sciendo
Control and Cybernetics
vol. **50** (2021) No. 1
pages: 145-168
DOI: 10.2478/candc-2021-0009

Towards cognitive decision support: A model of behavioural assessment of multi-criteria methods*

by

Ewa Roszkowska[1] and Tomasz Wachowicz[2]

[1] University of Bialystok, Warszawska 53,
15-063 Bialystok, Poland
e.roszkowska@uwb.edu.pl
[2] University of Economics in Katowice, 1 Maja 50,
40-287 Katowice, Poland
tomasz.wachowicz@uekat.pl

In the dynamic, interactive context characteristic of negotiations, a cognitive support system based on restructurable modeling provides a richer basis for support.

(Kersten and Cray, 1996; Abstract)

Abstract: The Negotiation Support Systems often implement multiple criteria decision aiding (MCDA) techniques for building a negotiation scoring system. Those formal models should meet the needs, motivations, expectations, and cognitive abilities of users. In this paper, we try to explore the effects of decision maker's subjective perception of ease of use, time requirements, interface, preference representation, and efficiency of a particular MCDA method on the choice regarding the future use of this method. The multinomial logistic regression model is built and analysed. The analysis is based on data from online decision making experiments, where three MCDA methods were implemented, i.e. AHP, SMART, and TOPSIS. The study provides several interesting findings, concerning the behavioural aspects of multiple criteria decision aiding in software support systems. Most of the users recommended TOPSIS as the best one for supporting decisions in the future. This is a fast technique, for which we used an attractive graphical interface, suggesting that these factors play a crucial role in the users' choices. However, the causative regression model showed that the user's positive experience in using a particular method, i.e. its effectiveness in solving an exemplary numerical case, has the highest impact on the

*Submitted: December 2020; Accepted: March 2021.

method's choice for future use. The second most important factor is the adequacy in representing the user's preferences by this method. We show, however, that the strengths of effects and their significance may vary across the methods. Understanding the decision maker's evaluations of the MCDA techniques may help build a cognitive negotiation support system that satisfies the user's expectations.

Keywords: decision support, behavioural decision analysis, preference analysis, AHP, SMART, TOPSIS

1. Introduction

The development of computer-aided decision support systems reaches back to the late 1960s, when scientists began to implement quantitative models to support decision-making and planning (Power, 2008). In the 1970s, special information tools were built to support the negotiation process, allowing for the effective matching of potential negotiators, collecting and comparing data, structuring and analysing problems, interpreting offers, and facilitating communication in the negotiation process (Bichler, Kersten and Strecker, 2003). Kersten and Lai (2007) distinguish a few negotiating support configurations, which differ as to the form of activity of the system, the formal models implemented, and the functions that support the negotiation process. These include decision support systems (DSS), negotiation support systems (NSS), electronic negotiating table (ENT), negotiating agents (NA), or negotiating assistant agents (NAA). The authors regard the electronic negotiation system (ENS) as a cluster – a kind of umbrella spread over its tools – used in negotiations conducted over the Internet and integrating various formal models and support procedures. They define the negotiation support system as "software which implements models and procedures, has communication and coordination facilities, and is designed to support two or more parties and/or a third party in their negotiation activities". NSS can offer three negotiation support levels, including process support, decision support, and negotiation automation (Jelassi, Kersten and Zionts, 1990; Kersten and Lai, 2007; Turel and Yuan, 2007; Yuan, Head and Du, 2003). The process-oriented support is focused on defining negotiating procedures and interaction to assure communication efficiency through electronic communication technology, information documentation, and coordination of negotiators' activities. Decision support pays particular attention to the structure of the problem and potential solutions, evaluating the negotiation offers, and suggesting optional, efficient, and fair solutions. It is based on computer algorithms and decision-making models and requires collecting and processing new information – i.e. the learning process, which leads to a modification of the decision-making problem or forms of communication under consideration (Kersten, 2003). Negotiation automation is oriented at moving some negotiation activities to be undertaken by a software agent.

One of the first systems, specifically designed to conduct negotiation processes over the Internet was Inspire (Kersten and Noronha, 1999). This system was initially created to explore intercultural negotiations for educational purposes and it uses analytical models to analyse decisions and facilitate the negotiation process. Inspire is a solution-based system that provides tools for preference elicitation, based on hybrid conjoint measurement, offers suggestions using a search-based offer generator, the analysis of incoming offers, and post-negotiation analysis of the efficiency of the negotiated agreement. It also visualises the progress of negotiation using negotiation history graphs and negotiation dance graph. It organises the negotiation history in the form of a negotiation transcript that the users can easily follow. Similar solutions were also used in Negotiation Support Systems designed later, such as Negoisst (Schoop, Jertila and List, 2003), SmartSettle (Thiessen and Soberg, 2003) Web Hipre (Mustajoki and Hämäläinen, 2000), TOBANS (Roszkowska and Wachowicz, 2016) or eNego (Wachowicz and Roszkowska, 2021).

An important issue is that the NSS users' errors in the prenegotiation phase (while using MCDA tools for building the negotiation offer scoring system) may result in unreliable support for negotiators. Consequently, the negotiators may misunderstand the progress and dynamics of the negotiation process and the counterparts' negotiation moves (concessions or reverse concessions they make), misvalue the scale of the reciprocity in concessions and the quality of the agreement (Kersten, Roszkowska and Wachowicz, 2017, 2018; Wachowicz, Kersten and Roszkowska, 2019). Therefore, from the viewpoint of efficient decision support offered in NSSs, the multiple criteria decision aiding methods and techniques play a critical role. To be appropriately and accurately used by the negotiators, the formal MCDA models, implemented in NSS, should meet their needs, motivations, cognitive abilities, and expectations towards the decision support tool. In such a situation, they would also result in high acceptance and subjective evaluation of their use and usefulness, which may result in users' willingness to use similar support models and tools in the future (Davis, 1989; Leoneti, 2016; Saaty and Ergu, 2015; Tecle, 1988). The satisfaction and acceptance of the MCDA tool may be easily described by a set of behavioural factors addressing, among others, the effort required by the tool, i.e. the ease of use of NSS, and the amount of time required for performing the preference analysis, the ability to correctly reflect the preferences, the interface's layout and functionalities, etc.

In view of the above, the goal of this paper is to investigate the impact of some selected behavioural factors on the intention to use (recommendation for future use of) a specific MCDA tool that can be implemented in NSS to support the prenegotiation preparation tasks related to determining the negotiation offer scoring system. We will try to verify whether particular patterns of users' subjective evaluations of selected MCDA methods discriminate in favour of selecting any of these methods by this user. To answer this question, we use the dataset from an experiment conducted in the online survey system (Wachowicz, Roszkowska and Filipowicz-Chomko, 2018). Three MCDA methods were investigated, i.e. Analytic Hierarchical Process (AHP) (Saaty, 2008), Simple Multiple Attribute Rating Technique (SMART) (Edwards and Barron, 1994), and Technique for Ordering Preferences by Similarity to Ideal Solution (TOPSIS) (Yoon and Hwang, 1981). We used the multinomial logistic regression model to measure the potential relationship between the behavioural factors and the intention to use. To test this model's effectiveness, the overall fit was determined, and the statistical tests for individual predictors and the validation of predicted probabilities were performed. Up to our knowledge, there are no similar studies that would experimentally verify how the subjective assessment of the MCDA method may affect the willingness for its future use by the decision maker (DM). By assessing the logistic model, we showed that the significance, effect, and contribution of each behavioural factor in the recommendation of the MCDA method vary across those methods.

The work consists of the following four sections. Section 2 discusses the behavioural aspects of negotiation support systems. In Section 3, the decision making experiment is described. The experimental results are presented in Section 4. In summary, we presented the final conclusions.

2. The behavioural aspects of negotiation support systems

One of the most critical elements of the negotiation process is the decision-maker, this fact imposing an important requirement on the design of negotiation support systems. Building a cognitive support system requires the formal implementation of behavioural theories regarding the system user's cognitive structure. Information systems that are used to support the negotiation process can exert impact by introducing, strengthening, or reducing cognitive biases. Kersten (2003) pointed out that software engineering of negotiation support systems should be based on two principles, concerning the use of mathematical models in the design and construction of systems and the use of behavioural and cognitive factors to determine the needs, capabilities, and requirements of system users. Further, Kersten and Cray (1996) argued that negotiation support should primarily be based on a descriptive model that analyses and explains users' cognitive perspectives and behaviour without accepting unrealistic assumptions about their rationality. Only after describing the users' cognitive level, it is possible to provide adequate predictive and prescriptive support at the instrumental level. Identifying such a user's cognitive structure, necessary to design the support that would meet her requirements, seems still to be a problem.

The way, in which the system interacts with the user seems to be important. The interaction between the user and the support system may be influenced by the experience, skills, and intuition of the decision-maker. Problems with the use of the system can result from an incomplete understanding of the decision support methods and procedures used, the complexity of the system, its requirements, difficulties in tracking the consequences of the information provided at the earlier stages of decision support, and its consequences for outcomes, etc. Hence, the cognitive support systems that implement the selection of appropriate formal models tailored to the needs, motivation, and abilities of the system's user are needed.

There are several negotiation support systems that implement formal multiple criteria methods such as SMART, TOPSIS, UTA for building negotiations offer scoring system. SMART, combined with conjoint analysis, is used in Inspire (Kersten and Noronha, 1999), TOPSIS in TOBANS (Roszkowska and Wachowicz, 2016), and UTA in eNego (Wachowicz and Roszkowska, 2021). The vital problem is the potential mismatch of the cognitive requirements of the MCDA method used and the user's cognitive capabilities (Kersten, Roszkowska and Wachowicz, 2017). In the literature, many papers recommend using a specific method for a given decision-making problem (Gershon and Duckstein, 1984; Gershon, 1981; Saaty and Ergu, 2015; Tecle, 1988; Wątróbski et al., 2019; Yoon and Hwang, 1981). Some of the work draws attention to the set of criteria related to the subjective evaluation of a method by its user. The most common are ease of use, time required to spend on preference analysis, efficaciousness of the tool (understood as the extent to which the preferences are adequately reflected by the method) and interface used to derive the preference information from the user. We will name such criteria 'behavioural factors'.

Duckstein et al. (1982) proposed the ease of computation and the interaction required between the decision support system and the decision-maker as useful criteria while comparing various methods.

Hobbs (1986) noticed "ease of use" as one of the criteria for choosing an MCDA method and formulated the following question to measure it: "How much effort and knowledge does the method require of decision-maker and analysts?". Ozernoy (1987) mentioned that while evaluating the methods, another issue is important, i.e. the amount of time the decision-maker has available to solve the problem, which affects the time pressure, and it may be the reason for inaccurate results when the tool is used in a hurry. In other papers, he also pays attention to the decision maker's acceptance of a particular method and ability to provide the preference information required by it.

Teckle (1988, p. 97) also pays attention to the amount of time that the decision-makers have available to elicit preference information and their ability to express the preference and interpret the system and the solution obtained. He reported that users "tend to prefer techniques that are conceptually easy to understand and relatively simple to apply to many kinds of real-world problems". He argued that "the level at which the decision-maker understands the functioning of the MCDM techniques also limit its usage. A technique requiring a great deal of educational preparation may be less attractive than a more intuitive technique. This is since the understanding of the technique is critical to the decision-maker in interpreting the meaning of the solution". When the decision-maker has to choose between the ease of use and accuracy of results, they often favour the former.

Finally, Saaty and Ergu (2015) proposed several criteria for evaluating MCDA methods: simplicity of execution, comprehensive structure, measurement scale, synthesis of priorities by merging functions, MCDA methodology, applicability to conflict resolution, trustworthiness, and validity of the approach. According to these authors, the method is rated high if it can be easily understood and implemented by most users in practice and adequately aggregates the preferences to produce the final evaluation.

Out of the aforementioned review of criteria used in the evaluation of MCDA methods, referred to by many researchers in their studies, four are most frequently noticed and address the behavioural factors, important from the viewpoint of cognitive decision and negotiation support systems. They are the ease of use, the time requirements/consumption, the interface design for the interaction with the user, and the accuracy of preference representation (see Table 1). Therefore, while designing our experimental study, we focused on these four major factors.

Table 1. Behavioural criteria of evaluation of multiple criteria

Criteria of evaluation	References
Ease of use	Hobbs, 1986; Saaty & Ergu, 2015; Duckstein et al., 1982; Ozernoy, 1992; Teckle, 1988
Time requirements	Ozernoy, 1987; Duckstein et al., 1982; Teckle, 1988; Gershon &Duckstein, 1984
Interface	Teckle, 1988
Preference representation	Saaty & Ergu, 2015; Teckle, 1988

3. Experimental setup

Our study used the results of the online multiple criteria decision-making experiment designed by the Electronic Survey Platform (ESP) as a hybrid of the classic online electronic survey and decision support system*. The experiment consisted of five main steps covering all the phases of the standard multiple criteria decision making process (Fig. 1).

*ESP website: https://wwd.ue.katowice.pl/index.php, date of access: 3.01.2021

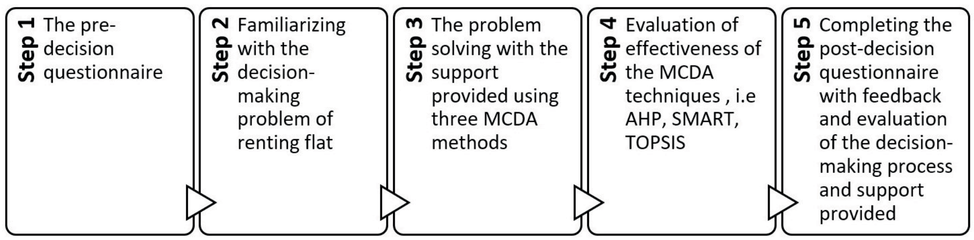

Figure 1. Steps of the ESP experiment

The following tasks and activities were required within each of the steps:

- **Step 1**: *Completing the pre-decision questionnaire*, which consisted of questions exploring the respondents' demographic characteristics and their decision-making experience.
- **Step 2**: *Familiarising with the decision making problem.* The decision-making problem implemented in the ESP required building the ranking of five alternatives, each describing a potential flat to rent. All five alternatives were described through five evaluation criteria. Note that the problem was tailored to the decision-making context typical for the students, who were our experiment participants.
- **Step 3**: *The problem solving with the support provided using three MCDA methods.* These methods were characterised by a different way of analysing preferences and the interface offered in this process. The AHP method used the pairwise comparison of criteria and options for each criterion, and the interactive sliders were used as part of its interface to declare the preferences by the users. The SMART method required assigning points to issues and options using the [0;100]-scale. Users had to type the rating manually from the keyboard. The check-up mechanism verified whether points were assigned following general requirements, i.e. the scores 100 and 0 were used to identify the best and the worst options. In TOPSIS, a pictogram interface was used, in which the quality stars were associated with a seven-step numerical Likert rating scale. The examples of all three interfaces user in the experiments are shown in Fig. 2.
  Each respondent had to evaluate the criteria and the options identified within each flat offer using all three MCDA techniques, starting from TOPSIS through AHP and ending with SMART.
- **Step 4**: *Evaluation of the effectiveness of MCDA techniques.* When the results of the SMART-, AHP- and TOPSIS-based analyses were displayed to the user in the form of the final rankings accompanied by the offer ratings (Fig. 3), the user was asked to answer the question:

Q1*: Look at the rankings obtained and decide which of them reflects your preferences best.*

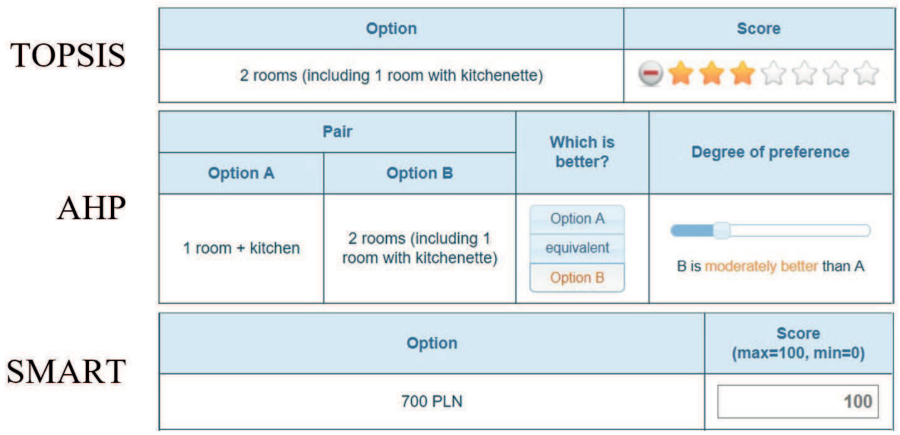

Figure 2. Examples of interfaces for MCDA techniques used in the ESP experiment

The method that the decision-maker chose at this stage will be named *effective* in solving the problem mentioned in the survey.

- **Step 5**: *Completing the post-decision questionnaire with feedback and evaluation of the decision-making process and support provided.* The questionnaire consisted of open and closed questions. It addressed problems related to ranking, evaluation of the support method, interface, and expectations of decision-makers regarding the representation of preferences in the decision support systems. In the post-decision questionnaire, respondents expressed their views on the usefulness of the MCDA methods using the 7-point Likert scale for the four basic criteria representing the behavioural factors distinguished from literature studies (see Table 1):
  (a) *ease of use* (difficult – simple),
  (b) *time requirements* (slow – fast),
  (c) *interface* (complicated – intuitive),
  (d) *preference representation* (poor – good).

Further, the general usefulness of the MCDA method was verified based on the participant's responses given in the post-decision making questionnaire.

Q2: *Which of the MCDA techniques used (SMART, AHP, TOPSIS, or none) would you recommend as the best one for supporting the multiple criteria decision analysis?*

We named this method *recommended.*

The study was conducted in several experimental series between 2014 and 2018. Participants were mostly the bachelor and master students of five Polish universities. In the end, 1839 completed surveys were analysed, this set not

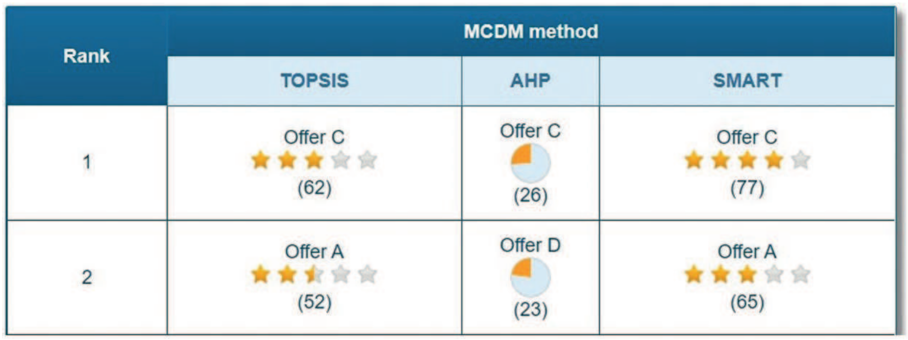

Figure 3. Part of the ranking of offers displayed to the user in the ESP experiment

including the records with the answer: "none" for question Q2. The average age of respondents was 21 years, and 62% of the study participants were female.

4. Results

4.1. The Multinomial Logistic Regression Model - a short overview

Multinomial logistic regression (MLR) is an extension of binary logistic regression. MLR is used when there are three or more categories of the dependent or outcome variable (Hosmer, Lemeshow and Sturdivant, 2013). The multinomial logit model requires simultaneously satisfying J–1 equations that specify the model. Let us assume that $X_1,\ X_2, \ldots, X_K$ are K predictors (continuous and/or categorical), and Y is an outcome variable with J nominal categories (ordered or unordered). Then, the multinomial logistic regression model is defined as follows:

$$logit\,(Y=j) = \ln\left[\frac{P\,(Y=j\,|\,X)}{P\,(Y=J\,|\,X)}\right] = \beta_{jo} + \beta_{j1}X_1 + \beta_{j2}X_2 + \ldots + \beta_{jK}X_K \quad (1)$$

where $j\ =\ 1,\ 2,\ \ldots,\ J\ -\ 1$.

Each of the logit equations is a linear function that models the logarithm of the ratio of probability of obtaining the resolution level j of the outcome variable Y and the probability of obtaining the variable's baseline resolution level. All logits are defined relative to such a predetermined baseline category, and because they are unordered, any of the J categories can be taken as the reference outcome. Logit coefficient (β_{jk}) provides information on how big change in the logit is made by a one-unit increase of the value of kth predictor (while the values of the other variables remain unchanged). Since $\sum_{j=1}^{J} P(Y=j|X)=1$

it is easy to establish that:

$$P(Y=j|X) = \frac{\exp(\beta_{jo}+\beta_{j1}X_1+\beta_{j2}X_2+\ldots+\beta_{jK}X_K)}{1+\sum_{j=1}^{J-1}\exp(\beta_{jo}+\beta_{j1}X_1+\beta_{j2}X_2+\ldots+\beta_{jK}X_K)} \tag{2}$$

$$P(Y=J|X) = \frac{1}{1+\sum_{j=1}^{J-1}\exp(\beta_{jo}+\beta_{j1}X_1+\beta_{j2}X_2+\ldots+\beta_{jK}X_K)}. \tag{3}$$

Parameters β_{jk} $(j=1,2,\ldots,J;\ k=1,2,\ldots,K)$ are estimated using the maximum likelihood method.

In this study, MLR is used to test the recommendation of three MCDA methods against behavioural factors. We used SPSS software version 22 for analysis.

4.2. Data analysis

The dependent variable used in the study was the recommendation of the MCDA method (REC) derived from the answer given to question *Q2*. The variable REC technically takes values AHP, SMART, and TOPSIS. Let us note that any category of the dependent variable can be chosen to be the reference one. The model will fit equally well, achieving the same likelihood and the same fitted values for the given data; only the parameter values and, of course, interpretation will differ. In our study, we used as reference category the one with the highest frequency, namely REC = TOPSIS.

Thirteen explanatory variables describing the behavioural factors of MCDA methods were primarily chosen based on the experiment data to build the MLR model. Twelve variables were linked to four questions regarding the decision maker's opinion on the functionality of MCDA methods:

- *ease of use* AHP, SMART, TOPSIS (E.AHP, E.SMART, E.TOPSIS),
- *time requirements* AHP, SMART, TOPSIS (T.AHP, T.SMART, T.TOPSIS),
- *interface* AHP, SMART, TOPSIS (I.AHP, I.SMART, I.TOPSIS),
- *preference representation* AHP, SMART, TOPSIS (P.AHP, P.SMART, P.TOPSIS).

Finally, the effectiveness of the MCDA technique was also included in this set as a variable named EFFEC with the resolution levels as follows: AHP, SMART, TOPSIS.

The structure of responses to questions Q1 and Q2 is presented in Table 2.

Table 2. Contingency table displaying the numbers of respondents who recommend (REC) and consider as effective (EFFEC) three MCDA methods in the ESP experiment

EFFEC	REC			
	AHP	SMART	TOPSIS	Sum
AHP	**111**	30	83	224
SMART	225	**281**	399	935
TOPSIS	198	79	**403**	680
Sum	564	390	885	1839

Chi-square test: χ^2 =129.550, df=4, p<0.001

From Table 2, it follows that there is a statistically significant relationship (chi-squared test: p<0.001) between the user's responses regarding the recommendation and effectiveness of the MCDA method. As the results show, more than half of the participants (50.8%) chose SMART as the most effective method for determining the exact ranking of alternatives, i.e. reflecting their preferences best. The second method was TOPSIS (40.0%), and the least effective in their opinion was AHP (9.2%). This may suggest that methods that require the direct distribution of preferences are more effective. Surprisingly, though, the results on the recommendation of MCDA methods vary greatly. The majority of participants identified TOPSIS as the recommended method (48.1%), while SMART was chosen as recommended only by 21.2% of respondents.

Let us notice that only 43.2% of all participants chose the same method simultaneously as they recommended and deemed effective (6.0% for AHP, 15.3% for SMART, and 21.9% for TOPSIS). Therefore, 56.8% of participants chose one method as effective, but another as recommended. So, the question arises, what are other characteristics of methods that may impact choosing them as recommended, even if they are not chosen as effective.

The non-parametric Kruskal-Wallis (K-W) test was performed to compare the values of independent variables for each category of the dependent variable, i.e. separately for the respondent who chose either AHP, SMART, or TOPSIS as a recommended method to determine whether the groups differed (Table 3).

The results in Table 3 indicate significant differences between the groups in terms of assessments of the behavioural factors linked to the functionality of the MCDA methods. Respondents with higher scores of evaluation *ease of use, time, interface, representation of preferences* for a particular MCDA method were more likely to recommend this method than those who recommended other methods (K-W test p<0.001).

In the MRL model, the number of variables is 13, while the number of events is $min(564, 390, 885) = 390$. Thus, the sample size is satisfactory as it meets the rule of a minimum of 10 events to every variable (Hosmer, Lemeshow and Sturdivant, 2013).

Table 3. Mean values of independent variables for three categories of the *recommended* variable (AHP, SMART, TOPSIS)

Variable	Recommended			Statistical comparison		
	AHP (N=564)	SMART (N=390)	TOPSIS (N=885)	K-W test	df	p-value
E.AHP	**5.415**	5.038	4.829	43.389	2	p<0.001
I.AHP	**5.248**	4.721	4.591	63.863	2	p<0.001
T.AHP	**4.502**	3.649	3.823	61.257	2	p<0.001
P.AHP	**5.353**	4.738	4.595	90.269	2	p<0.001
E.SMART	5.145	**6.133**	5.236	122.189	2	p<0.001
I.SMART	4.979	**5.831**	5.012	99.208	2	p<0.001
T.SMART	4.658	**5.710**	4.600	124.053	2	p<0.001
P.SMART	4.559	**5.967**	4.687	234.784	2	p<0.001
E.TOPSIS	5.904	6.272	**6.329**	43.031	2	p<0.001
I.TOPSIS	5.608	6.064	**6.068**	55.748	2	p<0.001
T.TOPSIS	5.628	5.864	**6.043**	36.858	2	p<0.001
P.TOPSIS	4.940	5.208	**5.802**	163.960	2	p<0.001

4.3. Building the multinomial logistic regression model

All predictors were significant in the univariate MLR-models, and they were used for building the multinomial logistic MLR-model. To improve the interpretation of multinomial regression coefficients, the predictors were rescaled using centering (Aiken, West and Reno, 1991). Table 4 contains the Likelihood Ratio chi-square test results for comparing the final model (i.e., containing all included predictors) against an Intercept Only model.

The null hypothesis that there is no difference between the intercept-only and final models is rejected. It confirms a relationship between the recommended MCDA method and the selected predictors. In our model, AIC and BIC and -2log likelihood are very close. A lower Akaike's Information Criterion (AIC) and BIC (Bayesian Information Criterion) for the final model compared to the intercept-only model suggest a good fit, as well as significant results of the Chi-Square test (Tabachnick, Fidell and Ullman, 2007).

Table 4. Model fit information

Model	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC	BIC	-2Log Likelihood	Chi-Square	df	Sig.
Intercept Only	3754.679	3765.713	3750.679			
Final	2966.230	3098.638	2918.230	832.449	22	0.000

For the MLR model, the pseudo R^2 statistics are treated as rough analogues to the R-square value in linear regression models. All are typically much lower than the R^2 statistics in linear regression. Values from 0.2 to 0.4 are considered "highly satisfactory" for the McFadden R^2 statistic (Tabachnick, Fidell and Ullman, 2007). In our case, it is equal to 0.217.

The estimates of the parameters of the final MRL model are presented in Table 5. Note that the centred predictors are represented in Table 5 with the prefix "c" in their names. The respondents that recommended the TOPSIS method are considered as the reference group. Note that in a model with a three-level independent variable, one of the comparisons of the resolution levels of this variable is redundant; therefore, only two first pairwise comparisons are statistically tested. In our case, we will omit the comparison between the recommended AHP and recommended SMART.

All standard errors below 2.0 indicate no numerical problems, such as multicollinearity, among the independent variables. The Wald statistic is the square of the ratio of the parameter estimate to its standard deviation. If the significance of the statistic is less than 0.05, then the parameter is useful to the model, i.e. independent variable is statistically able to differentiate between the recommended AHP vs the recommended TOPSIS (or recommended SMART vs recommended TOPSIS). Exp(β) predicts the change in odds for the unit increase in the corresponding explanatory variable, where odds ratios less than one correspond to decreases and odds ratios in excess of one correspond to increases.

The results from Table 3 indicate a statistically significant relationship between the following independent variables: EFFEC, *interface* (I.TOPSIS), and *preference representation* (P.TOPSIS) for TOPSIS; *interface* (I.AHP), *preference representation* (P.AHP), and *time requirements* (T.AHP) for AHP when the group that recommended AHP with the one recommending TOPSIS was compared (REC=AHP vs REC=TOPSIS). An average decision-maker, i.e. the one with an average value of all exploratory variables, who chooses TOPSIS as an effective MCDA technique is by 0.407 (exp(-0.900)) less likely to recommend AHP than TOPSIS (or is by 1/0.407=2.460 more likely be in the TOPSIS-recommending group than in AHP-recommending group).

When the comparison between the recommendation of SMART vs recommendation of TOPSIS is conducted, one can identify the statistically significant impact of the following variables on the decision-maker's choices: effectiveness (EFFEC), *time requirements* (T.TOPSIS), and *representation of preferences* (P.TOPSIS) for TOPSIS; *easy of use* (E.SMART), *preference* (P.SMART) and *time requirements* (T.SMART) for SMART. An average decision-maker that chooses TOPSIS as effective is by 0.137 (exp(-1.989)) less likely to recommend SMART than TOPSIS group (or is by 1/0.137=7.302 more likely be in TOPSIS-recommending group than in the SMART-recommending one).

4.4. Evaluation of the recommendation of the MLR model

The classification shown in Table 6 is considered an indicator of the final MLR model's usefulness.

The correctly classified cases are the bolded ones on the diagonal (273 cases in the AHP-recommending group, 197 cases in the SMART-recommending group, and 677 cases in the TOPSIS-recommending group). The final model accurately predicted 62.4% of the cases. We can see that the TOPSIS-recommending group had a much higher level of prediction accuracy (76.5%) compared to the other two groups. The correct classification was 48.4% for the AHP-recommending group and 50.5% for the SMART-recommending one. Such a prediction accuracy structure follows the observation from Hosmer, Lemeshow and Sturdivant (2013) that MLR generally produces the best predictions for the largest group.

In order to calculate the classification accuracy, we can also consider the marginal frequencies for groups recommending AHP, SMART, and TOPSIS, which are 30.7%, 21.2%, and 48.1%, respectively (derived from Table 2). We calculate the proportion of by chance accuracy rating (Petrucci, 2009), i.e. $0.307^2 + 0.212^2 + 0.481^2 = 0.37055$, which is 37.06%. This proportion is com-

Table 5. Parameter estimates for the final MRL model. The reference group are the participants that recommended TOPSIS

Variable	β	Standard error	Wald	df	Sig.	Exp (β) (odds ratio)	95% confidence interval for exp(β)	
							lower	upper
AHP recommended								
Intercept	-0.900	0.101	79.454	1	0.000	0.407		
EFFEC (=AHP)	0.796	0.187	18.183	1	**0.000**	2.217	1.538	3.197
EFFEC (=SMART)	0.339	0.131	6.631	1	**0.010**	1.403	1.084	1.815
cI.TOPSIS	-0.215	0.070	9.437	1	**0.002**	0.806	0.703	0.925
cP.TOPSIS	-0.640	0.059	119.244	1	**0.000**	0.527	0.470	0.592
cT.TOPSIS	0.013	0.058	0.046	1	0.830	1.013	0.903	1.135
cI.AHP	0.263	0.056	21.765	1	**0.000**	1.301	1.165	1.453
cP.AHP	0.407	0.053	60.046	1	**0.000**	1.503	1.356	1.666
cT.AHP	0.092	0.042	4.843	1	**0.028**	1.096	1.096	1.189
cE.SMART	-0.064	0.051	1.603	1	0.205	0.938	0.938	1.036
cP.SMART	-0.083	0.045	3.387	1	0.066	0.921	0.921	1.005
cT.SMART	0.067	0.044	2.336	1	0.126	1.069	1.069	1.166
SMART recommended								
Intercept	-1.989	0.145	187.427	1	0.000	0.137		
EFFEC (=AHP)	0.569	0.270	4.458	1	**0.035**	1.767	1.042	2.997
EFFEC (=SMART)	1.190	0.161	54.920	1	**0.000**	3.286	2.399	4.501
cI.TOPSIS	-0.005	0.086	0.004	1	0.952	0.995	0.841	1.177
cP.TOPSIS	-0.591	0.066	79.529	1	**0.000**	0.554	0.487	0.631
cT.TOPSIS	-0.137	0.068	4.062	1	**0.044**	0.872	0.762	0.996
cI.AHP	0.027	0.058	0.217	1	0.641	1.027	0.917	1.151
cP.AHP	-0.004	0.053	0.005	1	0.944	0.996	0.897	1.106
cT.AHP	-0.058	0.047	1.562	1	0.211	0.944	0.861	1.034
cE.SMART	0.156	0.071	4.837	1	**0.028**	1.169	1.017	1.344
cP.SMART	0.639	0.065	97.044	1	**0.000**	1.894	1.668	2.151
cT.SMART	0.288	0.056	26.145	1	**0.000**	1.334	1.195	1.490

Table 6. Classification table for various levels of REC variable

Predicted recommendation				
Observed recommendation	AHP	SMART	TOPSIS	Percent correct
AHP	**273**	60	231	48.4%
SMART	62	**197**	131	50.5%
TOPSIS	135	73	**677**	76.5%
Overall percent	25.6%	17.9%	56.5%	62.4%

pared with an overall percentage of the final model. The classification accuracy rate should be at least 25.0% higher than the proportion of by chance accuracy rate of 37.06%. It must, therefore, be by at least at $1.25 \times 37.06\% = 46.32\%$ for the MLR model to be considered adequate. Because 62.4% of correctly classified cases exceeds the proportion of by chance accuracy rate for this data (just calculated 46.32%), the model has adequate accuracy.

4.5. Discussion

One may perceive the results presented in previous sections as evident. They confirm the general intuition that the user's recommendations of the method for future use are strongly related to evaluating its efficiency in supporting the current decision-making problem and the perception regarding the general functionality of the decision support tool that implemented this method. However, the interesting finding is that not all of these behavioural factors affect the recommendation for each method, and between the methods, the impact of them is not equal. An impact of a few of them also poses interpretational problems. To make the discussion over the general results easier, we summarise the effects of all behavioural factors from our study on changes in the method's recommendation in Table 7.

When we look at the impact of EFFEC on change in the recommendation of the MCDA methods (from the baseline choice REC=TOPSIS identified for the decision-maker with an average evaluation of characteristics of all techniques analysed), one can observe that performance of each particular method in solving the problem was the major factor that made the odds for choosing this method significantly increase. If AHP performed effectively (EFFEC=AHP), it made the decision-maker's odds to recommend it over TOPSIS increase 2.217 times, while when SMART performed (EFFEC=SMART) well, the odds for recommending SMART increased by the factor of 3.286. However, note that nominally considering AHP as effective made the chances for the final recommendation of AHP still by 10% lower than for TOPSIS (i.e. the odd ratio determined with $\exp(\beta)$ of intercept is equal to $2.217 \times 0.407 = 0.9$).

Table 7. Summary of an impact of predictors on changes in odds of recommending one MCDA method over the baseline one (TOPSIS)

Variable	**Recommendation**	
	AHP vs TOPSIS	SMART vs TOPSIS
EFFEC (=AHP)	2.217	1.767
EFFEC (=SMART)	1.403	3.286
cE.TOPSIS	*ns*	*ns*
cE.AHP	*ns*	*ns*
cE.SMART	*ns*	1.169
cI.TOPSIS	0.806	*ns*
cI.AHP	1.301	*ns*
cI.SMART	*ns*	*ns*
cP.TOPSIS	0.527	0.554
cP.AHP	1.503	*ns*
cP.SMART	*ns*	1.894
cT.TOPSIS	*ns*	0.872
cT.AHP	1.096	*ns*
cT.SMART	*ns*	1.334

ns – non-significant

The situation is even less optimistic for SMART. Nominally, the DMs who considered SMART effective have still more than two times higher odds for choosing TOPSIS than SMART (the odds ratio is equal to $1/(0.137 \times 3.286) = 2.22$. There are apparently other incentives that drive the average DMs to choose TOPSIS despite its lack of effectiveness in both situations, i.e. even though the results obtained by other methods (AHP and SMART) are considered to support their decision better in the problem under consideration. Globally, the probability for an average DM to recommend AHP equals 26.3%, to recommend SMART – 8.9%, and to recommend TOPSIS – 64.8% (see formulas (2) and (3)).

The second factor affecting the changes in odds of recommendation most strongly describes the DM's subjective perception of how well each of the MCDA methods represents their preferences. This is the only factor, within which the compensation of evaluations of each method in pairs occurs. For instance, if the belief that TOPSIS represents DMs preferences well increases by one unit, the odds for recommending TOPSIS increase $1/0.527 = 1.9$ times, yet when the belief in a good representation of preferences by AHP increases by one unit, the odds for recommending AHP increase 1.503 times. If DM evaluates both of these methods proportionally higher, the result is that she will be more willing to recommend TOPSIS than AHP. Her odds for recommending TOPSIS over AHP will increase $1/(0.527\ 4 \times 1.503) = 1.26$ times. But if DMs considers AHP to reflect preferences in a better than average way (one unit increase in evaluation) while TOPSIS worse than in average way (still of one unit), the chances for recommending AHP over TOPSIS increase $(1/0.527 \times 1.503) = 2.85$ times. Such DM's odds for choosing AHP are nominally higher than for choosing TOPSIS by 15% $(2.85 \times 0.407 = 1.15)$. Similar regularity can be observed for comparing the recommendation of SMART over TOPSIS. DM who considers that SMART reflects her preferences better than average, will have nearly two times higher chances (1.894) to recommend SMART than TOPSIS. If she considers TOPSIS to perform here better than in an average way – the odds for recommending the latter will increase $1/0.554 = 1.805$ times. If she evaluates the preference representation of both these methods higher, the compensation is nearly full (odds in choosing SMART over TOPSIS do not change). However, contrary to the AHP-to-TOPSIS comparison, such simultaneous positive opinion as to preference representation by SMART and negative for TOPSIS will still not make the chances to recommend the former nominally higher than to recommend TOPSIS.

When we move further to the remaining variables describing the methods' functionality, no such compensation in evaluation can be noticed, and an impact on the odds ratio tends to be weaker. We find that no perception of the easiness of the AHP or TOPSIS method may significantly change the odds to choose any of these two methods. Similarly, the evaluation of the user interface that the DSS implemented to handle both SMART and TOPSIS did not affect the changes in recommendation of any of these two methods. Interestingly, the DM's perception of the ease of use of SMART affects the changes in odds of recommending it over TOPSIS. Her opinion on the interface implemented in TOPSIS does not change this effect. An increase in the evaluation of the ease of use of SMART by a unit value makes the odds to recommend SMART over TOPSIS increase 1.169 times. Despite its significance, it does not change much if we analyse the odds nominally. For the evaluation of the interface, perfect compensation occurs only for the AHP-to-TOPSIS comparison. The simultaneous enthusiastic evaluation of the AHP interface and unenthusiastic of the TOPSIS interface result in no changes in the odds ratio of the recommendation of one of these two methods compared to an average DM $(0.806 \times 1.301 = 1.05)$.

Finally, the DMs' evaluation of the time requirements of the MCDA method affects their recommendation, but in a compensatory way, when SMART and TOPSIS are compared, and in a non-compensatory manner, when AHP-to-TOPSIS comparison is conducted. A more optimistic evaluation of the time requirements of AHP increases the odds ratio of recommending it over TOPSIS but only slightly (by 9.6%). However, this increase is not disturbed by the evaluation (positive or negative) of TOPSIS. When recommendation of SMART over TOPSIS is considered, an optimistic evaluation of time required to spend for the SMART algorithm that increases the odds for recommending SMART 1.334 times may be reduced to 16% only, if it is accompanied by a simultaneous optimistic evaluation of time spend on TOPSIS $(0.872 \times 1.334 = 1.16)$.

To summarise, the recommendation of any technique depends on the mix of different behavioural factors. The chances for recommending AHP over

TOPSIS depend mostly on the fact if the former occurred to be effective, but also on how much better it is evaluated in terms of the interface the DSS offered for it and preference representation over TOPSIS. The positive evaluation of time required by the AHP algorithm may also increase the chances for its recommendation by the user. If we consider an adherent of AHP (who gained a positive experience by its use and evaluates it higher than average in terms of interface, preference representation, and time required, and AHP results supported her best), her odds for recommending AHP are nominally nearly two times higher ($4.75 \times 0.407 = 1.9$) then recommending TOPSIS. An increase of chances for recommending SMART over TOPSIS also depends on whether it occurred to be effective, and the second biggest role plays the preference representation. However, no user's opinion on SMART or TOPSIS interface affects changes in recommendation but the sole satisfaction from the ease of use and evaluation of how it is time-consuming. However, a strong SMART adherent positively affected by the aforementioned behavioural factors of SMART will have only 36% higher chances to recommend this method over TOPSIS ($3.286 \times 1.169 \times 1.894 \times 1.334 \times 0.137 = 1.36$).

5. Conclusions

This study aimed to identify the factors that are considered by decision-makers when choosing the MCDA technique for solving problems in the decision support system. These factors were linked to the users' subjective evaluation of MCDA methods—they had a behavioural nature. The behavioral model we had tested identified the following descriptors, which bear an impact on the recommendation of TOPSIS, AHP, and SMART techniques that are related to the DM's previous experience with the use of each method: (1) perception of the effectiveness of the method in solving an exemplary MCDM problem, i.e. how well it supports the decision, builds reliable ranking or rating of offers; (2) evaluation of *ease of use* of this method that allows DM to go through the support protocol without any cognitive problems; (3) evaluation of the quality of *interface* that may be offered in DSS for this method, which facilitates the interaction and providing the necessary preferential data; (4) evaluation of *time requirements*, i.e. how much time-consuming is the preference elicitation process, and (5) evaluation of *preference representation*, i.e. subjective perception of how well the preferences imparted during the elicitation process are represented by the method while aggregating them into a final decision recommendation. The overall evaluation of the multinomial logistic regression model, statistical tests of individual variables, goodness-of-fit statistics, and predicted probabilities assessment were presented in detail.

The findings from this study suggest that behavioural factors play an important role in selecting the MCDA method. Generally, DMs would mostly use the quickest and easiest method with a pictorial interface, namely – TOPSIS. However, it does not mean that it should be a universal recommendation. The most critical factor in our model occurred to be the direct experience with the method used in a preceding exemplary exercise (numerical example), which affected the evaluation of its effectiveness. Therefore, while designing the behavioural decision support system that responds to its user's cognitive requirements, it may be profitable to organise a pre-decision-making phase, in which the DM will have an opportunity to solve a series of quick decision-making examples with various support mechanisms implemented. The method she feels best with should be a good alternative to the quickest one, especially when the preference representation starts to play a role. A well-designed interface may also increase the chances for other, usually more time-consuming methods such as AHP, in our case.

These observations may be further supported by the future analysis of the open question that we used in the post-decision-making questionnaire in our study. The quick analysis of the answers showed that the respondents, who recommended the TOPSIS method, claimed it was *quick and easy*. Although some respondents noted potential inaccuracies in the qualitative evaluation of options (Likert's seven-step scale), they argued that this did not directly affect its results (the rankings of offers). They treated the star rating as *very intuitive*. Those who chose AHP considered it as *easy* but *time-consuming*. They found the time required by this method as a trade-off with the precision of the scoring system it results in. Support through SMART was evaluated as *clear, fast, and easy*. A wide range of rating points allows for a more precise declaration of preferences.

However, it is worth noting that when designing the experiment, we did not randomise the order of the MCDA methods in the decision support protocol across the users. Consequently, each user started the respective analysis with the TOPSIS method and ended with SMART. Using the same order of methods within the entire sample does not allow to capture some specific psychological effects that might affect the results, i.e. the users' option regarding the use and usefulness of the methods. These may be, for instance, order effect and learning effect (Chrzan, 1994; Strack, 1992). For instance, the learning effect may occur, resulting in increasing problem understanding and better recognising the preferences when using the following MCDA methods. Therefore, according to the fixed order of methods, the better effects of decision analysis could be observed for the methods used as second or third (i.e., AHP or SMART) than for the first one (TOPSIS). This could also result in worse opinion regarding the use and usefulness of the latter. Interestingly, no such effect could be observed in our study, as the most frequently recommended method was TOPSIS, followed by AHP and SMART. This may, however, indicate the negative effect of fatigue (Savage and Waldman, 2008). The respondents being tired after cognitively engaging analysis using TOPSIS and AHP may not perform in SMART well and therefore evaluate it as least effective and recommend it least frequently. Therefore, future research is required in which our sample will be extended with new respondents to whom the methods will be offered in a different order. This will allow us to confirm that the results obtained here are independent of an order effect.

We perceive the study presented here as a starting point for further analysis of the behavioural aspects of decision support systems and designing the cognitive DSSs and NSSs. Such systems are – as Gregory Kersten perceived them – user-oriented systems responsive to their users' cognitive possibilities and information processing style. Our subsequent experimental studies will test the potential interactions between the factors and enrich the set of factors by those describing the DM's cognitive profile. Some specific information processing inventories may be used here, such as the General Decision Making Style Inventory (Scott and Bruce, 1995), Rational-Experiential Inventory (Epstein et al., 1996), or even a modified Cognitive Reflection Test (Toplak, West and Stanovich, 2014).

Acknowledgements

This research was supported by the grant from the Polish National Science Centre (2016/21/B/HS4/01583).

Bibliography

Aiken, L. S., West, S. G. and Reno, R. R. (1991) *Multiple Regression: Testing and Interpreting Interactions.* Sage Publications, Inc.

Bichler, M., Kersten, G. and Strecker, S. (2003) Towards a structured design of electronic negotiations. *Group Decision and Negotiation*, **12**(4), 311–335. https://doi.org/10.1023/A:1024867820235

Chrzan, K. (1994) Three kinds of order effects in choice-based conjoint analysis. *Marketing Letters*, **5**(2), 165–172. https://doi.org/10.1007/BF00994106

Davis, F. D. (1989) Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319–340.

Edwards, W. and Barron, F. H. (1994) SMARTS and SMARTER: Improved simple methods for multiattribute utility measurement. *Organisational Behavior and Human Decision Processes*, **60**(3), 306–325.

Epstein, S., Pacini, R., Denes-Raj, V. and Heier, H. (1996) Individual differences in intuitive–experiential and analytical–rational thinking styles. *Journal of Personality and Social Psychology*, **71**(2), 390–405.

Gershon, M. and Duckstein, L. (1984) A procedure for selection of a multiobjective technique with application to water and mineral resources. *Applied Mathematics and Computation*, **14**(3), 245–271. https://doi.org/10.1016/0096-3003(84)90024-9

Gershon, M. E. (1981) *Model choice in multi-objective decision-making in natural resource systems* [Dissertation]. University of Arizona.

Hobbs, B. F. (1986) What can we learn from experiments in multiobjective decision analysis? *IEEE Transactions on Systems, Man, and Cybernetics*, **16**(3), 384–394.

Hosmer, D. W., Lemeshow, S. and Sturdivant, R. (2013) *Applied Logistic Regression*. Wiley & Sons.

Jelassi, T., Kersten, G. and Zionts, S. (1990) An Introduction to Group Decision and Negotiation Support. In: C. A. Bana e Costa, ed., *Readings in Multiple Criteria Decision Aid*. Springer, 537-568.

Kersten, G. E. (2003) The Science and Engineering of E-Negotiation: An Introduction. *HICSS*, 3, 27–1.

Kersten, G. E. and Cray, D. (1996) Perspectives on representation and analysis of negotiation: Towards cognitive support systems. *Group Decision and Negotiation*, **5**(4), 433–467. https://doi.org/10.1007/BF02404644

Kersten, G. E. and Lai, H. (2007) Negotiation Support and E-negotiation Systems: An Overview. *Group Decision and Negotiation*, **16**(6), 553–586. https://doi.org/10.1007/s10726-007-9095-5

Kersten, G. E. and Noronha, S. J. (1999) WWW-based negotiation support: Design, implementation, and use. *Decision Support Systems*, **25**(2), 135–154.

Kersten, G. E., Roszkowska, E. and Wachowicz, T. (2018) Representative Decision-Making and the Propensity to Use Round and Sharp Numbers in Preference Specification. In: Y. Chen, G. E. Kersten, R. Vetschera and H. Xu, eds., *Group Decision and Negotiation in an Uncertain World. GDN 2018*, Springer, **315**, 43–55.

Kersten, G., Roszkowska, E. and Wachowicz, T. (2017) The Heuristics and Biases in Using the Negotiation Support Systems. In: M. Schoop and D. M. Kilgour, eds., *Group Decision and Negotiation. A Socio-Technical Perspective*. Springer International Publishing, 215-228 https://doi.org/10.1007/978-3-319-63546-0_16

Leoneti, A. B. (2016) Considerations regarding the choice of ranking multiple criteria decision making methods. *Pesquisa Operacional*, ***36*****(**2), 259–277.

Mustajoki, J. and Hämäläinen, R. P. (2000) Web-Hipre: Global Decision Support By Value Tree And AHP Analysis. *INFOR: Information Systems and Operational Research*, **38**(3), 208–220. https://doi.org/10.1080/03155986.2000.11732409

Petrucci, C. J. (2009) A primer for social worker researchers on how to conduct a multinomial logistic regression. *Journal of Social Service Research*, **35**(2), 193–205.

Power, D. J. (2008) Decision support systems: A historical overview. In: *Handbook on Decision Support Systems 1*. Springer, 121-140.

Roszkowska, E. and Wachowicz, T., eds. (2016) *Negocjacje. Analiza i wspomaganie decyzji*. Wolters Kluwer. https://www.legimi.pl/ebook-negocjacje-analiza-i-wspomaganie-decyzji-tomasz-wachowicz-ewa-roszkowska,b149781.html

SAATY, T. (1980) *The Analytic Hierarchy Process.* McGraw-Hill.

SAATY, T. L. (2008) Decision making with the analytic hierarchy process. *International Journal of Services Sciences*, **1**(1), 83–98.

SAATY, T. L. AND ERGU, D. (2015) When is a decision-making method trustworthy? Criteria for evaluating multi-criteria decision-making methods. *International Journal of Information Technology & Decision Making*, **14**(06), 1171–1187.

SAVAGE, S. J. AND WALDMAN, D. M. (2008) Learning and fatigue during choice experiments: A comparison of online and mail survey modes. *Journal of Applied Econometrics*, **23**(3), 351–371. https://doi.org/10.1002/jae.984

SCHOOP, M., JERTILA, A. AND LIST, T. (2003) Negoisst: A negotiation support system for electronic business-to-business negotiations in e-commerce. *Data & Knowledge Engineering*, **47**(3), 371–401.

SCOTT, S. G. AND BRUCE, R. A. (1995) Decision-making style: The development and assessment of a new measure. *Educational and Psychological Measurement*, **55**(5), 818–831.

STRACK, F. (1992) "Order Effects" in Survey Research: Activation and Information Functions of Preceding Questions. In: N. Schwarz and S. Sudman, eds., *Context Effects in Social and Psychological Research.* Springer, 23-34. https://doi.org/10.1007/978-1-4612-2848-6_3

TABACHNICK, B. G., FIDELL, L. S. AND ULLMAN, J. B. (2007) *Using Multivariate Statistics* **5**. Pearson Boston, MA.

TECLE, A. (1988) *Choice of multicriterion decision making techniques for watershed management.* Ph.D. Dissertation. University of Arizona.

THIESSEN, E. M. AND SOBERG, A. (2003) Smartsettle described with the montreal taxonomy. *Group Decision and Negotiation*, **12(**2), 165.

TOPLAK, M. E., WEST, R. F. AND STANOVICH, K. E. (2014) Assessing miserly information processing: An expansion of the Cognitive Reflection Test. *Thinking & Reasoning*, **20**(2), 147–168. https://doi.org/10.1080/13546783.2013.844729

TUREL, O. AND YUAN, Y. (2007) User Acceptance of Web-Based Negotiation Support Systems: The Role of Perceived Intention of the Negotiating Partner to Negotiate Online. *Group Decision and Negotiation*, **16**(5), 451–468. https://doi.org/10.1007/s10726-006-9069-z

WACHOWICZ, T., ROSZKOWSKA, E. AND FILIPOWICZ-CHOMKO, M. (2018) What Impacts a Choice of Decision Support Method in Multiple Criteria Decision Making Problem? In: X.-j. Jiang, H.-y. Xu, Sh.-w. He and G. Y. Ke, eds., *Proceedings of the 18th International Conference on Group Decision and Negotiation.* Nanjing University of Aeronautics and Astronautics, 275-279.

WACHOWICZ, T., KERSTEN, G. E. AND ROSZKOWSKA, E. (2019) How do I tell you what I want? Agent's interpretation of principal's preferences and its impact on understanding the negotiation process and outcomes.

Operational Research, **19**(4), 993–1032. https://doi.org/10.1007/s12351-018-00448-y

Wachowicz, T. and Roszkowska, E. (2021) Holistic Preferences and Prenegotiation Preparation. In: D. M. Kilgour and C. Eden, eds., *Handbook of Group Decision and Negotiation* (2nd ed.). Springer, Cham. 255–289. https://doi.org/10.1007/978-3-030-12051-1_64-1

Wątróbski, J., Jankowski, J., Ziemba, P., Karczmarczyk, A. and Zioło, M. (2019) Generalised framework for multi-criteria method selection. *Omega*, **86**, 107–124. https://doi.org/10.1016/j.omega.2018.07.004

Yoon, K. and Hwang, C. L. (1981) *Multiple Attribute Decision Making-Methods and Applications: A State-Of-The-Art Survey*. Springer-Verlag.

Yuan, Y., Head, M. and Du, M. (2003) The effects of multimedia communication on web-based negotiation. *Group Decision and Negotiation*, **12**, 89–109. https://doi.org/10.1023/A:102301680437