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An empirical study to measure the use and impact of an imprecise information approach in the decision support system ENTSCHEIDUNGSNAVI

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ABSTRACT

In a rational multi-criteria decision-making (MCDM) process based on multi-attribute utility theory (MAUT), the decision-maker defines quantitative parameters to identify the most promising alternative. However, it is often difficult to determine these parameters precisely. Therefore, the literature suggests using imprecise information, which allows the decision-maker to determine imprecise preference statements and parameters. This paper investigates the utilization and impact of an imprecise information approach regarding probabilities, utility functions, and objective weights in the decision support system ENTSCHEIDUNGSNAVI. We examined 1511 personal student decisions. First, we analyzed how often imprecise information was utilized. Second, we surveyed how helpful participants found the use of imprecise information. Third, we investigated the impact of imprecise information in the three aforementioned categories on the final ranking of alternatives. We assessed how robust the rank of the best alternative remained by using Monte Carlo simulations in which evenly distributed values were drawn from all imprecisely defined intervals. This demonstrates the robustness of our results across varying levels of input uncertainty. Most participants chose imprecise parameters in their decisions. Moreover, most participants found it helpful to use imprecise information in all categories, with imprecise objective weights being the least helpful. In about 83% of the decisions, the best-ranked alternative is robust against the imprecise intervals the decision-maker chooses. Overall, our results show that incorporating imprecision improves the practical usefulness of MCDM-Support-Systems. We recommend that a robust MAUT-based system should address all three types of imprecision, guide probability and utility elicitation, support realistic trade-offs, and visualize how input uncertainty affects ranking stability helping decision-makers form sound judgements.

1. Introduction

A rational multi-criteria decision-making (MCDM) process based on multi-attribute utility theory (MAUT) presents many difficulties for the decision-maker (DM) both in the decision front end and in the decision back end. In the decision front end, DMs structure the decision situation. Therefore, they formulate the decision statement, identify the objectives, and determine the alternatives. Studies have shown that individuals cannot identify all relevant objectives or alternatives in a decision situation (Bond et al., 2008; Siebert and Keeney, 2015). Decision analysts are often involved to support (DMs) throughout these steps. However, individuals are typically on their own when making personal decisions. As this paper focuses on personal decision-making, we refer exclusively to DMs in the following. In the decision back end, DMs develop the consequences table and evaluate the alternatives. Developing the consequences table means each alternative has to be rated on a scale for each objective. In evaluating the alternatives, the DMs indicate their preferences in the model. One difficulty is determining precise values for the quantitative parameters needed to calculate the utility of every alternative in MAUT. This paper focuses on the decision back end and the difficulty of determining quantitative parameters.

The DM determines the following quantitative parameters in the decision back end: utility functions, objective weights, and consequences. In the case of uncertainty, several consequences are defined depending on the state of a possible influence factor. Moreover, DMs determine probabilities for all these states. For a high-quality decision, these quantitative parameters should be realistic and not distorted by any biases (see, e.g., (Kahneman, 2011), (Montibeller and von Winterfeldt, 2015)). Probabilities are sometimes unknown or cannot be estimated accurately. Many individuals struggle with the interpretation and determination of probabilities and tend to overestimate or

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underestimate probabilities (see, e.g., (Tversky and Kahneman, 1973)). While determining utility functions or objective weights, sometimes DMs are unable to determine their preferences precisely and consistently with their values. It may even be that they have no stable preferences at all. This complicates the determination of utility functions and objective weights.

The approach of partial, imprecise, or incomplete information is used in literature to support the DM in determining these quantitative parameters. Because partial, imprecise, and incomplete information are used interchangeably, we only use the term 'imprecise information' in this paper. In MCDM, imprecise information allows the DM to avoid giving exact statements about consequences, probabilities, or preferences, i.e., utility functions and objective weights. Sometimes it is sufficient, for example, to specify intervals or ranks. With the help of different methods, it is then still possible to identify the best alternative using MAUT.

The approach of imprecise information is already being used in many MCDM-Support-Systems to simplify the application for the DM. These systems are designed to assist in making complex decisions by considering various criteria and alternatives. The use of imprecise information can help integrate (imprecise) assessments from DMs, leading to a more realistic representation of the decision-making environment and their uncertainties determining the decision parameters in the situation. However, to the best of our knowledge, research has yet to be conducted to explore the practical use of an imprecise information approach in a MCDM-Support-System. Specifically, there is a lack of insights into how frequently individuals actually rely on imprecise information in decision situations. Moreover, there are no practical insights of how helpful DMs find the approach of imprecise information and whether it influences their decision-making process. Furthermore, it is relevant to investigate whether the use of imprecise information impacts the selection of the best alternative in practice, especially in scenarios where DMs need to make a single choice. A deeper understanding of these aspects could not only enhance existing MCDM-Support-Systems but also lead to new approaches for assisting DMs and improving the system's efficiency. Therefore, conducting further empirical studies is essential to better understand the actual practical benefits and effects of employing imprecise information in the decision-making process in decision support systems (DSS).

To fill this research gap and improve the implementation of an imprecise information approach in a MCDM-Support-System, this paper investigates using an imprecise information approach in the MCDM-Support-System Entscheidungsnavi and analyzes how to deal with this in MCDM-Support-Systems. The Entscheidungsnavi is a web tool for decision skill training. It supports the DM throughout the whole decision-making process in selection or ranking problems. It offers the DM the possibility to use imprecise information concerning three categories: probabilities, utility functions, and objective weights. For a detailed description and explanation of the Entscheidungsnavi, see (von Nitzsch et al., 2020), (Peters et al., 2024), and (Hannes and von Nitzsch, 2024). The idea of imprecise information in the Entscheidungsnavi for all three categories (probabilities, utilities, and objective weights) is to identify a mean μ and a degree of precision ε, resulting in an interval of the parameters. The degree of precision ε represents a range around the mean μ. If DMs define $\varepsilon = 0$, they can precisely elicit the parameter, whereas $\varepsilon > 0$ means using imprecise information, i.e., intervals for their parameters. The handling of imprecise information differs for each category and is explained in Section 3.

We examined 1511 personal selection decisions analyzed by students in the Entscheidungsnavi regarding three research questions. First, we analyzed how often imprecise information was used. Second, we surveyed how helpful the participants found the use of imprecise information. Third, we examined the impact of imprecise information in the three categories mentioned above on the final ranking of alternatives. We investigated how stable the rank of the best alternative remained using Monte Carlo simulations. We split the participants into two groups to examine the research questions in more detail. In Group non-zero, the default setting in the Entscheidungsnavi was imprecise parameters for all categories. In Group zero, the default setting was precise parameters. So, the participants had to actively choose an imprecision if they wanted. All research questions were analyzed with the complete data set and the two different groups. By collecting the data with the Entscheidungsnavi and checking it manually, we can assume that the decision situations are adequately modeled, the consequences are non-distorting, and the DMs have defined their preferences according to their value system. The very large data set, the student-relevant and, therefore, real decision-making problems, and the analysis of these decisions regarding the application and effects of an imprecise information approach in a scientifically sound decision support system make our study unique and valuable for future research questions in this area.

The paper is structured as follows: after a brief literature review of the application of imprecise information in Section 2, the methodology of the Entscheidungsnavi, which permits the use of imprecise information concerning probabilities, utility functions, and objective weights, is explained in Section 3. In Section 4, the results of the empirical study are presented to answer the research questions. In Section 5, we discuss the results, and in Section 6, we give a conclusion and discuss limitations. Furthermore, we specify conditions under which the imprecise information approach used in the Entscheidungsnavi facilitates sound decision-making and provide suggestions for further research.

2. Relevant research on imprecise information

Several approaches deal with imprecise information. Some focus on specific categories of imprecise information such as objective weights, utilities, or probabilities. Others consider a combination of two or all of them. Furthermore, the approaches differ in the implementation of imprecise information. In the following, we give an overview of relevant research on imprecise information. It should be noted that each article has made a contribution in its respective context. In the following, we refer to deficiencies when not all categories of imprecise information are covered and addressed, as this reflects the objective of our paper. However, we want to emphasize that each approach has their specific purpose and focus and, thus, does not always aim to address all categories of imprecise information.

(Fishburn, 1965) was one of the first researchers to recognize the problem of determining the exact probabilities of the states of nature. He developed several approaches for four measures of probabilities: null measure, ordinal measure, sets of inequalities, and bounded interval measure. To find the best alternative with imprecise information about the probabilities, the concept of linear programming is used in many approaches (e.g., (Kmietowicz and Pearman, 1982; Kmietowicz and Pearman, 1984), (Sarin, 1978)). (Weber, 1985; Weber, 1987) contributed to the research on imprecise information in utility functions relying on stochastic dominance or linear programming concepts. (von Nitzsch and Weber, 1988) present an interactive procedure on a micro-computer to determine consistent bounds for utility functions. (Armbruster and Delage, 2015) extend the concept of stochastic dominance by considering more features of the utility functions than those used in the first- and second-order stochastic dominance frameworks like S-Shape or prudence information. Furthermore, they model the decision-making problems as robust utility maximization problems, optimization problems with stochastic dominance constraints, or robust certainty equivalent maximization problems to determine the best alternative. Moreover, many approaches for unknown or imprecise objective weights were developed in the past (see, e.g., (Carrizosa et al., 1995), (Hazen, 1986), (Kirkwood and Sarin, 1985)). (de Almeida et al., 2016) and (de Almeida-Filho et al., 2017) give a broad overview of this topic and categorize the approaches using forms of imprecise information (e.g., interval weights (Li et al., 2012; Mustajoki et al., 2005; Park, 2004; Puerto et al., 2000; Steuer, 1976), partial/incomplete information on weights (Barron, 1992; Mármol et al., 2002; Punkka and Salo, 2013; Salo

and Hämäläinen, 2001; Salo and Punkka, 2005), or unknown weights (Hazen, 1986; Lotfi et al., 1992)). Furthermore, they develop and validate based on the tradeoff procedure (Keeney, 1992; Keeney and Raiffa, 1976) the FITradeoff (Flexible and Interactive Tradeoff) approach which enables a flexible and interactive process handling the problem of imprecise statements of the DM. Their approach is related to the multi-attribute value theory (MAVT) scope considering deterministic (not probabilistic) consequences. They even develop a DSS to support the DM in MCDM. However, this approach requires that the DM can rank the objective weights. Additionally, the DM has to define the value functions. See (Keeney and Raiffa, 1976) for the difference between value and utility functions. (de Almeida et al., 2024) analyze the properties of FITradeoff to explore how holistic judgments can be integrated into its mathematical model and assess implications such as preference relationships and optimal alternatives. They propose a heuristic to reduce the number of questions during elicitation through decomposition and address potential inconsistencies arising from conflicting information between decomposition and holistic judgments, along with strategies for resolution.

Other approaches allow the DM to make imprecise statements in more than one category, e.g., utility/value functions and objective weights (Eum et al., 2001; Park et al., 2001; Lee et al., 2002; Park et al., 1996) or probabilities and utility/value functions (Danielson, 2004; Danielson et al., 2003; Liesiö and Salo, 2012; Moskowitz et al., 1993). The approach of (Sarabando and Dias, 2010) focuses on group decisions and considers uncertainty concerning the DMs' weights. It allows imprecise information about the weights and consequences of each alternative in each objective and uses a Monte Carlo simulation to test the robustness of the ranking of alternatives. However, ordinal information on the weights and cardinal information on the values are required. Nevertheless, these approaches do not help the DM to identify the best alternative if imprecision exists in all three categories (probabilities, utilities, and objective weights).

(Jiménez et al., 2002) developed a DSS for multi-attribute utility evaluation, which allows using imprecise statements for all categories. Value ranges can describe the consequences under uncertainty without giving any information about the form of the probability distribution. However, the system uses the mean of the ranges in the evaluation. This means that imprecise information is allowed, but the imprecise ranges are adjusted by the mean value in the evaluation and, therefore, not considered. They offer three ways to assess the utility functions: the certainty equivalent method/probability equivalent method, piecewise linear utility functions, and subjective scales. The DM can give imprecise statements for all of them, which leads to an interval of utility functions or values. Intervals can also be specified for determining objective weights by the tradeoff method or pre-emptive ordering. A sensitivity analysis can check the robustness of the final ranking. However, the input parameters for the sensitivity analysis are limited to objective weights and utility functions. The DSS of (Mateos et al., 2007) contains no option to check the result for sensitivity or robustness. The DSS introduced by (Danielson et al., 2007) also uses imprecise information in the mentioned categories. The tool works with interval boundaries, comparative value relations, and so-called focal points representing the best value for the variables in an interval. Moreover, the DSS offers different evaluation methods like ordinal ranking, cardinal ranking, or pairwise comparisons. However, due to the complexity, DMs might need the help of an expert.

Current research such as (Chergui and Jiménez-Martín, 2024) and (Da Silva et al., 2023) provide literature reviews and comparative analyses on partial or imprecise information methods within MAVT/MAUT. (Chergui and Jiménez-Martín, 2024) focus on weighting methods when DMs provide ordinal information about the relative importance of objectives and additional information on the strength of the differences between the ranked objectives in forms of precise/imprecise cardinal information, ratio-based methods, a ranking of differences, a semantic scale, or preference statements. They examine previous analyses that compare the performance of these weighting methods using both empirical and simulated data, employing various quality measures. The objective is to identify weighting methods that can be recommended for specific situations (depending on the available information) or to highlight any necessary comparative analyses that should be conducted to formulate a recommendation. (Da Silva et al., 2023) conduct a systematic review of the literature on multicriteria decision-making methods that address imprecise information regarding objective weights and value/utility functions. 105 peer-reviewed articles identified in the Web of Science (Main Collection) were analyzed using bibliometric analysis. Additionally, a comprehensive analysis of both their bibliometric and content aspects was conducted to highlight key directions and trends within this area of knowledge. The paper aims to offer both academic institutions and organizational/productive sectors valuable guidelines for achieving increasingly reliable decision-making in real-world situations by leveraging the advantages of partial information. In their conclusions, they emphasize that although there are many theoretical concepts for imprecise information, only a few of them have been applied to solve practical problems. They assume that this is due to the lack of user-friendly DSS to effectively implement such methods.

We want to address this issue and examine the imprecise information approach of the DSS Entscheidungsnavi (von Nitzsch et al., 2020; Peters et al., 2024; Hannes and von Nitzsch, 2024) in this paper. The Entscheidungsnavi allows imprecise statements resulting in parameter intervals in all categories and provides different evaluation methods like sensitivity analysis and robustness checks. Moreover, it helps the DM with an intuitive interface to identify the best alternative. In Section 3, the model of the Entscheidungsnavi and how imprecise information is incorporated are explained.

3. The model: imprecise information in the Entscheidungsnavi

The mathematical model used in the Entscheidungsnavi for illustrating a MCDM process is the additive model of the MAUT (Keeney, 1992; Keeney and Raiffa, 1976; Fishburn, 1967; Keeney, 1972). To support the DM in determining the quantitative parameters for this model, the Entscheidungsnavi enables the DM to give imprecise statements in three categories: probabilities, utility functions, and objective weights. Moreover, with the help of a Monte Carlo simulation, it is possible to evaluate the robustness of the alternative ranking, including imprecise information. (Peters et al., 2024) give a detailed description of methods for dealing with imprecise information in the Entscheidungsnavi.

3.1. Additive model

In the additive model, the available alternatives are ranked according to their utilities. The alternative with the highest utility represents the best alternative and should be selected by the DM. To calculate the utilities, DMs must first define a set of objectives $\mathbb{O} = \{O_1, \ldots, O_I\}$ and a set of alternatives $\mathbb{A} = \{A_1, \ldots, A_J\}$ for some natural numbers I,J for the decision situation. Subsequently, they have to evaluate the consequences x_{ij} of all J alternatives in the respective I objectives with $1 \leq i \leq I$ and $1 \leq j \leq J$. The utility of each alternative A_j is calculated using formula (1) for the additive expected utility (Bernoulli, 1954; Von Neumann and Morgenstern, 1961).

$$EU(A_j) = \sum_{i=1}^{I} w_i \left[\sum_{k=1}^{K_{ij}} P\left(s_{ij}^k\right) U_i\left(x_{ij}^k\right) \right] \tag{1}$$

$$\sum_{i=1}^{I} w_i = 1 \tag{1a}$$

$$\sum_{k=1}^{K_{ij}} P\left(s_{ij}^k\right) = 1 \tag{1b}$$

w_i represents the weight of objective O_i. The sum of all objective weights must equal one (1a). To model decisions under uncertainty, different states s_{ij}^k can be determined that occur with a corresponding probability $P\left(s_{ij}^k\right)$ and result in some consequence x_{ij}^k with $1 \leq k \leq K_{ij}$. K_{ij} represents the number of states for the consequence x_{ij}^k. The probabilities of all states for every ij add up to one (1b). Finally, U_i represents the utility function of objective O_i. Utility functions are used to map the DM's preferences.

The Entscheidungsnavi supports the DM in determining all these parameters by providing different methods. To specify the probabilities $P\left(s_{ij}^k\right)$ for all defined influence factors, the DM can directly rate them on a cardinal scale from 0 to 100%. The utility functions U_i can be defined for two different kinds of objectives: objectives with a verbal and a numerical scale. Utility functions for objectives with a verbal scale can be determined with a direct rating function $DR\left(x_{ij}^k\right)$ like in formula (2a). Utility functions for objectives with a numerical scale can be determined with a predefined exponential utility function with a variable parameter c_i of risk aversion, as in formula (2b). A positive c_i indicates a risk averse behavior whereas a negative c_i indicates a risk seeking behavior. If $c_i = 0$, the DM is risk neutral. The Entscheidungsnavi focuses on linear and non-linear, one-dimensional utility functions in the form of exponential ones since these are the forms most frequently used in practice (Vilela and Oluyemi, 2022) and these forms allow the modelling of risk averse, risk neutral and risk seeking behavior. Moreover, if DMs choose their objectives fundamentally enough, i.e., mean objectives are not considered, the preferences in these objectives can be described with sufficient precision using exponential utility functions (von Nitzsch, 2024). x_i^- to x_i^+ is the interval of values for the objective O_i, where x_i^- and x_i^+ denote the worst and best attainable values for objective O_i, respectively. The preference direction (i.e., whether higher or lower numerical values are preferred) is implicitly captured by this definition: x_i^- is always mapped to the lowest utility (0) and x_i^+ to the highest utility (1), independent of whether the underlying objective is to be minimized or maximized.

Discrete utilities for objectives with a verbal scale:

$$U_i\left(x_{ij}^k\right) = \begin{cases} 0 \text{ if } x_{ij}^k = x_i^- \\ DR\left(x_{ij}^k\right) \text{ if } x_{ij}^k \in (x_i^-, x_i^+) \\ 1 \text{ if } x_{ij}^k = x_i^+ \end{cases} \tag{2a}$$

Exponential utility function for objectives with a numerical scale:

$$U_i\left(x_{ij}^k\right) = \begin{cases} \dfrac{1 - e^{-c_i \frac{x_{ij}^k - x_i^-}{x_i^+ - x_i^-}}}{1 - e^{-c_i}} \text{ if } c_i \neq 0 \\ \dfrac{x_{ij}^k - x_i^-}{x_i^+ - x_i^-} \text{ if } c_i = 0 \end{cases} \tag{2b}$$

Furthermore, the objective weights w_i are determined using the tradeoff method (Keeney and Raiffa, 1976). In contrast to the other methods, this method requires DMs to think in two dimensions since they must weigh what deterioration in one objective, they will accept in exchange for an improvement in another (tradeoff). This makes the determination of the objective weights more complicated than determining the other parameters where only one dimension is relevant at a time.

3.2. Imprecise information

The idea of imprecise information in the Entscheidungsnavi for all three categories (probabilities, utilities, and objective weights) is to identify a mean μ and a degree of precision ε, which allows an interval of the parameters (Peters et al., 2024). If DMs define $\varepsilon = 0$, they can precisely elicit the parameter, whereas $\varepsilon > 0$ means that they use imprecise information.

3.2.1. Imprecise probabilities

While determining the probabilities of the states of an influence factor S_δ, the degree of precision $\varepsilon_{P(S_\delta)}$ indicates the accuracy with which the probabilities are specified. $\varepsilon_{P(S_\delta)}$ can be between 0% and 50% and determined individually for each influence factor. If $\varepsilon_{P(S_\delta)} = 0\%$, the DM decides to determine the probabilities precisely. If $\varepsilon_{P(S_\delta)} \neq 0\%$, the DM makes use of imprecise information and decides to choose intervals for the probabilities instead of exact values. Then, the interval of the probabilities is dynamic based on the value $P\left(s_\delta^f\right)$ and calculated as follows:

$$P^{min}\left(s_\delta^f\right) = P\left(s_\delta^f\right) - \varepsilon_{P(S_\delta)} min\left\{P\left(s_\delta^f\right), 1 - P\left(s_\delta^f\right)\right\} \tag{3a}$$

$$P^{max}\left(s_\delta^f\right) = P\left(s_\delta^f\right) + \varepsilon_{P(S_\delta)} min\left\{P\left(s_\delta^f\right), 1 - P\left(s_\delta^f\right)\right\} \tag{3b}$$

$1 \leq f \leq K_\delta$ represents the states of the influence factor S_δ and K_δ the number of states. The largest interval results at $P\left(s_\delta^f\right) = 50\%$. As described in formula (1b), the probabilities have to sum up to one. To comply with this condition, the probabilities are normalized. For a detailed description of this step, see (Peters et al., 2024). To analyze the research questions, we calculated an average degree of precision $\overline{\varepsilon_{P(S_\delta)}}$ for the defined influence factors. The influence factor S_δ can be used for several alternatives and/or objectives. For this reason, the notation differs from that in formula (1).

3.2.2. Imprecise utility functions

Utility functions are determined depending on the type of objective (verbal or numerical scale). The procedure for imprecise utility functions for objectives with verbal scales is analogous to that for probabilities (see, Section 3.2.1). ε_{U_i} that can range from 0 to 50% is the degree of precision for a discrete utility scale of the objective O_i. The interval of the discrete utility function is determined as follows:

$$U_i^{min}\left(x_{ij}^k\right) = U_i\left(x_{ij}^k\right) - \varepsilon_{U_i} min\left\{U_i\left(x_{ij}^k\right),\ 1 - U_i\left(x_{ij}^k\right)\right\} \tag{4a}$$

$$U_i^{max}\left(x_{ij}^k\right) = U_i\left(x_{ij}^k\right) + \varepsilon_{U_i} min\left\{U_i\left(x_{ij}^k\right),\ 1 - U_i\left(x_{ij}^k\right)\right\} \tag{4b}$$

For objectives with a numerical scale, the utility functions are determined as an exponential utility function, as in formula (2b). Imprecise information is given by a possible interval of the parameter c_i, as in formulas (5a) and (5b). The degree of precision for an exponential utility function ε_{c_i} can range from 0 to 10.

$$c_i^{min} = c_i - \varepsilon_{c_i} \tag{5a}$$

$$c_i^{max} = c_i + \varepsilon_{c_i} \tag{5b}$$

For our analysis, we calculate an average degree of precision for utility functions determined for objectives with verbal scales $\overline{\varepsilon_{U_i}}$ and numerical scales $\overline{\varepsilon_{c_i}}$.

3.2.3. Imprecise objective weights

The objective weights w_i are determined by eliciting the exchange rates between two objectives (tradeoff method (Keeney and Raiffa, 1976)). Therefore, the DM can choose one reference objective with which all other objectives are compared. Furthermore, DMs have to formulate preference statements for all these pairs of objectives

(tradeoffs) and have to determine how much deterioration in one objective they would be willing to accept in order to improve the other objective, i.e., only a ratio of the weights is requested. With n objectives, n-1 of these trade-off statements are needed to calculate the objective weights as the sum of all objective weights has to be one.

In contrast to determine a single parameter, the simultaneous consideration of two objectives and their bandwidths is more complex for the DM. Thinking in two dimensions is not trivial for many DMs and can cause difficulties. The ENTSCHEIDUNGSNAVI supports the DM using indifference curves and different explanation variants of the tradeoff statements (von Nitzsch et al., 2020). It starts showing one indifference curve and the corresponding descriptions to the DMs. If they are not able to adjust their indifference curve, they can immediately use the precision interval to create preference intervals. Fig. 1 shows the user interface of the ENTSCHEIDUNGSNAVI in this step. For a detailed description of the functionalities in the ENTSCHEIDUNGSNAVI, see Peters et al. (2024).

The ENTSCHEIDUNGSNAVI calculates the objective weights based on the tradeoffs defined by the DM. Therefore, it determines the appropriate (imprecise) indifference curves for each tradeoff. DMs can adjust the tradeoff statements or indifference curves until they fit their preferences. If DMs cannot determine exact indifference curves or preference statements, they can define the upper and lower end of a hypothetical alternative resulting in a two-dimensional area of indifference curves (see, Fig. 1). If that is the case, a degree of precision $\varepsilon_{w_i} > 0$ exists. After determining all tradeoffs (n-1) including possible imprecisions, the ENTSCHEIDUNGSNAVI calculates the objective weights w_i and the relative degree of precision ε_{w_i}. If the DM chooses imprecise tradeoff statements, it results in an interval, as in formulas (6a) and (6b). For a detailed explanation, see Peters et al. (2024).

$$w_i^{min} = w_i - \varepsilon_{w_i} \tag{6a}$$

$$w_i^{max} = w_i + \varepsilon_{w_i} \tag{6b}$$

It is important to emphasize that DMs are never confronted with the objective weight values in the assessment phase. Their task is merely to determine the (imprecise) trade-off statements so that the ENTSCHEIDUNGSNAVI can calculate the objective weights w_i and their possible ranges ε_{w_i} on this basis. For our analysis, we calculate an average degree of precision for objective weights $\overline{\varepsilon_{w_i}}$.

3.3. Ranking the alternatives using Monte Carlo simulation

With a robustness check in the ENTSCHEIDUNGSNAVI, the DM can check the stability of their ranking of alternatives. To that end, the ENTSCHEIDUNGSNAVI makes use of a Monte Carlo simulation (Kalos and Whitlock, 2009). Evenly distributed random values are drawn from the intervals of parameters which are imprecisely defined by the degree of precision $\varepsilon_{P(S_\delta)}$, ε_{U_i}, ε_{c_i}, and ε_{w_i} (see, Section 3.2). In this paper, we use 100,000 simulation steps to answer the research questions.

The procedure of drawing random probability values for the influence factors S_δ is iterative. Firstly, the value $P(s_\delta^f)$ with the greatest probability interval is determined using a random drawing. Secondly, the range of the next smaller probability interval is recalculated so that an empty solution space is excluded and all other probabilities can lie within their intervals. Thirdly, the value $P(s_\delta^f)$ of the next smaller probability interval is determined in analogy to step 1. These steps are repeated until every state has been assigned a probability. The utilities are calculated by randomly drawing values from the respective intervals. For discrete utility functions, random values are drawn from the interval bounded by formulas (4a) and (4b). For exponential utility functions, a random c_i from the interval bounded by formulas (5a) and (5b) is drawn to calculate the corresponding utility with the help of formula (2b). The objective weights are randomly drawn from the interval bounded by formulas (6a) and (6b) and are normalized afterward. After drawing and determining all relevant parameters, the expected utilities are calculated using formula (1) for every alternative. Finally, the resulting rankings from the Monte Carlo simulations are compared with the ranking of alternatives based on the mean values of the intervals of parameters. Fig. 2 shows the user interface of the robustness check in the ENTSCHEIDUNGSNAVI. The alternatives are ordered according to the ranks based on mean values.

The robustness check presents two results for every alternative: frequency of rank, and range of expected utilities. The frequency of rank indicates how often an alternative has ended up in the respective ranking positions in the simulations. If the first (second, third, …) ranked alternative results in 100% of the simulations on the first (second, third, …) rank position, the result is robust to imprecise information for the parameter combination used. In the example in Fig. 2, this applies to the fifth, sixth, and seventh-ranked alternatives. If the first (second, third, …) ranked alternative results in <100% of the simulations on the first (second, third, …) rank position, imprecise information impacts the result, e.g., in Fig. 2, the first-ranked alternative is in first place in only 51% of the simulations. In the remaining simulations, it ended up in second to fourth place, depending on the parameters drawn from imprecise intervals. The frequency of rank represented by the

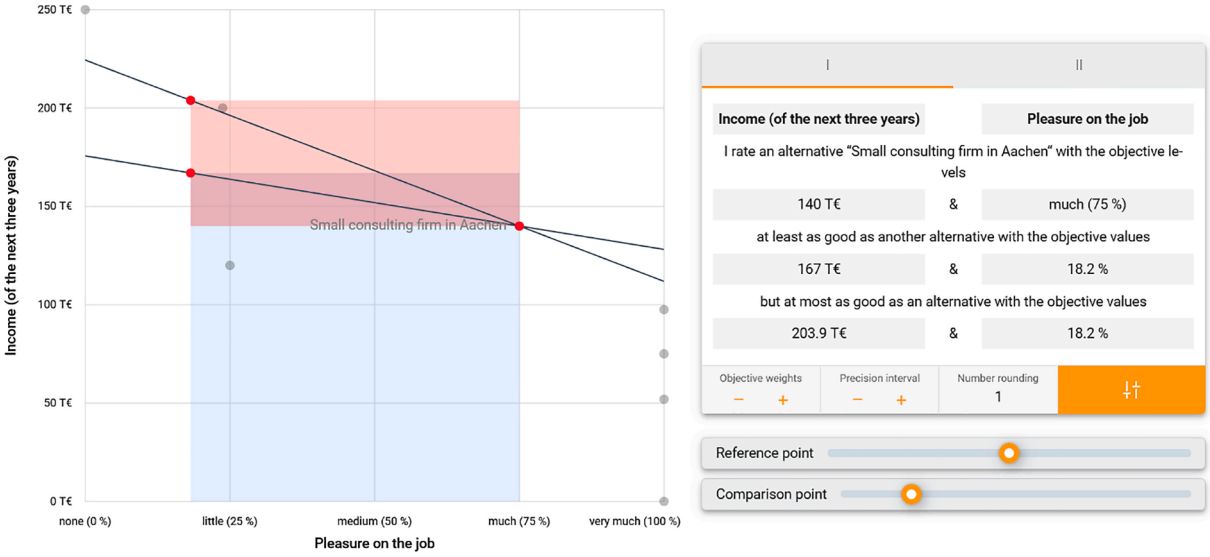


Fig. 1. Determining imprecise tradeoff statements in the ENTSCHEIDUNGSNAVI.

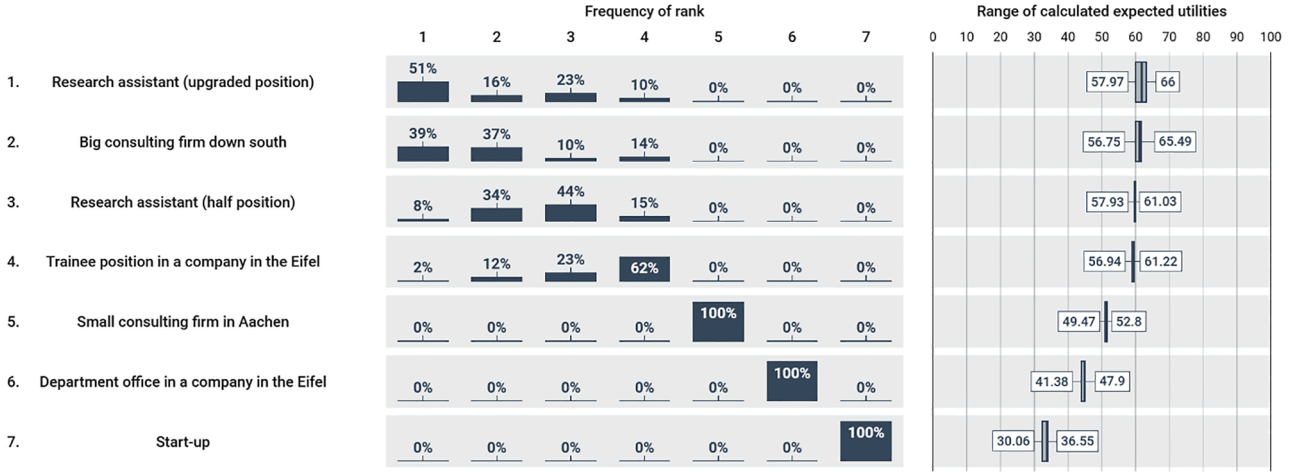


Fig. 2. Robustness check in the ENTSCHEIDUNGSNAVI.

probabilities can be compared with the rank acceptability index of the stochastic multicriteria acceptability analysis (SMAA) by (Lahdelma and Salminen, 2016; Tervonen and Figueira, 2008). SMAA is a simulation-based approach designed for discrete multicriteria decision-making problems where information may be uncertain, imprecise, or partially absent. In SMAA, various types of uncertain information are represented using probability distributions. The main measure in SMAA is the rank acceptability index b_i^r, which quantifies the range of preferences that assign alternative x_i to rank r. It represents the probability that the alternative achieves a particular ranking. Notably, the first rank acceptability index b_i^1 is particularly significant as it reflects the probability that the alternative is deemed the best option. For alternatives deemed inefficient, this first rank acceptability index is zero. In Fig. 2, the alternatives 5.−7. have a frequency of rank of zero for the first rank which can be compared to the first rank acceptability index b_i^1. Moreover, they have a stable ranking position, i.e., 100% probability that the corresponding alternative achieves the 5th/6th/7th rank. This information can be used to exclude these alternative from further investigation if DMs want to choose the best alternative.

The range of calculated expected utilities shows the minimum and maximum utilities the alternatives have achieved in the simulations. For a more detailed description, see Peters et al. (Peters et al., 2024).

4. Empirical findings on the impact and degree of utilization of imprecise information

4.1. Data set and participants

The data set was collected during the winter terms 2018/2019, 2019/2020, and 2020/2021 at a large university in Germany. A voluntary project within the course "Decision Theory" enabled the students to improve their final grade by a third (e.g., B to B+). The task was to analyze a decision situation (selection problem, where the DM seeks one choice) with the ENTSCHEIDUNGSNAVI. The most popular topic for the participants was career planning after studying (28%), followed by organizing their study program (22%) and planning leisure activities (18%). The less frequently chosen topics were, for example, purchase decisions, political decisions, or housing decisions.

The students only received a better grade if all steps in the ENTSCHEIDUNGSNAVI were completed with a reasonable effort. The decision situations had to be fully structured, including formulating the decision statement, identifying all relevant objectives, and determining the alternatives. Furthermore, the consequences table had to be developed as undistorted as possible. Moreover, the alternatives had to be evaluated, which included determining the utility functions and the objective weights. Therefore, the students had to define their preferences in a way consistent with their values. Content and technical support were given via mail, telephone, or consultation hours. After submission, every decision situation was checked manually by the paper's authors to ensure that the decision situation was completed carefully and appropriately. In addition, participants had to fill in a short questionnaire about the difficulty and usefulness of each step and input options in the ENTSCHEIDUNGSNAVI.

Overall, 1755 full-time students enrolled in business, engineering, or computer sciences study programs participated. 244 out of 1755 decision situations could not be considered because the participants did not spend the appropriate effort. Thus, the existing data set consists of 1511 carefully analyzed decision situations. The decisions provide information about essential decision parameters (i.e., decision statement, objectives and their weights, alternatives, consequences table, and utility functions), including imprecision regarding probabilities, utility functions, and objective weights.

The participants spent an average of 9.8 h on their decision situation. They identified, on average, 4.69 ($\sigma = 1.48$) objectives and 5.92 ($\sigma = 2.18$) alternatives; the maximum number for objectives was 24 and for alternatives 23. Moreover, on average, they identified 2.56 ($\sigma = 2.62$) influence factors (maximum: 24; minimum: 0) to model uncertain scenarios.

4.2. Procedure

To examine the research questions in more detail, we split the participants into two groups and varied the default degrees of precision in the ENTSCHEIDUNGSNAVI. For Group non-zero (958 participants), the default setting for the degrees of precision was not zero, which resulted in imprecise intervals for probabilities, utility functions, and objective weights in every newly analyzed decision situation. For Group zero (553 participants), the default setting for all degrees of precision was set to zero. So, the participants had to actively choose a degree of precision if they wanted. To simplify implementation in the ENTSCHEIDUNGSNAVI, participants in the winter semesters 2018/2019 and 2019/2020 were assigned to Group non-zero, and participants in the winter semester 2020/2021 were assigned to Group zero.

All research questions were analyzed with the complete data set and the two groups. To answer the first research question, 'How often is imprecise information used?' the data was analyzed to determine how often the DMs use imprecise information in total and imprecise information in the three categories (probabilities, utility functions, objective weights). For this purpose, the total number of imprecise parameters, the number of decision situations in which imprecise information was used, and the average degrees of precision were examined. The second

research question, 'How helpful do participants find the use of imprecise information?' can be answered based on the questionnaire. We asked the participants how helpful they found using imprecise information about the three categories (probabilities, utility functions, and objective weights). The participants could answer on an integer scale from 1 (unnecessary) to 6 (very helpful) – assuming that 3.5 is the neutral midpoint, i.e., they had to decide whether they considered it helpful or unnecessary. To analyze the third research question, 'What impact does imprecise information have on the final ranking of alternatives', we performed a Monte Carlo simulation described in Section 3.3. Therefore, we allowed imprecise information in all three categories and analyzed how often the best alternative calculated by the mean values of the intervals of parameters takes first (second, third) place in the 100,000 simulations. To examine the impact of imprecise information on the individual categories more closely, we have again carried out Monte Carlo simulations in which imprecise information is permitted in only one of the three categories. Using this information, we analyze the impact of imprecise information in the three categories on the stability of the best alternative in every decision situation.

4.3. Results

4.3.1. How often is imprecise information used?

The results are summarized in Table 1.

In Group non-zero, 99.90% of the participants used imprecise information in at least one category in their decision situation. In Group zero, the utilization was lower and amounted to 69.80%. This variation is also reflected in the individual categories. In all categories, participants in Group zero used imprecise information less than participants in Group non-zero. This is illustrated by the number of decisions as well as the total number and the average values. In Group non-zero, the use of imprecise information in the different categories was similar in the decisions (probabilities: 99.72%, utility functions: 96.97%, objective weights: 97.91%). However, the use of the various categories differed in Group zero. The participants employed imprecise objective weights less (19.71%) than imprecise probabilities (58.94%) or utility functions (60.22%). A more detailed analysis of the results in Group non-zero shows that most participants chose a degree of precision greater than or equal to the default setting for the categories probabilities and utility functions. However, 95.62% of participants in Group non-zero used a degree of precision for imprecise objective weights that was lower than the default setting. Considering the number of all imprecise values independent of the decisions in the complete data set, imprecise probabilities were used most (86.84%), followed by utility functions (69.81%) and objective weights (52.22%). The standard deviation (σ) reflects the variability of the project-level mean values.

4.3.2. How helpful do participants find the use of imprecise information?

The results are summarized in Table 2. he results of the questionnaire show that all in all, the participants found the use of imprecise information on probabilities most helpful ($\mu = 4.24$; $\sigma = 1.3$), followed by imprecise utility functions ($\mu = 4.16$; $\sigma = 1.15$). The specification of imprecise preference statements for the objective weights was perceived as least helpful ($\mu = 3.98$; $\sigma = 1.35$). In Group zero, the participants rated the helpfulness significantly lower than in Group non-zero. Moreover, in Group zero, the imprecise probabilities and utility functions were assessed as being about equally helpful (3.93 and 3.96), while in Group non-zero, they were assessed somewhat differently (4.41 and 4.28). However, the helpfulness of imprecise objective weights was rated lowest in both groups. In addition, participants who used imprecise probabilities, utility functions, or objective weights in their decisions rated the helpfulness significantly higher than those who used precise parameters. Both groups again rated imprecise objective weights as least helpful.

4.3.3. What impact does imprecise information in the three categories have on the final ranking of alternatives?

To answer this research question, we focused on the best alternative ranked by utilities in every decision. The analysis of the Monte Carlo simulation of the decision situations implementing imprecise information yielded the result shown in Fig. 3. We analyzed all categories of imprecise information together (overall) and, in addition, the three categories of imprecise information more closely permitting imprecise information in only one of the three categories in the Monte Carlo simulations. Moreover, we differentiated between the complete data set as well as Group non-zero and Group zero.

Considering all kinds of imprecise information, the first place is stable in 83.3% of the decisions. This means that in all 100,000 simulations (100%), the best alternative calculated by the mean values of the interval of parameters takes first place, and, therefore, the best alternative does not change. If the first place is not 100% stable, an additional analysis revealed that the second (third) placed alternative came out in the first place in 17.2% (3.6%) of the decisions. In Group zero, the first place is stable for 88.8% of the decisions. In Group non-zero, the percentage of the decisions in which the first alternative is robust was 81.1%.

Considering the individual categories, imprecise utility functions have the greatest impact on the stability of the best alternative compared to the impact of imprecise probabilities and objective weights, as the lowest number of decisions has a minimum frequency in the first

Table 1
Results - how often is imprecise information used?.

Imprecise…		Group non-zero[2]				Group zero[3]	Complete data set
		All	$< \varepsilon$	$= \varepsilon$	$> \varepsilon$		
…information[1] (in %)		99.90	-	-	-	69.80	88.88
…probabilities (in %)	**Participants**	99.72	9.69	40.73	49.30	58.94	87.57
	In total[4]	99.28	8.59	55.84	34.84	52.01	86.84
	$\overline{\varepsilon_{P(S_8)}}$	12.43 ($\sigma = 5.35$)	5.84 ($\sigma = 1.86$)	10 ($\sigma = 0$)	18.20 ($\sigma = 4.95$)	6.41 ($\sigma = 8.23$)	10.84 ($\sigma = 6.78$)
…utility functions	**Participants (in %)**	96.97	20.25	58.87	17.85	60.22	83.52
	In total[4] (in %)	88.85	10.47	37.12	41.26	38.42	69.81
	$\overline{\varepsilon_{u_i}}$	7.47 ($\sigma = 5.66$)	3.05 ($\sigma = 1.03$)	5 ($\sigma = 0$)	12.08 ($\sigma = 6.23$)	5.03 ($\sigma = 8.83$)	6.60 ($\sigma = 7.06$)
	$\overline{\varepsilon_{c_i}}$	0.60 ($\sigma = 0.59$)	0.28 ($\sigma = 0.10$)	0.5 ($\sigma = 0$)	1.07 ($\sigma = 0.71$)	0.28 ($\sigma = 0.52$)	0.48 ($\sigma = 0.58$)
…objective weights (in %)	**Participants**	97.91	95.62	0.10	2.19	19.71	69.29
	In total[4]	78.18	75.82	0.11	2.24	9.45	52.22
	$\overline{\varepsilon_{w_i}}$	1.21 ($\sigma = 0.02$)	1.30 ($\sigma = 0.86$)	5 ($\sigma = 0$)	9.96 ($\sigma = 0.08$)	0.12 ($\sigma = 0.01$)	0.80 ($\sigma = 0.02$)

[1] The participants use imprecise information in their decision situation, no matter in which category.
[2] For Group non-zero, the default setting was $\varepsilon_{P(S_8)} = 10\%$, $\varepsilon_{U_i} = 5$, $\varepsilon_{c_i} = 0.5$, and $\varepsilon_{w_i} = 5\%$. $\langle \varepsilon$ represents the group of students who decrease the default value, $= \varepsilon$ represents those who unchanged the parameter, and $\rangle \varepsilon$ those who increased the uncertainty.
[3] For Group zero, the default setting was zero for all degrees of precision.
[4] All defined probabilities/utility functions/objective weights were analyzed.

Table 2
Results - how helpful do participants find the use of imprecise information? The participants could answer on a scale from 1 (unnecessary) to 6 (very helpful).

Imprecise…	Group non-zero n = 958	Group zero n = 553	Participants using imprecise… n = [890[1]; 1262; 1047]	Participants using precise… n = [126[1]; 249; 464]	Complete data set n = 1511
…probabilities	4.41 (σ =1.21)	3.93 (σ =1.39)	4.47 (σ =1.19)	3.94 (σ =1.41)	4.24 (σ =1.30)
…utility functions	4.28 (σ =1.03)	3.96 (σ =1.31)	4.25 (σ =1.08)	3.73 (σ =1.40)	4.16 (σ =1.15)
…objective weights	4.10 (σ =1.35)	3.79 (σ =1.33)	4.11 (σ =1.34)	3.71 (σ =1.34)	3.98 (σ =1.35)

The pairwise comparison is highly significant between Groups non-zero and zero and between participants using imprecise parameters and those using precise ($p < 0.001$).

[1] 495 out of 1511 participants did not use influence factors in their decisions.

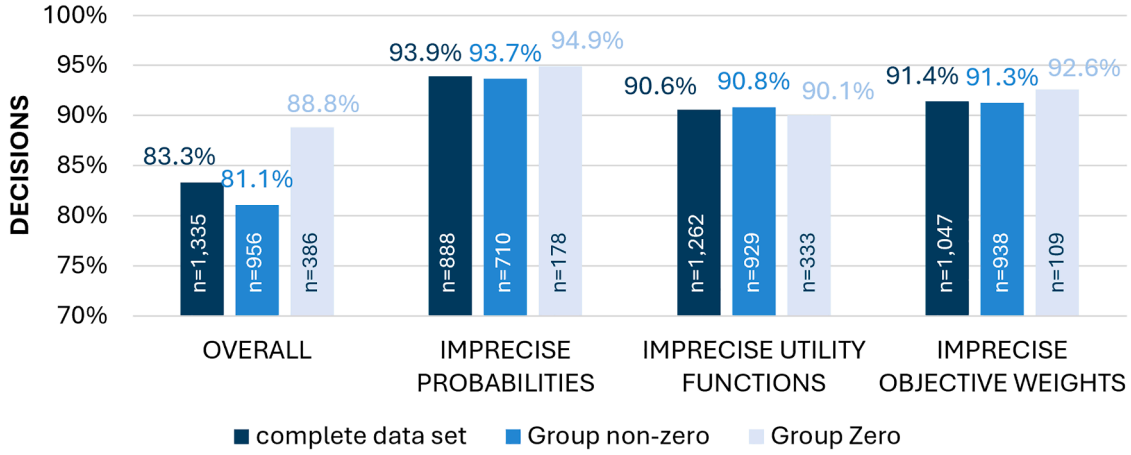


Fig. 3. Number of decisions in which the best alternative was 100% stable in the Monte Carlo simulations.

place of 100%. Imprecise objective weights lead to slightly higher stability, and imprecise probabilities have the lowest impact on 100% stability of the best alternative. However, there are no major differences between the categories, as the frequencies vary between 90 and 94%. The analyses of the various groups show no major differences in the categories. On top of that, we analyzed that there exists no statistical correlation between the average degrees of precision and the stability of the best alternative.

We also examined more closely the decisions that do not show 100% stability for the best alternative. In some cases, imprecise information had a high impact. Fig. 4 shows the worst-case scenarios, i.e., the decisions in which the imprecise information had the greatest impact on stability. Again, imprecise information was examined as a whole and in individual categories, as well as for the complete data set and the different groups.

In the worst case, the stability of the best alternative was 33.5% considering all categories of imprecise information representing a decision in Group non-zero. In Group zero, the value was higher (45.5%). The highest impact of imprecise information on the stability of the best alternative and, thus, the lowest stability is achieved with imprecise probabilities (33.4%), followed by imprecise utility functions (45.3%) and imprecise objective weights (45.5%). In general, stability was higher in Group zero than in Group non-zero. However, there were almost no differences in cases of imprecise utility functions.

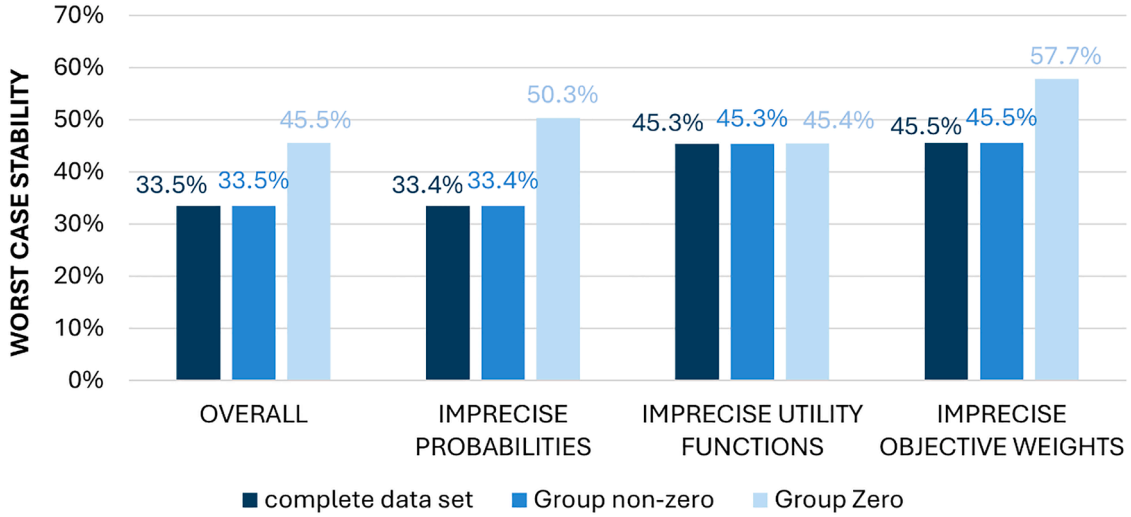


Fig. 4. Worst case stability of the best alternative in the Monte Carlo simulations using imprecise information.

5. Discussion

The paper shows that the imprecise information approach used in the Entscheidungsnavi is a valid and accepted concept for determining parameters in a DSS under MAUT. About 89% of the participants use imprecise information for at least one parameter in their decision. Even in Group zero, where the participants had to actively choose a degree of precision, almost 70% made imprecise statements, resulting in intervals of the quantitative parameters. In Group non-zero, almost all of them used imprecise information. Moreover, the participants generally found using imprecise information more helpful than unnecessary. These results show the need for imprecise information in a DSS to support the DM eliciting the quantitative decision parameters.

Our results also show that the use of the imprecise information approach differed between the categories. The participants found imprecise objective weights less important, as they used them the least (in about 69% of the decisions), followed by imprecise utility functions (about 84%) and imprecise probabilities (about 87%). In Group zero, the use of the categories differed even more. Imprecise objective weights were only used in approximately 20% of the decisions, with an average $\epsilon$of 0.12%. The detailed analysis of Group non-zero shows that in contrast to the other categories, most participants reduced the default degree of precision for objective weights.

We also showed that both the use of imprecise information and its perceived helpfulness differed across categories. Imprecise objective weights were not only the least used by the participants but were also perceived as the least helpful. This applies to the participants who have used imprecise information and those who have not.

These results could indicate that an imprecise information approach regarding probabilities and utility functions, like in the Entscheidungsnavi, benefits the participants more than imprecise information regarding objective weights. The lower utilization and evaluation of imprecise objective weights could be explained by the fact that the tradeoff method using indifference curves generally requires a higher understanding of the topic than the determination of the other parameters. The DM has to think in two dimensions (tradeoff between two objectives), which is not trivial. Moreover, indifference curves for tradeoff statements are generally more difficult to interpret than a direct rating of probabilities or utilities. If imprecise information is added, the process becomes much more complicated, and DMs may tend to disregard imprecise information even though they are unsure of their preference statements.

Assessing objective weights through indifference curves to identify the appropriate tradeoffs can be a challenging task for DMs. Merely providing DMs with the option of imprecise information appears inadequate. Therefore, it is recommended to streamline this process to better assist DMs in this essential and critical undertaking. E.g., Edwards and Barron (Edwards and Barron, 1994) developed an approach to simplify the determination of objective weights in MAUT. In their approach called SMARTS, they use a swing elicitation procedure and determine the weights in two steps: determining the rank order of the weights and determining the weights themselves. An extension of this approach (SMARTER) does not even require the second step. DMs can identify their best alternative using a Rank Order Centroid (ROC) weights table to simplify this challenging task. However, ROC weights lead to the identification of the best alternative in only 75–87% of the cases. Another solution, which we believe is better, is to focus on tradeoffs that are as realistic as possible, i.e., the tradeoffs should be as close as possible to real alternatives to create a good understanding for DMs. This approach could also be supported by additional evaluation methods. A sensitivity analysis could be used to understand how different objective weights impacts the ranking of alternatives. In the Entscheidungsnavi, the sensitivity analysis enables to change parameters while the ranking changes simultaneously. Moreover, an objective weight analysis can help DMs to analyze the best alternative without any preference statements. It is based on a simulation approach in which different objective weight combinations are algorithmically chosen in each calculation step resulting in different rankings of alternatives. The analysis shows in how many cases an alternative takes first place and which average objective weights lead to this result. For a detailed description, see (Peters et al., 2024).

The analysis of the different groups (non-zero and zero) shows the expected effect. Significantly more participants use imprecise information if the default setting in the Entscheidungsnavi already specified this. In Group non-zero, almost all participants use imprecise information, and there are no big differences in the frequency of use of the different categories of quantitative parameters. Several researchers have shown that the decision architecture can nudge the DMs decision (see, e.g., (Thaler and Sunstein, 2021)). In our study, the default setting of imprecision in Group non-zero also led to it being used more frequently. Thus, the determination of the parameters could be influenced by nudging in this group. In addition, the status quo bias (Kahneman et al., 1991; Samuelson and Zeckhauser, 1988) could also play a role. Maybe some participants were too lazy or did not think about the default setting and accepted them even though they did not need any imprecision in their decision problem. In Group zero, where the participants had to actively choose a degree of precision, more than half of the participants still used imprecise information regarding probabilities (about 59%) and utility functions (about 60%). That could mean the DMs felt unsure about determining these parameters and, therefore, chose imprecise information. However, the percentages are significantly lower than in Group non-zero.

According to MAUT, the DM should always choose the alternative with the highest utility in selection problems, which makes the ranking of the other alternatives unimportant for the implementation of the decision situation. The results of the third research question show that the parameter intervals resulting from imprecise information in the Entscheidungsnavi, in general, have no big impact on the stability of the best alternative ranked with MAUT. In only about 17% of the decisions, there could be a change of the best alternative due to a corresponding combination of imprecise parameters. If the simulations are carried out only for individual categories (probabilities, utility functions, or objective weights), the percentage of those cases is even lower (about 6%, 10%, and 9%). This could lead to the conclusion that precise preference statements and parameters in MCDM-Support-Systems are not so important since the best alternative does not change with imprecise information in most cases.

However, our results show that, in particular, for objective weights, the best alternative varied very sensitively. The relatively low selected imprecision for objective weights (see, $\overline{\varepsilon_{w_i}}$) led to a similar impact as, e.g., imprecise probabilities, which, on average, were chosen much more generously by the participants. If the participants were to choose larger ϵvalues for their objective weights, the impact on the stability of the ranking would be even more significant. This means that DMs are confronted not only with their unsureness regarding the determination of objective weights but also with an unsure ranking and best alternative. This makes decision-making considerably more difficult.

The assumption that the tradeoff method prevents the participants from using imprecise parameters due to the two-dimensional thinking and the fact that the result is very sensitive for imprecise objective weights could lead us to assume that the ranking would be less stable if a different, easier determination of the objective weights were used. In that case, participants might use imprecise objective weights more often, which leads to a bigger impact on the result. This hypothesis could be investigated in future research work.

6. Conclusion

This paper analyzes the use and impact of an imprecise information approach in the DSS Entscheidungsnavi and demonstrates the practical relevance of this approach. 1511 decision situations analyzed with the DSS were evaluated. Our results show that integrating imprecise

information in the Entscheidungsnavi supports the DM and the decision-making process. Most participants used imprecise information in their decision situations in at least one category, i.e., imprecise probabilities, utility functions and/or objective weights, and found this helpful. However, we observed different usage behaviors in the categories. Imprecise probabilities and utility functions were used more frequently and with considerably larger intervals than imprecise objective weights. This is probably due to the tradeoff method used in the Entscheidungsnavi, which is already complicated enough and, therefore, not easy to understand for DMs. Moreover, we show that in many cases, the decision remains stable despite imprecise information. In about 83% of the decisions, the best alternative was robust. This means that no matter which parameters were taken from the defined imprecise intervals in the simulations, the best alternative did not change. As expected, the comparison of Group non-zero (default: imprecise inputs, i.e., $\varepsilon > 0$) and zero (default: precise inputs, i.e., $\varepsilon = 0$) showed that the participants in Group zero used imprecise information significantly less than in Group non-zero. This difference could be explained by the status quo bias and nudging. In Group non-zero, only very few participants actively chose precise parameters. In addition, no major differences were identified between the frequency of use in the categories.

6.1. Usefulness of imprecision

Our results show that imprecise information is not only frequently used by DMs but is also perceived as helpful in a wide range of decision situations. This finding has broader implications for the field of decision-making beyond the specific DSS considered in this study.

A key explanation for this observation is that DMs are often unable to specify precise preferences. This may be due to two main reasons. First, preferences may not yet be fully formed at the time of decision-making. In many real-world situations, preferences emerge gradually through learning, reflection, and increased understanding of the decision context. In such cases, requiring precise inputs may impose an unrealistic burden on DMs, and the use of imprecise information provides a more adequate representation of their current state of knowledge. Second, even when underlying preferences exist, DMs may not be able to articulate them precisely due to cognitive limitations and well-documented behavioral biases. Research in behavioral decision theory has shown that preference elicitation is susceptible to framing effects, anchoring, and preference reversals (e.g., (Kahneman and Tversky, 1979), (Slovic, 1995)). These effects suggest that precise quantitative inputs may not necessarily reflect stable or "true" preferences, but may instead be influenced by the elicitation procedure itself. From this perspective, the use of imprecise information should not be interpreted merely as a simplification mechanism, but rather as a more realistic representation of human decision-making. Our results, therefore, support the view that decision models should accommodate imprecision as an inherent feature of preferences, rather than as a deviation from an idealized precise model.

Importantly, our findings also show that imprecision does not necessarily reduce decision quality. In a large majority of cases, the best alternative remained stable despite variations within the specified parameter intervals. This suggests that requiring high levels of precision may often be unnecessary, as robust decisions can be identified even under considerable uncertainty.

6.2. Limitations

Our results are related to the sample of participants, which only consists of students who attended lectures on decision theory, and the DSS Entscheidungsnavi, which uses specific imprecise information approaches. The students have extensive knowledge about the decision-making procedure and may not be representative for every group of people. Moreover, they received a reward for careful processing. So, some might use more imprecision than they would usually do to show increased effort, even though they were explicitly told to state their preferences. In particular, the fact that imprecise objective weights are less important for DMs should not be generalized. This may only apply to DSS or approaches that use the tradeoff method including indifference curves, like the Entscheidungsnavi. Other tools that use simpler objective weighting methods may lead to higher use of imprecise objective weights. The approach and methodology are, therefore, very decisive for the results. Future research could investigate this in more detail as the sensitivity of imprecise objective weights on the result presented in this paper also shows the importance of this topic. Furthermore, the Entscheidungsnavi relies exclusively on exponential utility functions. As explained in Section 3.1, preferences in fundamental objectives can be represented with sufficient accuracy using this functional form. Nevertheless, our results could be verified with other forms of these functions in future research.

6.3. Practical implications

In general, our results indicate useful practical application contributions to integrate imprecise information approaches in MCDM-Support-Systems. We want to highlight and recommend the following:

- A useful MCDM-Support-System based on MAUT should ideally include all three categories of imprecise information. The high number of uses of this approach suggests its practical relevance.
- Particular attention should be paid to the determination and explanation of probabilities and utility functions, as many DMs are uncertain about the assessment of these parameters.
- Tools for determining objective weights via indifference curves should be implemented in a way that highlights realistic and practically relevant trade-offs. This helps DMs form clearer judgments, enabling a more effective approach to determine objective weights.
- An MCDM-Support-System should include mechanisms that visualize the impact of imprecise inputs on the resulting rankings. This allows the DM to detect situations in which decisions remain stable despite uncertainty. Using this information DMs can understand that additional precision is not necessary to find the best alternative.
- However, if different ranges of imprecise information lead to unstable rankings, the system should actively flag this situation and encourage DMs to refine the parameters where feasible.

Beyond the specific design recommendations for MCDM-Support-Systems, our findings have broader implications for how decision-making processes should be supported. Given that preferences are often not precisely known or cannot be reliably elicited, MCDM-Support-Systems should not only allow for imprecise inputs but also actively support the process of preference formation and refinement. In particular, systems should provide feedback on how different parameter ranges affect the resulting rankings. This can help DMs understand the consequences of their uncertainty and support a learning and reflection process through which preferences may become more stable over time. Furthermore, MCDM-Support-Systems should be designed in a way that mitigates the influence of cognitive biases in the elicitation process. While it may not be possible to eliminate such biases entirely, tools can support DMs by making potential inconsistencies or instabilities in their inputs transparent. This enables users to critically reflect on their inputs and adjust them if necessary.

In this context, evaluation methods such as robustness analyses play a central role. By showing whether a decision remains stable across a range of parameter values, such methods help DMs distinguish between situations where additional precision is necessary and those where it is not. This contributes to more efficient and informed decision-making processes. In the Entscheidungsnavi, such support mechanisms are already implemented to a certain extent. In particular, the system provides a robustness analysis that systematically varies parameters within the specified intervals and visualizes the resulting changes in rankings.

This allows DMs to identify whether a decision is stable or sensitive to their imprecise inputs. In addition, the system enables users to iteratively refine their inputs. By observing how changes in parameter ranges affect the outcome, DMs can engage in a structured reflection process. This supports a better understanding of the relevance of different parameters and helps to identify which aspects of the decision require more precise specification and which do not.

Future research should not only focus on improving methods for handling imprecise information, but also on how MCDM-Support-Systems can facilitate reflection and learning processes for DMs. In particular, feedback mechanisms that illustrate how parameter ranges affect the resulting rankings can help users better understand the implications of their imprecision and support the gradual refinement of preferences. At the same time, a certain degree of imprecision is inherent to many decision problems and cannot be fully eliminated. Therefore, the goal should not be to enforce artificial precision, but to help DMs distinguish between unavoidable uncertainty and reducible imprecision.

Overall, our results suggest that the integration of imprecise information approaches should be complemented by mechanisms that support reflection, learning, and transparency, thereby aligning MCDM-Support-Systems more closely with the realities of human decision-making.

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CRediT authorship contribution statement

Mendy Tönsfeuerborn: Writing – review & editing, Writing – original draft, Software, Resources, Project administration, Methodology, Formal analysis, Conceptualization. **Rüdiger von Nitzsch:** Writing – review & editing, Supervision, Software, Project administration, Conceptualization.

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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