Our paper is structured as follows. First, we outline the theoretical background (Sect. 2) and describe the dataset (Sect. 3). Section 4 presents the applied method of analysis, followed by the results (Sect. 5) and the discussion (Sect. 6). Finally, we conclude with a summary of our findings and discuss their implications (Sect. 7).

2 Theoretical Background

In this investigation, students were guided through a step-by-step decision-making procedure using the decision support tool entscheidungsnavi.com [19]. The tool supports decision-makers in applying value-focused thinking, MAUT and debiasing measures. Additionally, it ensures a standard procedure for all participants and reduces behavioral influences such as biases introduced by decision analysts. Figure 1 describes the steps to follow to get to a personal decision matrix.

In the first step, decision-makers are encouraged to carefully phrase their decision statement. The rationale is that the framing of the question determines the scope of the possible alternatives. Thus, techniques are used to support the decision-maker in this process. For example, the tool asks the user to think about their fundamental values related to the decision statement. It also gives "impulse questions" to help the user to widen perspective.



Fig. 1 Steps for generating a decision matrix in the Entscheidungsnavi

In the second step, value-focused thinking is applied. As proposed by Ralph Keeney [5, 20], value-focused thinking focusses on generating and articulating objectives prior to generating alternatives. Research has shown that applying this method has multiple advantages [7]. For example, using objectives to generate alternatives can lead to more than double the number of alternatives [21]. Additionally, it helps decision-makers identify opportunities to prevent future problems rather than react to decision problems [5]. In addition to formulating objectives first, the tool also employs techniques to support the users in generating a comprehensive set of objectives. For example, decision-makers are asked to create wish lists, analyze problems and shortcomings, and adopt different perspectives.

In a third step, decision-makers are asked to generate possible alternatives to achieve each of their fundamental objectives. Gradually, they increase the number of fundamental objectives they consider in generating alternatives, until all fundamental objectives are considered simultaneously.

On the backend of the process, MAUT is applied to assess the value of each alternative against the fundamental objectives (consequence table). First, decision-makers create scales for each objective. These scales are later used to rate the different alternatives. Second, the decision-maker accounts for uncertainty by defining influencing factors affecting an alternative in a particular objective. The decision-maker estimates the likelihood of a scenario occurring and evaluates it across all objectives.

Then, the tool supports the user in converting the given values into utility functions. In this step, the tool checks for monotonicity in preferences, and the decision-maker adjusts the utility function to his/her risk attitude. Additionally, the decision-maker quantifies preferences based on trade-offs between his/her objectives. The trade-off methodology for identifying preferences has been chosen because direct ratings are susceptible to biases and decision-makers do not reflect on range compressions sufficiently [22].

Finally, decision-makers are presented with their decision structure and a ranking of their alternatives. Decision-makers are asked to adjust their assumptions and evaluations until the result best reflects their preferences and beliefs. Decision-makers can apply sensitivity analyses, Monte-Carlo simulations, and robustness checks, and the tool demonstrates the effect of these changes on the ranking of their alternatives.

3 Dataset

The used dataset consists of 945 decision structures generated by students. In 2019 and 2020, 500 and 458 decision structures were generated, respectively. Thirteen of the decisions were incomplete and have been removed. On average, each student spent 8.8 h developing his/her decision structure using the decision support tool Entscheidungsnavi. Each participant submitted a file containing all information entered at each step of the decision process, comments, and considerations. For our analysis, the consequence table, utility values, and objective weights were extracted and further analyzed using MATLAB.

Figure 2 shows an overview of the number of objectives and alternatives considered by decision-makers in this study. On average, each decision structure consists of 4.61 objectives and 5.97 alternatives. In this study, each decision-maker chose a decision question independently. The most chosen decision question (325 of 945) is about career planning, such as internships and jobs. One hundred eighty-four decision-makers addressed educational matters in their decision question. The remaining decision-makers focused on international experience (110), purchasing decisions (46), and personal lifestyle decisions (280).

4 Method

To investigate the influence of an incomplete set of objectives on identifying the most promising alternative, we created two models. The first model contains the complete set of objectives as generated by the students. In this model, the alternative with the maximum expected utility is identified as the benchmark. The second model contains a subset of the objectives after deliberate elimination.

In both models, the overall utility of each alternative was calculated using the additive model (1), where x is the alternative in question, k_i is the weight of objective i, and $u_i(x)$ is the utility of alternative x for objective i.

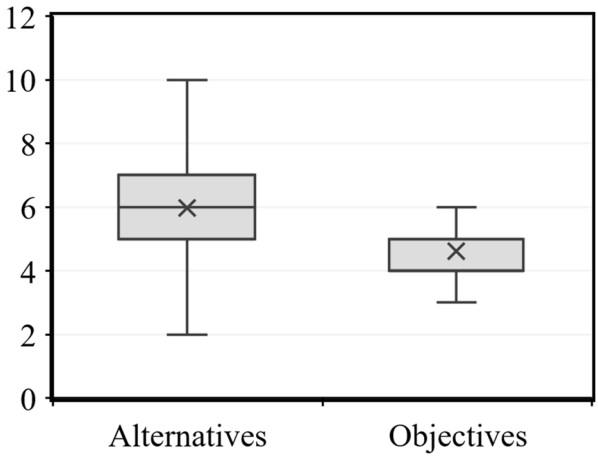


Fig. 2 Distribution of decisions based on the number of objectives and alternatives considered per decision. The graph presents the maximum and minimum value without the outliers. The cross provides the average value

$$u(x) = \sum k_i u_i(x) \tag{1}$$

In a second step, we systematically eliminated a proportion of objectives using MATLAB. The resulting number of eliminated objectives is rounded up to the nearest integer.

First, we investigate the effect of omitting a proportion of objectives on performance and proportion value lost (PVL). Performance describes the percentage of decisions that match the alternative with the highest expected utility in model 1. PVL is calculated following Barron [2] according to Formula (2), where B denotes the expected utility of the best alternative (maximum expected utility). W represents the expected utility of the worst alternative (minimum expected utility). R is the expected utility of the selected alternative as calculated in model 1, while the alternative was selected because it provides the maximum expected utility in model 2 (subset of objectives considered).

$$PVL = \frac{B - R}{B - W} \tag{2}$$

Three factors that may influence performance and PVL when omitting objectives are examined. First, the influence of the weight of the omitted objectives is investigated. Three scenarios are considered: (1) objectives are eliminated randomly, i.e., assuming equal weights; (2) objectives are eliminated in a descending weight order; and (3) objectives are eliminated in an ascending weight order. In the second and third scenario, if equal weighted objectives exist, only one objective is eliminated. For example, if the objective with the highest weight is to be eliminated and two or more objectives have the maximum weight, then only one of the objectives is eliminated.

The second influencing factor is consensus on the ranking of alternatives among the individual objectives. This is identified based on the correlations of the ranks of alternatives for each of the objectives. The average correlation between all objectives is calculated from the objective correlation matrix.

The third influencing factor is consensus on the best alternative. The alternative that is most frequently ranked the best in the individual objectives is identified using a tallying heuristic. Consensus is measured as the percentage of objectives that rank the identified alternative as the best.

5 Results

First, the effect of omitting objectives on performance and PVL is examined. A correlation coefficient of -0.48 shows that the higher the proportion of omitted objectives, the lower the chance of identifying the most promising alternative (performance). When misidentifying the most promising alternative, the average PVL increases with the number of omitted objectives. The correlation coefficient is 0.31. For example, if decision-makers eliminate 20% of their objectives, there is a 28% chance that they will not identify the most promising alternative and will

Table 1 Average performance and PVL for each proportion of eliminated objectives

Proportion of eliminated objectives	Avg. performance	Avg. PVL
0.20	72%	8%
0.40	62%	12%
0.60	42%	21%
0.80	26%	29%
0.90	4%	33%

Table 2 Correlation coefficient of proportion of omitted objectives with performance and PVL for each elimination method

	Random	**Descending**	**Ascending**
Performance	−0.48	−0.43	−0.51
PVL	0.31	0.23	0.34

choose an alternative with an average PVL of 8%. Table 1 shows the average values of performance and PVL for each proportion of omitted objectives.

The effect of omitting objectives on average performance and PVL can be influenced by multiple factors. The first influencing factor analyzed is the weight of the omitted objectives. The change in the correlation coefficients as a result of the elimination criteria illustrates the moderating effect of the weight of the omitted objectives. Both correlation coefficients for the performance and PVL become stronger when eliminating objectives in an ascending order and weaker when eliminating objectives in a descending order. Table 2 shows the correlation coefficients for each elimination method.

The average values of performance and PVL for each proportion of eliminated objectives show the influence of objective weights. Figure 3 shows that the average performance is consistently highest when objectives are eliminated in an ascending order. For example, when 20% of the objectives are eliminated randomly, the average performance is 72%. In contrast, eliminating 20% of the objectives in an ascending order yields an average performance of 80%. The performance reduces to 63% when objectives are eliminated in a descending order. Simultaneously, the average PVL is lowest when objectives are eliminated in an ascending order and highest when they are eliminated in a descending order.

The second influencing factor investigated is consensus on the ranking of alternatives. This is measured by the average correlation of the utilities of alternatives per objective. Results show that a higher average correlation leads to better performance and lower PVL. Figure 4 illustrates the influence of positive (3595 decisions) and negative (940 decisions) average correlations on the average performance and PVL. For example, eliminating 20% of the objectives when there is a negative correlation leads to a suboptimal decision in 43% of the cases with an average PVL of 17%. In contrast, when there is a positive correlation, the risk decreases to 25% with an average PVL of 5%.

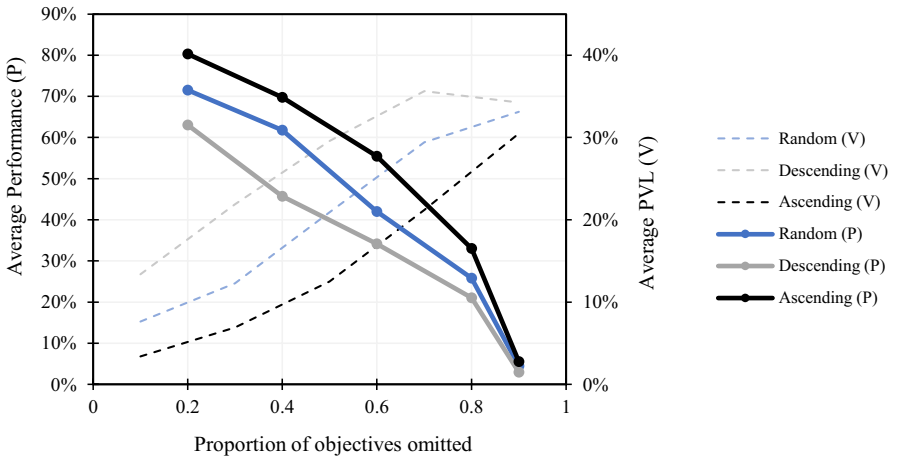


Fig. 3 Influence of the weight of omitted objectives on average performance and average PVL

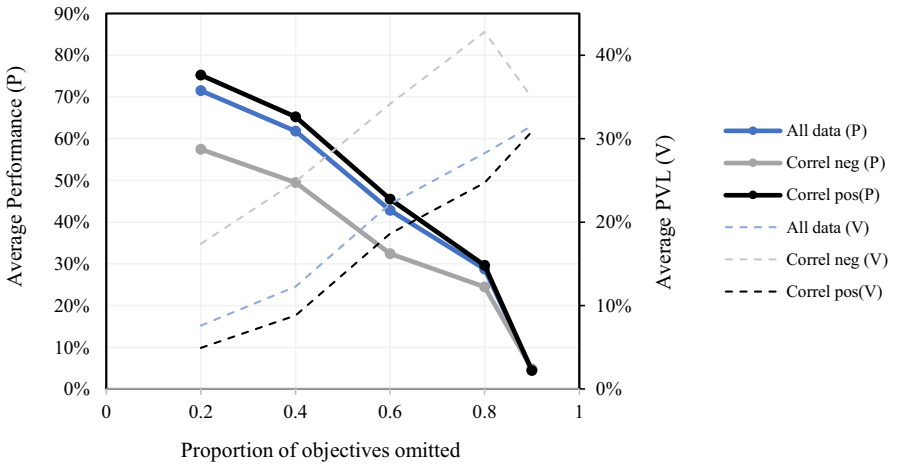


Fig. 4 Influence of average correlation of rankings on average performance and average PVL

A third factor that can influence the average performance and PVL is consensus on a best alternative. Results in Fig. 5 show that if one alternative is considered the best in more than 50% of the objectives (2870 decisions), chances of identifying the most promising alternative are higher, while a consensus in 50% of the objectives or less (1855 decisions) performs worse. For example, omitting 20% of the objectives leads to an average performance of 69% and a PVL of 7% when there is a consensus in 50% of the objectives or less. If there is a consensus in more than 50% of the objectives, the average performance increases to 75% with a PVL of 8%.

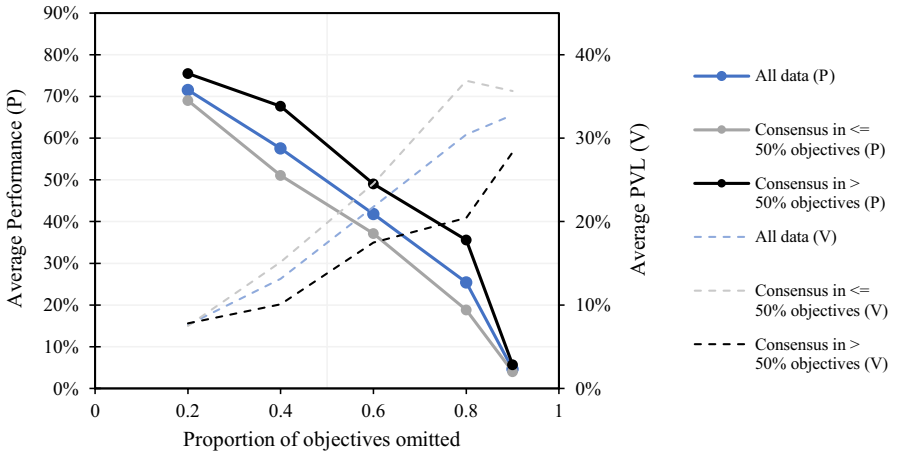


Fig. 5 Influence of percentage of objectives with consensus on the best alternative on average performance and average PVL

An analysis of the two measures, performance and PVL, of the different decision questions (career, international experience, etc.) did not show any significant differences.

6 Discussion

Five recommendations can be derived from the results. First, when developing the decision structure, it is recommended that decision-makers invest in identifying their objectives to increase the chance of identifying the most promising alternative. Similarly, if simplification of the decision structure is desired, the proportion of omitted objectives should be chosen carefully, bearing in mind the consequences. Omitting 20% of the objectives can lead to a suboptimal decision in more than 25% of the cases in our study.

Second, it is recommended that decision-makers give special importance to important objectives when identifying their objectives and when simplifying their decision structure. The results show that dismissing an important objective can significantly decrease the chance to identify the most promising alternative. In the case of omitting 20% of the objectives, the performance dropped from 80 to 63% when omitting the most important objective.

Further, it is recommended that decision-makers try to identify more objectives if there are considerable differences in the ranking of alternatives for the individual objectives. Similarly, when simplifying a decision structure, eliminating objectives when there is a low correlation increases the risk of misidentifying the most promising alternative. For example, eliminating 20% of the objectives when there is a negative correlation leads to a suboptimal decision in 43% of the cases. In contrast, when there is a positive correlation, the risk decreases to 25%.

If decision-makers recognize that one alternative performs best in more than 50% of the objectives, the risk of misidentifying the most promising alternative when simplifying the decision structure is lower. If this is not the case, omitting objectives for simplification or failing to identify relevant objectives leads to a higher risk of misidentifying the most promising alternative. More specifically, when eliminating 20% of the objectives, the performance can drop from 75 to 69%.

Finally, these recommendations hold true for all decision topics, given that no differences were found when analyzing data in the different categories.

7 Conclusion

The goal of this study is to understand the consequences of an incomplete set of objectives on identifying the most promising alternative for an individual decision-maker. Using a large dataset, we found the following tendencies. The higher the proportion of neglected objectives, the lower the chance to identify the most promising alternative. For example, omitting 20% of the objectives randomly can lead to choosing a different alternative than the most promising alternative in more than 1 of 4 decisions, while omitting 60% of the objectives leads to a suboptimal alternative in more than 50% of the cases in this dataset. This is accompanied by an increase in average PVL.

Our data suggest that this effect is not influenced by the type of decision. However, the weight of the objective does influence the performance and average PVL. The higher the weight of the ignored objective, the lower the performance and the higher the average PVL.

Furthermore, it is conceivable that when there is a consensus among the objectives about the utility of each alternative, the most promising alternative would be correctly identified with fewer objectives. Two analyses were made. First, consensus on the ranking of alternatives is considered. This was identified using correlations. Second, consensus on the most promising alternative is studied. This is identified using a tallying heuristic. Results indicate that a high average correlation between the ranking of alternatives leads to a higher likelihood of identifying the most promising alternative when omitting objectives.

Comparing our findings with the ones reported in literature, some tendencies are affirmed, but some cannot be replicated. Most of the previous research relied on simulations to generate attributes and alternatives as well as weights of the attributes. By relying on a dataset of 945 observed decisions, our findings provide empirical validation of previous results. For example, Barron and Barrett [15] have shown that eliminating the least important objectives leads to a better performance (correctly identifying the most promising alternative) than eliminating the same number of objectives randomly (ignoring the weights of the attributes). This is in line with our finding that eliminating objectives in an ascending order leads to better performance than randomly eliminating objectives. In their case, focus is on incomplete information on weights. Their study uses a simulation (EMAR) to estimate the weights of the attributes based on given ranks of the

Table 3 Average weight of objective and average consensus on best alternative for the negatively correlated decision structures with unequal weights

	PVL ≤ 10%	PVL > 10%
Avg. weight of objective	0.37	0.34
Avg. consensus on best alternative	0.48	0.42

attributes. Additionally, their 500 random matrices all consisted of 9 attributes and 15 alternatives.

In other cases, analysis of previous concepts has shown different results when applied to our dataset. For example, previous work has concluded a minimum number of attributes needed for a PVL loss of maximum 10% [17]. One of their findings is that one attribute (with the maximum weight) is sufficient if the attributes are negatively correlated and have unequal weights [17]. These findings could not be replicated in our dataset. Applied to our dataset, this was the case in about half of the cases (53%). One explanation is that the PVL is influenced by factors other than the negative correlation and the distribution of weights (equal versus unequal). For example, in the cases of negative correlation and unequal weights of attributes, we have found that the weight of the attribute is slightly higher in the cases where the PVL is less than or equal to 10%. Similarly, the consensus on the best alternative is also higher. This is shown in Table 3. Thus, it can be inferred that the weight of the objective as well as the consensus on the best alternative can lead to a higher PVL even when there is a negative correlation and unequal weights.

Additionally, some of our findings expand previous analyses. For example, to our knowledge, the influence of consensus on the most promising alternative has not been investigated. As mentioned previously, this can help decision-makers when simplifying decisions and when identifying objectives.

Notice that the used dataset focuses on a population of students limiting the number of decision topics. Further studies might include other types of decision-makers and related decision topics. Additionally, it is assumed that the best alternative identified with additive MAUT is the most promising alternative. The accuracy of this benchmark is at the core of decision theory, i.e., how to identify the most promising alternative. Thus, as new findings emerge, this assumption may prove inaccurate.

In conclusion, our findings provide empirical evidence on the importance of generating objectives in increasing the chances of identifying the most promising alternative. These results further support the concept of value-focused thinking [5, 6], in the sense of giving special importance to the process of generating and articulating objectives. To that end, decision-makers are encouraged to apply this knowledge to improve their decision-making skills by using the various techniques that stimulate identifying a more complete set of objectives [1, 10].

Funding Open Access funding enabled and organized by Projekt DEAL.

Data Availability The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to them containing information that could compromise research participant privacy.

Declarations

Competing Interest The authors declare no competing interests.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

References

1. Bond SD, Carlson KA, Keeney RL (2010) Improving the generation of decision objectives. Decision Anal 7. https://doi.org/10.1287/deca.1100.0172
2. Barron FH (1987) Influence of missing attributes on selecting a best multi attributed alternative. Decision Sci 18
3. Von Winterfeldt D (1980) Structuring decision problems for decision analysis. Acta Psychologica 45
4. Buede DM (1986) Structuring value attributes. Interfaces 16
5. Keeney RL (1994) Creativity in decision making with value-focused thinking. Sloan Manag Rev 35
6. Keeney RL (1996) Value-focused thinking: identifying decision opportunities and creating alternatives. Eur J Oper Res 92
7. León OG (1999) Value-focused thinking versus alternative-focused thinking: effects on generation of objectives. Org Beh Human Decision Proc 80. https://doi.org/10.1006/obhd.1999.2860
8. Bond SD, Carlson KA, Keeney RL (2008) Generating objectives: can decision makers articulate what they want?. Manag Sci 54. https://doi.org/10.1287/mnsc.1070.0754
9. Montibeller G, Von Winterfeldt D (2015) Cognitive and motivational biases in decision and risk analysis. Risk Anal 35
10. Keeney RL (2013) Identifying, prioritizing, and using multiple objectives. EURO J Decision Proc 1. https://doi.org/10.1007/s40070-013-0002-9
11. Keeney RL (1996) Value-focused thinking. Harvard University Press
12. Eden C (2004) Analyzing cognitive maps to help structure issues or problems. Eur J Oper Res 159
13. Gentry E (2013) A hybrid method for generating objectives
14. Montibeller G, Von Winterfeldt D (2015) Biases and debiasing in multi-criteria decision analysis. in 2015 48th Hawaii International Conference on System Sciences. IEEE
15. Barron H, Barrett BE (1999) Linear inequalities and the analysis of multi-attribute value matrices. Decision Science and Technology: Reflections on the Contributions of Ward Edwards
16. Albar FM, Kocaoglu DF (2009) Few or more attributes: deleting criteria using sensitivity analysis. in PICMET'09–2009 Portland International Conference on Management of Engineering & Technology. IEEE
17. Fasolo B, Mcclelland GH, Todd PM (2007) Escaping the tyranny of choice: when fewer attributes make choice easier. Marketing Theory 7
18. Fry PC, Rinks DB, Ringuest JL (1996) Comparing the predictive validity of alternatively assessed multi-attribute preference models when relevant decision attributes are missing. Eur J Oper Res 94
19. Von Nitzsch R, Tönsfeuerborn M, Siebert JU (2020) Decision skill training with the Entscheidungsnavi. in In: de Almeida AT, Morais DC (eds) Innovation for systems information and decision. INSID 2020. Lect Notes Bus Info Proc 405

20. Keeney RL (1996) Value-focused thinking: identifying decision opportunities and creating alternatives. Eur J Oper Res 92. https://doi.org/10.1016/0377-2217(96)00004-5
21. Siebert J, Keeney RL (2015) Creating more and better alternatives for decisions using objectives. Oper Res 63. https://doi.org/10.1287/opre.2015.1411
22. Von Nitzsch R, Weber M (1993) The effect of attribute ranges on weights in multiattribute utility measurements. Manag Sci 39