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Heuristics in multi-criteria decision-making: The cost of fast and frugal decisions

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ABSTRACT

There has been an ongoing debate in research regarding the use of heuristics in decision-making. Advocators have succeeded in showing that applying heuristics not only reduces effort but can even be more accurate than analytical approaches under certain conditions. Others point out the biases and cognitive distortions inherent in disregarding information. Researchers have used both simulations and experiments to study how the use of heuristics affects the decision's outcome. However, a good decision is determined by the process and not a lucky outcome. It is a conscious reflection on the decision-maker's information and preferences. Therefore, a heuristic must be assessed by its ability to match a structured decision processing all available information. Thus, the question remains: how often does the reduction of information considered in heuristic decisions lead to a different recommended alternative? We applied different heuristics to a dataset of 945 real, personal decisions. We have found that by using heuristics instead of a fully developed decision structure, in 60.34% of cases, a different alternative would have been recommended to the decision-maker leading to a mean relative utility loss for the deviating decisions of 34.58%. This shows that a continuous effort to reflect on the weighing of objectives and alternatives leads to better decisions.

1. Introduction

In recent years, lots of research has been devoted to decision-making and the value of consciously reflecting on a decision (Brusovansky et al., 2018; Canellas, 2017; Canellas and Feigh, 2017; Hafenbrädl et al., 2016; Del Campo et al., 2016; Siebert and Keeney, 2015). Siebert and Keeney (2015) show that putting more effort into the first steps of a decision-making process, i. e., the reflection on objectives, can lead to more and better alternatives. However, consciously reflecting on a decision also involves putting thought into weighing these objectives and alternatives until a decision is made. In contrast, heuristic decision-making shortens this effort by deciding based on a reduced amount of information. Research and literature on these heuristics provide two opposite schools of thought. There is literature on biases and cognitive distortions that warn of the negative effects of ignoring information when applying heuristics (Kahneman, 2011; Tversky and Kahneman, 1974). In contrast, some studies demonstrate how ignoring information in certain situations, e.g., in predictions and estimations or portfolio investment decisions, can lead to better outcomes (Gigerenzer et al., 1999, 2008; Dawes, 1979; Demiguel et al., 2009). These schools of thought differ in the way how heuristics are applied.

A more negative perception of heuristics results of implicit applications. Kahneman (2011) refers to heuristics when they are only implicitly applied by the decision-maker in reactive decisions. These types of decisions are prone to biases. A more positive perception of heuristics is a result of studies that investigate how heuristics can be explicitly applied. In 1956, Simon (1956) already stated that decision-makers often follow a more satisfactory rather than an optimization approach to decision-making. This means that instead of consciously weighing objectives and alternatives decision-makers prefer a fast and frugal approach until a satisfactory alternative is found. Time restrictions and cost for information are drivers for heuristic strategies (Bröder, 2000; Newell and Shanks, 2003; Rieskamp and Hoffrage, 1999; Payne et al., 1988; Böckenholt and Kroeger, 1993). These also called fast-and-frugal heuristics have been proven to be well suited to describe actual decision-making (Hafenbrädl et al., 2016; Scheibehenne et al., 2007).

Heuristics are not only used due to information reduction. There can also be positive effects of disregarding information when looking at the outcomes of a decision. For example, applying criterion weights like equal weights to a linear model can improve model predictions (Dawes, 1979). Studies with applications to investment decisions show that heuristics are often competitive to optimization-based decisions (Demiguel et al., 2009; Methling and Von Nitzsch, 2019). In noisy environments with ambiguous information, heuristics can even make better predictions about missing information than optimizations based on existing information (Gigerenzer and Selten, 2001). Further reasons for de-

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viating performances of different decision-making strategies are found in the distribution of information and the decision structure, i. e., objectives and alternatives (Canellas, 2017; Canellas and Feigh, 2017; Canellas et al., 2014; Hogarth and Karelaia, 2006; Katsikopoulos and Martignon; 2006).

It is for sure interesting to see how well a heuristic decision performs compared to a consciously reflected decision. Heuristics reduce the amount of information considered for the decision so understanding the effects on the decision is of utmost importance. However, a decision must not be evaluated based on its outcome. Inferences based on decision outcomes are prone to errors because decision outcomes can be influenced by chance and lucky and unlucky circumstances. In addition, in truly personal, preference-based decision situations, it will be close to impossible to judge based on the outcome whether a decision-maker has chosen the right alternative for their own well-being (Katsikopoulos et al., 2018). The quality of a decision needs to be evaluated by the time it is made (Howard, 1988; Spetzler et al., 2016). Therefore, studies that compare decision strategies by their outcomes miss out the right questions. How often does the reduction of information considered in heuristic decisions lead to recommending a different alternative? And, how much worse is the alternative?

In this study, a unique data set of 945 structured decisions is used. Based on this dataset, in a computational experiment, heuristics are applied that reduce information to different levels and investigate how the ranking and evaluation of alternatives change. This answers the still open question of whether a different alternative would be recommended if decision-makers did not consciously weigh up their decision but used a heuristic instead. Thus, this work adds to the literature such as Siebert and Keeney's (2015) study of the impact of additional considerations at different stages of decision-making . While they prove the value of additional reflection in the first steps, i. e., the identification of objectives and alternatives, this study investigates the value of additional reflection in the later steps, i. e., the weighing of objectives and alternatives. This study has been facilitated with a decision skill training software called "Entscheidungsnavi" which is publicly available under www.entscheidungsnavi.com. We have used these decisions to investigate the effects of applying decision heuristics instead of using the full set of information and investigate whether the decision domain, e.g., purchase or career decision, makes a difference. We have found that by applying heuristics instead of using the fully developed decision structure, in 60.34% of cases, a different alternative would have been recommended leading to a mean relative utility loss for the deviating decisions of 34.58%.

2. Theory

In multi-criteria decision-making, different value models have been developed to evaluate decisions. These models allow comparing alternatives based on their evaluation of pre-defined objectives (Siebert and Keeney, 2015; Keeney and Von Winterfeldt, 2007). In situations of riskless choice, additive value models have proven valuable (Dyer and Sarin, 1979). In comparison, multi-attribute utility theory expands the additive value model to situations with uncertain outcomes by allowing consideration of different outcomes depending on future scenarios (Keeney and Raiffa, 1993).

$$EU(a) = \sum_{i=1}^{n} p(s_i)\left(w_1 u_1(a_{i1}) + w_2 u_2(a_{i2}) + \cdots + w_m u_m(a_{im})\right) \tag{1}$$

In the notation of the expected utility $EU(a)$ of an alternative a (Eq. (1)), $p(s_i)$ represents the probability of a scenario i, n shows the total number of considered scenarios, $u_j(a_j)$ defines the utility of an alternative a in objective j, and w_j describes the relative weight of an objective j. This additive utility model requires the objectives to be preferentially independent. Hence, decision-makers shall not change preference for an objective depending on the evaluation of a different objective. Additional information on the methodological requirements and concepts of independence are discussed in the literature (Keeney and Raiffa, 1993; Fishburn and Keeney, 1974; Von Winterfeldt and Edwards, 1986).

An evaluation of alternatives is done by measuring the level of achievement across the objectives for every scenario s_i. Thus, scales (also called attributes, criteria or descriptors) are needed (Keeney and Von Winterfeldt, 2007; Keeney and Raiffa, 1993; Bana E Costa et al., 1999). These measures are further transformed into utilities u [0, 1] via a utility function u_j per objective j. In every objective, the probability-weighted product sum of the utilities per scenario defines the expected utility of an alternative. For aggregating the expected utilities across different objectives, they are weighted with their objective weight w_j.

The elicitation of objective weights w_j can be approached, e. g., via direct ratings or by defining trade-offs. Direct ratings require a direct assessment of the relative importance of every objective. However, studies demonstrate that decision-makers only partly reflect the range of the underlying scale which leads to biases in decision-making (Von Nitzsch and Weber, 1993). When assessing trade-offs the elicitation reflects the scale range explicitly by comparing utilities of alternatives with opposite characteristics (Keeney and Raiffa, 1993). The relative weight of an objective is calculated via Eq. (2) and a statement of indifference.

$$w_i = \frac{u_j(b_j) - u_j(a_j)}{u_i(a_i) - u_i(b_i)} w_j \tag{2}$$

A statement of indifference describes two alternatives (a and b) with the same characteristics in all objectives but two (objectives i and j) that the decision-maker finds equally attractive (Keeney and Raiffa, 1993). Detailed examples and illustrations can be found in the literature, e.g., in a publication by Keeney (2002).

In contrast to a detailed analysis, decisions are often made with incomplete information (Orasanu and Connolly, 1993). In general, information captures all decision-relevant data on alternatives, their characteristics and evaluations, uncertainties and estimations on potential outcomes as well as a decision-maker's preference. Case-specific definitions of the term information have been given in multiple papers (Weber, 1987; Kim and Ahn, 1999; Kmietowicz and Pearman, 1984; Kirkwood and Sarin, 1985). In literature, the question of how decision-making strategies and a reduced amount of information, e. g., heuristic or intuitive decision-making, can affect the outcome of a decision has been thoroughly discussed (Brusovansky et al., 2018; Hafenbrädl et al., 2016; Demiguel et al., 2009; Katsikopoulos and Martignon, 2006; Gigerenzer et al., 1999; Thunholm, 2003). In summary, studies investigate the effects of decision-making that disregards information on objectives, preferences, or evaluations.

Four heuristics, i.e. Minimalist, Take the best, Tallying, and Mapping, have been identified that exploit these different levels of information reduction. They can be described using cognitive building blocks: rules of search, stopping, and decision (Gigerenzer et al., 1999; Gigerenzer and Selten, 2001; Gigerenzer and Gaissmaier, 2011).

The first heuristic is the Minimalist. Gigerenzer et al. (1999) propose the Minimalist as a model of one-reason decision-making. Hence, this heuristic shows the lowest amount of information needed for deciding and considers only one random objective (search rule). Then, the scores of the alternatives in this objective are compared (stopping rule). The alternative with the higher value is inferred to have a higher value for the decision-maker (decision rule).

The Take the best heuristic also belongs to the class of one-reason decisions. Thus, only one objective is considered in choosing an alternative. However, in this heuristic, the preferences of the decision-maker are considered and the objective with the highest validity or importance is considered (search rule and stopping rule). For this objective, the heuristic compares the scores of all alternatives. It is inferred that the alternative with the higher score has a higher value for the decision-maker (decision rule) (Gigerenzer et al., 1999; Gigerenzer and Gaissmaier, 2011).

Tallying and Mapping are heuristics of the class of trade-off decision-making (Gigerenzer and Gaissmaier, 2011). Both heuristics consider all objectives in random order (search rule), thus, ignore information on preferences. While Tallying stops when in each objective the alternative with the highest score is identified Mapping identifies all alternatives that are above the median score in an objective (stopping rule). Tallying chooses the alternative with the highest sum of positive values across all objectives (Von Helversen and Rieskamp, 2008). Mapping chooses the alternative that is favored by most objectives (decision rule) (Gigerenzer and Gaissmaier, 2011).

3. Methodology

This study is based on a set of 945 personal decisions. These personal decisions are used to understand how disregarding information affects identifying the most promising alternative in multi-attribute decision-making. Hence, the quality of the decision structures is of utmost importance. It needs to be ensured that the decision-makers have identified all relevant and important objectives and alternatives, and have assessed them thoroughly. In every decision structure, the identified alternatives need to be assessed across objectives reflecting the relative weight of the objectives and the strength-of-preference for different outcomes within the objective. Thus, each decision is developed through a step-by-step decision-making process using the decision skill training software “Entscheidungsnavi” (Von Nitzsch et al., 2020). The decision-makers are supported by using value-focused thinking in the decision frontend, multi-attribute utility theory (MAUT) in the decision backend, and providing de-biasing measures in a well-structured decision-making process. The entire process has been described in detail by Von Nitzsch et al. (2020) including graphical illustrations. Additional descriptions and illustrations of an application are discussed by Höfer et al. (2020). The following section describes the key elements of the process.

3.1. Experimental design

The experiment was conducted with students at RWTH Aachen University who possessed basic knowledge of decision theory and decision analysis techniques. The students were introduced to the study at the beginning of the semester and were free to choose a personal decision. The students worked on their decision structures at their own pace during the semester and were incentivized by a final exam bonus to submit their decision structure via the “Entscheidungsnavi” software. The final exam bonus was granted to students who submitted a detailed decision structure including a decision question, objectives and alternatives, evaluations of alternatives per objective including utility functions and objectives weights, as well as detailed comments reflecting on their thought process. Further, they could get additional coaching and consultation from the chair by student research assistants. For further information on the steps of the software, we encourage the reader to visit www.entscheidungsnavi.com.

The computational experiment was about comparing to what extent a decision that was structured in multi-attribute utility theory deviates when information is reduced. In order to ensure that all relevant and important information on objectives and alternatives is identified, value-focused thinking is applied and supported with best practices from the decision analysis literature. Presenting value-focused thinking, Keeney (1994), (1996) argues that alternatives are merely means to achieve values so that the decision-making process should start with identifying and structuring these values. This differentiates value-focused thinking from alternative-focused thinking by first articulating values explicitly and using them to recognize decision opportunities (rather than problems) and to generate alternatives. This process delivers multiple benefits (León, 1999). It was shown that using objectives in creating alternatives results in slightly more than double the number of alternatives (Siebert and Keeney, 2015). With the structured approach of the decision software, support is given to identify these values in the first place. Examples from the literature that are included in the software are creating a wish list, analyzing problems and shortcomings, adopting different perspectives (Parnell et al., 2013; Parnell and Miller, 2016). In pursuit of comprehensiveness, the initial list of objectives is developed with minimal restrictions, i. e., without ranking or priorities. Thus, it may include items that are not fundamental objectives. Therefore, the tool provides guidance for structuring the objectives. To distinguish between fundamental and means objectives, the decision-maker answers the question ‘Why is it important?’ (Keeney, 1996). If the objective is only important because it facilitates another objective, then this objective is a means objective. A fundamental objective refers to the values of the decision-maker that are important in the decision context by themselves. Further, the decision-maker is assisted in creating alternatives by being challenged to think about alternatives to best achieve each of these objectives. First, each objective is considered separately. Then, the decision-maker gradually generates alternatives that would be good for multiple objectives simultaneously.

The decision-maker needs to develop scales to measure these objectives. The decision-maker can either define discrete numerical, discrete verbal, or continuous scales. Further, scenarios s_i need to be defined that affect the score of an alternative in a particular objective depending on their probabilities $p(s_i)$. For every scenario the decision-maker needs to assess the likelihood and evaluate the alternative in all objectives. Subsequently, the scales and assessments of alternatives need to be transformed to utilities $u_j(a_{ij})$. Here, the decision-maker is supported with an exponential utility function that already considers the range [x-, x+] defined with a continuous scale in step one and requires only the definition of the risk parameter c (see Eq. (3)). The software supports the elicitation of the parameter c, e. g., via the bisection method which asks the user to define a certainty equivalent that would be equally attractive to a lottery with equal chances for two given outcomes.

$$u(x) = \begin{cases} \frac{1-e^{-c\frac{x-x^-}{x^+-x^-}}}{1-e^{-c}} & for\ c \neq 0 \\ \frac{x-x^-}{x^+-x^-} & for\ c = 0 \end{cases} \tag{3}$$

In case, the decision-maker has defined discrete scales, the software ensures the quality of the decision by checking the monotonicity of preferences while the decision-maker can reflect an individual behavior towards risk and a personalized value function (for a graphical illustration see Von Nitzsch et al. 2020).

The decision-maker must express preferences for the objectives to determine objectives weights. The objectives weights for the aggregation of an alternative’s total utility are determined by a tradeoff methodology because direct ratings are prone to biases and decision-makers do not sufficiently reflect on range compressions (Von Nitzsch and Weber, 1993). The software allows to display all reasonable statements of indifference to ensure the consistency of preferences. In two-dimensional charts with scales for two fundamental objectives on the axes at a time, indifference curves indicate all alternatives that would be equally valuable to the decision-maker based on their current objective weights. In the last step, the software shows the rank-order of alternatives and the decision-maker is asked to reflect on the decision based on the decision model. Using Monte-Carlo Simulations, sensitivity analyses, and robustness checks, the decision-makers can understand their decision to the best possible extent and adapt the assumptions and evaluations until the decision model best reflects their preferences and beliefs (for a detailed explanation and graphical illustration see Von Nitzsch et al., 2020).

3.2. Dataset

The set of decisions has been developed in the years 2019 and 2020. The participants spent on average 8.8 hs on their decision. They submitted files of their decision problem fully capturing all their steps, comments, and considerations. The consequence table, the utility values, and the objectives weights were extracted and further investigated using Matlab. In total, we received 500 decision problems in 2019 and

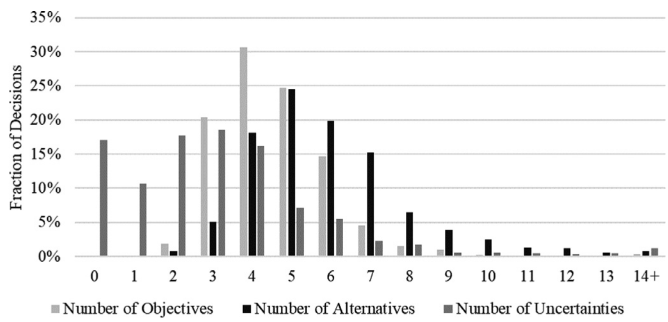

Fig. 1. Histogram on numbers of objectives, alternatives, and uncertainties considered per decision.

458 in 2020. In total, 13 of the decision problems were incomplete and have been removed.

Fig. 1 shows the number of objectives and alternatives that were considered for the different decisions. On average, 5.97 alternatives have been evaluated against 4.61 objectives. The types of decisions the participants faced were widely spread. The largest share of participants (325 of 945) focused on career decisions like deciding on internships and choosing the right job. Education related decisions, i. e., decisions on courses, masters, or their curriculum, were chosen by 184 students. Going abroad or identifying the most promising alternative to gain international experience was picked as a subject by 110 participants and 46 participants focused on purchasing decisions like choosing the right smartphone, notebook, or car to buy. The remainder of 280 decisions was categorized as other personal decisions like personal lifestyle decisions, e. g., deciding on a diet like omnivore, vegan or vegetarian, deciding on how to integrate sports for healthy living, and deciding on living arrangements.

3.3. Data analyses

In the empirical methodology, the consequence table and the decision-makers' preferences are used as a starting point. Hence, for every decision, a vector denoting the decision-maker's objectives weights and a table determining the expected utility of alternatives across the objectives are given. First, the alternative with the highest expected utility is identified to form the benchmark. Second, the performance of the different heuristics is determined by two measures. The first measure looks at the fraction of decisions where the heuristic points to the same alternative, i. e., an alternative with the highest expected utility. In addition, a second measure considers the relative loss of utility. The relative loss of utility PVL describes the utility loss compared to the worst-case utility loss when choosing the minimum expected utility alternative. It is described in Eq. (4) and derived from the proportion value lost criterion described by Barron (1987). B represents the expected utility of the maximum expected utility alternative, W denotes the expected utility of the minimum expected utility alternative, and R describes the expected utility of the alternative that is recommended by the heuristic.

$$PVL = \frac{B - R}{B - W} \tag{4}$$

In case a heuristic recommends more than one alternative, the average expected utility of the recommended alternatives is used. This measure will allow deeper insights into the value of heuristics.

In the computational experiment, the four heuristics, i.e. Minimalist, Take the best, Tallying, and Mapping, are applied to the dataset using a simulation in Matlab. In Table 1, an example of a consequence table is shown that will be used to explain the application of the heuristics. The alternative with the highest expected utility is alternative 3. When applying the Minimalist heuristic, an objective is chosen randomly, e.g., objective 4. The alternative(s) with the highest value for this objective is (are) compared with the alternative(s) with the highest expected utility. In this example, the Minimalist would lead to choosing alternative 1, because it provides the highest utility in objective 4, while the most promising alternative was alternative 3. This leads to a relative utility loss of 4%. In contrast, the application of the Take the best heuristic does not consider a random objective but the one with the highest objectives weight, i.e., objective 2 with a relative weight of 30%. In this example, the Take the best heuristic would lead to choosing alternative 3 without a loss of utility. However, two additional exceptions need to be made. First, if the consequence table contains two equally rated alternatives in the single objective with the highest objectives weight, all other alternatives and the particular objective are removed and the methodology is applied again to the two remaining alternatives. Second, if there is no single most important objective, the heuristic could only recommend an alternative that dominates all other alternatives in these most important objectives.

The Tallying heuristic incorporates all objectives and disregards their weights. For every objective, the alternative with the highest value is identified. Then, for each alternative, the number of objectives for which this alternative has the highest value is summed. The heuristic determines the alternative(s) with the highest sum. In the example, alternative 1 is rated best in objectives 1, 4, and 5, while alternative 3 is rated best in objectives 2 and 3. Hence, Tallying would lead to choosing alternative 1 and a relative utility loss of 4%. When applying the Mapping heuristic, the estimate used is the median of the values of all alternatives for each objective (Step 1). All alternatives with values higher than the median are marked positive (Step 2). Then, for each alternative, the number of positive marks across all objectives is summed (Step 3). The heuristic identifies the alternative(s) with the highest sum. In the example, alternative 2 would be chosen because it is rated above the median in 4 of 5 objectives. This leads to a relative utility loss of 32%.

4. Results

The results in Table 2 show how often the heuristics have led to the alternative with the highest expected utility. Based on these results, the Take the best heuristic leads to the same alternative as the benchmark decision in 50.16% of cases. The Minimalist only matches the decision in 26.67% of cases. Both heuristics are one-reason decisions, however, the additional reflection on the weights of the objectives in the Take the best heuristics leads to a better match with the benchmark decision. The trade-off heuristics, Tallying and Mapping, show average results of 44.66% and 37.14% with a better fit shown by the Tallying heuristic.

More insights can be derived by calculating the relative loss of utility. The relative loss of utility considers the range of potential outcomes and uses the difference between the best and worst alternative, i. e., the maximum and the minimum expected utility, as a denominator. On average, a heuristic decision led to a relative loss of utility of 21.09%. In Table 3, the greatest loss of utility is associated with heuristic decisions applying the logic of the Minimalist. However, the more information that is considered, the less utility is lost. When rank-ordering all alternatives in all objectives and using this information as positive or negative cues, the relative loss of utility can almost be halved down to 16.14% as demonstrated by the Mapping heuristic. Combined with Table 2, this shows that although the Mapping heuristic does not have the same probability of identifying the maximum expected utility alternative compared to the Take the best heuristic, it limits the number of bad recommendations, i. e., recommending a low expected utility alternative.

Further analysis shows the standard deviation of relative loss of utility per heuristic. Table 4 shows that the Mapping heuristic provides the smallest average deviations while the Minimalist shows the largest deviations in relative loss of utility.

When analyzing the relative loss of utility in more detail, the heuristics show very different performances. Although the Mapping heuristic is less likely to match the initial decision than Take the best and Tallying, the Mapping heuristic shows the smallest relative loss of utility and the smallest standard deviation of losses across all decision types.

Table 1
Example of a consequence table with utilities per objective and alternatives. Numbers in brackets indicate the relative objective weight.

	Objective 1 (20%)	Objective 2 (30%)	Objective 3 (20%)	Objective 4 (15%)	Objective 5 (15%)	Expected Utility
Alternative 1	0.6	0.4	0.2	0.8	0.8	0.52
Alternative 2	0.5	0.6	0.4	0	0.6	0.45
Alternative 3	0.4	0.7	0.6	0.6	0.2	0.53
Alternative 4	0.3	0.3	0.2	0.2	0.4	0.28

Table 2
Proportion of decisions where the heuristic points at the same alternative.

Topic	Decisions	Minimalist	Take the best	Tallying	Mapping
Career	325	28.31%	50.46%	46.15%	37.23%
Education	184	26.09%	57.61%	50.54%	41.30%
International exp.	110	31.82%	59.09%	52.73%	36.36%
Purchasing	46	13.04%	32.61%	30.43%	26.09%
Other Personal	280	25.36%	44.29%	38.21%	36.43%
All	945	26.67%	50.16%	44.66%	37.14%

Table 3
Relative loss of utility when choosing an alternative recommended by the different heuristics.

Topic	Minimalist	Take the best	Tallying	Mapping
Career	32.23%	17.14%	16.85%	15.33%
Education	30.73%	17.00%	15.42%	14.48%
International exp.	26.75%	12.77%	14.04%	16.81%
Purchasing	36.14%	19.82%	21.67%	20.90%
Other Personal	34.18%	21.74%	22.16%	17.12%
All	32.07%	18.10%	18.05%	16.14%

Table 4
Standard deviation of relative loss of utility when choosing an alternative recommended by the different heuristics.

Topic	Minimalist	Take the best	Tallying	Mapping
Career	33.69%	28.03%	23.62%	20.19%
Education	31.86%	28.34%	21.71%	20.05%
International exp.	30.07%	24.55%	23.16%	22.14%
Purchasing	32.81%	23.66%	25.91%	22.89%
Other Personal	34.84%	31.28%	27.16%	22.45%
Standard deviation	33.35%	28.69%	24.64%	21.28%

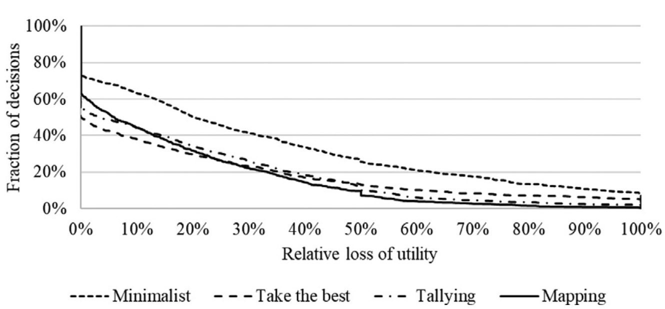

Fig. 2. Fraction of heuristic decisions with a relative loss of utility greater than x.

In Fig. 2, the chart shows the fractions of heuristic decisions that lead to a relative loss of utility greater than a given loss. If the decision-maker wants to minimize the fraction of decisions with any loss of utility, the Take the best heuristic is most promising as shown on the left. However, if the decision-maker wants to minimize the fraction of decisions with a relative loss of utility greater than, e. g., 25%, then the Mapping heuristic is more promising. Heuristic decisions with Mapping lead to a relative loss of utility greater than 25% in only 25.7% of cases compared to 30% for Take the best. Hence, the value of a heuristic to a decision-maker beyond its ability to match a fully structured decision needs to consider the decision-makers risk preference. The extrapolation of the data shows that when using the Take the best heuristic it is 6.38 times more likely to choose the worst alternative, i. e., the minimum expected utility alternative, than when using the Mapping heuristic.

As discussed in the prior section, the different heuristics do not always lead to a single recommended alternative. Hence, in a situation where, e. g., the number of positive cues for multiple alternatives is the same, the heuristic is not very helpful. In Table 5, the ratios of decisions where the heuristics recommend a single alternative are displayed. The Take the best heuristic offers a single recommendation in 91.22% of cases while Mapping only recommends a single alternative in 52.80% of cases. This must also be reflected when considering the different heuristics.

Focusing on decisions with a single recommended alternative only, the fraction of matching recommendations differ a lot. Table 6 shows that Tallying provides the closest match with a matching recommendation in 71.77% of cases. Take the best still increases to 54.99% but is outperformed by both Tallying and Mapping model. The Minimalist remains the worst match.

Again, more insights can be derived when looking at the relative loss of utility per heuristic decision in Table 7. However, the general trend as shown in Table 3 remains. The more information that is considered, the less utility is lost.

5. Discussion

The participants of the study were allowed to freely choose their decision topic. When looking at the different decision topics, purchasing decisions do not seem to be best suited for heuristic decision-making. Compared to other decision topics the heuristics show the worst average match and the highest average loss of utility. This might be led back to different characteristics of the decision type. When deciding which item to buy, e.g., which laptop, the alternatives are given by what is on offer in a store. Also, the consideration of test articles and platforms already offers decision criteria and evaluations. Hence, in purchasing decisions, the participants spend on average the shortest amount of time with 511 min (compared to an average of 528 min) to identify the greatest numbers of objectives (5.28 compared to an average of 4.61) and alternatives (6.24 compared to an average of 5.97). However, further analysis of the whole data sample does not reveal any significant correlation of relative loss of utility per heuristic with the amount of time spent in developing the decision. In addition to the time taken to generate the objectives and alternatives, we tested the effect of the number objectives, alternatives, and uncertainties considered on the relative loss of the utility. Only the heuristic Mapping shows a significant correlation of -0.09 (p-value < 0.01) with the number of alternatives. The more alternatives are considered, the smaller the average loss of utility when

Table 5
Proportion of decisions where the heuristic leads to a single recommended alternative with absolute numbers in brackets.

Topic	Minimalist	Take the best	Tallying	Mapping
Career	65.85% (214)	92.62% (301)	64.62% (210)	50.46% (164)
Education	64.67% (119)	94.57% (174)	65.22% (120)	53.80% (99)
International exp.	63.64% (70)	88.18% (97)	61.82% (68)	53.64% (59)
Purchasing	58.70% (27)	82.61% (38)	63.04% (29)	45.65% (21)
Other Personal	61.79% (173)	90.00% (252)	57.50% (161)	55.71% (156)
All	63.81% (603)	91.22% (862)	62.22% (588)	52.80% (499)

Table 6
Proportion of decisions where the heuristic points at the same alternative under the condition that the heuristic leads to a single recommendation.

Topic	Minimalist	Take the best	Tallying	Mapping
Career	42.99%	54.49%	71.43%	73.78%
Education	40.34%	60.92%	77.50%	76.77%
International exp.	50.00%	67.01%	85.29%	67.80%
Purchasing	22.22%	39.47%	48.28%	57.14%
Other Personal	41.04%	49.21%	66.46%	65.38%
All	41.79%	54.99%	71.77%	70.34%

Table 7
Relative loss of utility when choosing an alternative recommended by the different heuristics under the condition that the heuristic leads to a single recommendation.

Topic	Minimalist	Take the best	Tallying	Mapping
Career	29.42%	16.85%	11.13%	7.92%
Education	29.62%	16.32%	8.36%	6.66%
International exp.	25.08%	11.73%	7.20%	14.07%
Purchasing	39.25%	19.23%	21.66%	17.40%
Other Personal	33.45%	21.39%	13.57%	11.49%
All	30.55%	17.60%	11.30%	9.91%

applying the heuristic. The number of objectives does not significantly influence the relative loss of utility. The number of uncertainties considered in the decision also does not significantly influence the relative loss of utility.

The results indicate a very strong performance of the Take the best heuristic. However, this may not be attributed to its inherent strength alone. The strong performance is also influenced by the difference in implementation. When comparing the Minimalist and Take the best heuristic, the indecision of the cases with two same-ranked best alternatives in the chosen objective leads to termination only for the Minimalist heuristic. When using the Take the best heuristic, in cases of two same-ranked best alternatives in the chosen objective, a second objective is considered. Therefore, the Take the best heuristic can lead to more matching recommendations. However, this limitation and difference in implementation is offset in the second analysis when looking at decisions with a single recommendation only.

A different limitation comes from the study's underlying assumptions about the application of the MAUT structure and the heuristics as the heuristics were applied in a computational experiment and not by the participants themselves. On the one hand, it is assumed that a decision-maker who applies a heuristic would be able to identify the same number of objectives and alternatives and base their decision on an equally detailed decision frame. On the other hand, it is assumed that the decision-makers would decide like the decision structure and the textbook application of MAUT or the heuristics recommend. Thus, in the second-year sample, the participants were asked on a scale from 1 "I do not agree at all" to 6 "I fully agree" the extent to which they confirmed the statement "I will implement the recommended alternative." 87% of the students indicated that they were rather implementing the alternative (median: 5, average: 4.72, n = 458 answers). While further research is needed to allow broader generalization of the results, especially for the application of the heuristics, this is a first indicator of the applicability of the experimental design. Further research could focus on better understanding the transition from a heuristic decision to a decision based on a detailed structure. This study has shown the type of decision structure for which heuristics are more likely to match a decision based on the textbook application of MAUT. On the one hand, however, it must be investigated in which type of decision structure (number of objectives and alternatives) the decision-makers would apply certain heuristics. On the other hand, it must be investigated whether the type of heuristic leads to a different decision structure. Thus, further experiments could investigate how the choice of methodology, i.e., heuristic decision based on Minimalist, Take the best, Tallying, or Mapping, or applying MAUT, affects the number of identified objectives and alternatives.

Further limitations of this study stem from the sample of participants. This study is focused only on students who already possessed knowledge of decision analysis and its techniques. Hence, they are more likely to exploit the benefits of a structured MCDM approach. In future research, it is to be analyzed to what extent heuristics might perform better when applied to decisions that were structured by novices. Studies have shown that teaching decision analysis techniques increases the quality of decision-making (Siebert et al., 2021). It is to be investigated whether heuristics perform better when the benchmark decision is of lesser quality.

6. Conclusion

This study evaluates how strongly the ranking of alternatives in a MAUT based decision structure changes when information is disregarded. This analysis is based on decision-related information that were created by conscious reflection of objectives weights, individual alternative comparisons, and aggregated utilities. This sharply differentiates this study from past research that predominantly focuses on a data base of simulations and decision outcomes instead of decision-making itself. Consciously reflected decisions and heuristic decisions differ the more, the less information is considered by the heuristic. Starting with the smallest amount of information the Minimalist only considers a rank order in a single, random objective. This leads to a recommendation of the maximum expected utility alternative in 26.67% of cases. Increasing the amount of information by considering all objectives and their weights including information on the rank order of the alternatives in the objective with the highest weight leads to a matching recommendation in 50.16% of decisions for the Take the best heuristic. When focusing only on decisions in which a heuristic recommends a single alternative, Tallying and Mapping recommend the maximum expected utility alternative in 71.77% and 70.34% of cases, respectively. Hence, the relative loss of utility can be reduced to 11.30% and 9.91%, respectively.

The results of the study allow conclusions beyond the discussion of relevance and performance of heuristics. On the one hand, the results show that participants can create information that they find relevant for their decision. On the other hand, this shows that this additional decision-relevant information can be decision determining. Skipping the steps of creating information on evaluations and preferences leads to an alternative that the decision-maker does not equally rate. On average, considering the information created by the decision-makers leads to an alternative other than the one recommended by the heuristic in 60.34% of cases. Quantifying the improvement by reflecting on objectives, more accurately evaluating the ranking of alternatives in objectives, and accepting the challenge of determining objective weights also supports the work of Siebert and Keeney (2015). They show the value of additional reflection in the first steps of the decision-making process. This study adds to this and points out that also in the later steps of weighing objectives and alternatives effort and reflection are essential for good decision-making. Hence, these results are a call-out for both decision-making competence and decision-making support. Not only the self-dependent effort also decision support tools, additional decision methodologies, and assistance and consultancy can help decision-makers to identify the alternatives that they believe to be best suited to solve their decision problem.

Declaration of Competing Interest

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

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