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Decision-makers' behavioral characteristics and multiple criteria decision-aiding. Impact of decision-making style and experience on methods' use, evaluation, and recommendation

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Abstract

The study aims to identify relationships among selected behavioral characteristics of decision-makers (DMs), i.e., experience in making complex decisions, decision-making style, and ability to use various multiple criteria decision-aiding (MCDA) methods coherently, and their impact on the evaluation of the latter functionality and recommendations for future use. The relationships were verified using experimental data through a structural equation model (SEM) and cluster analysis for three MCDA methods, i.e., AHP, SMART, and TOPSIS. One of the strongest effects identified by SEM was observed between coherence in methods' use and the DM's opinion on their functionality. DM's satisfaction and future willingness to use MCDA tools are related to the positive experience gained from using these tools in advance. Decision-making styles shape method selection, with TOPSIS favored by highly experienced DMs, SMART by highly rational, and AHP by those with low experience and a rational approach.

Keywords: *multiple criteria decision-making, behavioral characteristics, decision-making style, AHP, SMART, TOPSIS*

1. Introduction

Multiple criteria decision-aiding (MCDA) is a methodology offering methods and techniques widely used to facilitate decision-makers (DMs) in solving real-world problems of various natures and contexts where multiple conflicting evaluation criteria are involved [36, 51, 80]. All multiple criteria methods and techniques differ at the technical level in, among others, describing the system of preferences, elicitation of weights, the mathematical algorithm utilized, and the level of uncertainty embedded in the data set. Moreover, they make many assumptions that limit their applicability. Hence, no method is

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universal enough to solve every problem [4, 64, 97, 135]. However, the consequences of the inappropriately used MCDA technique may be a misleading or unsatisfactory solution, wrong decisions incurring losses in time, energy, and money, and the resulting DM's discouragement from future use of MCDA techniques [49]. Therefore, many studies offer various recommendation procedures on which method for which problem to use [30, 47, 108, 110, 132]. According to them, such recommendation depends on many factors, including the size and type of problem, type of data, way of preference elicitation, and the number of DMs.

Other studies point out that some behavioral issues may also play a role in evaluating and accepting the MCDA methods by DMs and hence be worth considering when searching for decision-aiding techniques adequate to particular decision-making problems and contexts [85, 86, 124, 129]. One of the crucial behavioral characteristics of DM is its cognitive capabilities, which are related to how DM processes information. Cognitive capabilities (and resulting cognitive styles) make DMs less or more prone to cognitive biases and heuristics that heavily affect decision-making. They can cause difficulties in providing accurate information about goals and preferences or understanding the mechanisms of action of algorithms and support methods [7, 50, 118, 125], which play a crucial role in successful problem analysis.

Researchers also noticed that different methods applied to the same problem with similar data could produce different results [61, 75, 97, 135]. One reason for such differences may be technical, i.e., the methods use different algorithms for preference elicitation and aggregation. However, the other reason may be the cognitive limitations of DMs that make them more or less able to operate with a particular MCDA algorithm efficiently. These cognitive limitations may be linked to other behavioral characteristics of DM, such as knowledge of MCDA tools, experience in their use, and general mathematical skills [75], which impact further behavioral evaluations such as understanding and acceptance of the applied method [5, 90]. Therefore, Roy and Słowiński [108] pay attention to intelligibility, axiomatic characterization, and weaknesses of the considered methods in selecting the MCDA method. It allows DMs to reduce the unpleasant feeling of *being manipulated by a black-box methodology* as they may more easily understand the way that the technique operates [97].

Finally, MCDA methods are usually not used without accompanying software support, i.e., decision support systems (DSS) [30, 89, 101]. DSSs perform all necessary computations but involve DMs in the preference elicitation process. Therefore, potential problems with using DSS, e.g., due to a poorly designed interface, may result in weak acceptance of the DSS and the MCDA method [104, 115]. Hence, in some recommendations on MCDA selection, the way of interacting with DSS is also raised as an issue [30, 47, 53, 91]. Additionally, research on cognitive styles confirms that if the decision support system considers the user's cognitive style, DSS is more effective and user-friendly [16, 77, 126].

As shown above, many studies extensively explore simple connections between selected issues of using MCDA tools. Some study the behavioral and cognitive aspects of multiple criteria decision support (see, e.g., [40, 48]), while others focus on analyzing the impact of these issues on the evaluation of DSS methods and systems [5, 27]. Finally, others examine the efficiency of different techniques used to support DMs in solving problems of various contexts and nature [30, 132]. However, there is still a lack of comprehensive empirical works investigating how all these issues interlace in the process of multiple criteria decision-aiding supported by software tools and what is the structure of significant causative relationships among them. The absence of such comprehensive studies makes it impossible to draw descriptive conclusions regarding how decision-making experience impacts cognitive capabilities and how both of these factors collectively influence a DM's ability to effectively use MCDA methods, evaluate their functionality, and ultimately determine their intent to use them in resolving future decision-making problems. This research gap is highly vital for behavioral operations research theory.

Therefore, this study aims to identify the structural relationships among the behavioral factors that impact the use and evaluation of MCDA methods. We verify experimentally:

- How do the behavioral factors represented by the decision-making style and the decision-making experience affect the DM's ability to use different MCDA methods coherently?
- How do the aforementioned behavioral factors and the resulting ability to coherently use the MCDA methods impact the subjective evaluation of the functionality of these techniques?

We also verify the relationships between the aforementioned behavioral factors and DM's considerations regarding which MCDA technique is best suited for supporting real-world decision-making problems. Based on our best knowledge, no empirical studies are investigating such a structure of relationships, which includes mediating mechanisms between the behavioral characteristics of DM and their direct and indirect impact on the perceived functionality (PF) of MCDA methods. Nor could we find earlier studies that link the behavioral factors with DMs' selection or recommendation of a multiple criteria decision-aiding method.

Our study uses the data from an online multiple criteria decision-making (MCDM) experiment, which consists of detailed transcripts of DM's performance when using online DSS as well as responses to a series of surveys. It allowed us to build the structural equation model (SEM), explaining the potential causal relationship among the factors describing the behavioral profile of DM and the decision-aiding results and their evaluation, and then investigate in a clustering-based approach the relationship between the enhanced cognitive profile and recommendations of MCDA methods for future analyses in solving the MCDM problems.

Such a formal approach allows us to establish an original, authorial contribution to the development of behavioral operations research theory. This contribution is comprised of quantitatively verified descriptive conclusions regarding the directions, strength, and significance of the impact of decision-making experience and cognitive style on a DM's ability to utilize three multi-criteria decision support methods i.e., Analytic Hierarchy Process (AHP) [109], Simple Multiple Attribute Rating Technique (SMART) [38], and Technique for Ordering Preferences by Similarity to Ideal Solution (TOPSIS) [60]. Additionally, it encompasses the evaluation and intention to use these methods in the future to resolve various multi-criteria decision problems. Apart from enhancing the science of behavioral operational research, our study has also practical contribution to DSS designers and decision analysts. It indicates the behavioral characteristics that should be considered while designing the cognitive support systems as defined by Kersten and Cray [67] and hence reduces, what was pointed out by Cassaigne et al. [26], as *a challenge for i-DMSS is to be flexible and adapt the cognitive style of the user of the system.*

This paper consists of six sections. In Section 2, following the Introduction, a literature review in terms of MCDA is provided with links to behavioral issues related to information processing style, decision-making experience, and DM's analytic abilities to show our motivation to build the causal model of the possible relationships. Then, the hypotheses are formulated, and the research model is proposed.

In Section 3, the experimental setup used to verify the model is described, as well as the notions and concepts used to formulate the key factors. Section 4 presents the results obtained through the structural equation model and cluster analysis. Finally, in Section 5, the results are discussed. The outlooks for future work showing how the model can be extended are discussed in Section 6.

2. Literature review and hypotheses development

DMs have various behavioral characteristics that influence their decision-making. These characteristics include (1) experience, skills, and knowledge about problem-solving and using multiple criteria methods, (2) cognitive abilities to work with MCDA techniques, and (3) decision-making style. In the following subsections, we discuss them and formulate hypotheses on their potential relationships.

2.1. The selection and use of multiple criteria decision-aiding methods

2.1.1. Choosing the MCDA method for solving a decision problem

Various MCDA methods can lead to different rankings; their selection is often subjective and dependent on DM. Some researchers proposed guidelines for selecting an appropriate method, for instance, the model choice algorithm [46, 47], the model selection process [122], interactive decision support systems [132], and expert systems [62, 101]. Alongside many alternative recommendations regarding selecting the MCDA technique, there is also no agreement on the criteria for choosing the most appropriate method. Several researchers suggest various criteria for evaluating MCDA methods [30, 53, 92, 110] that focus on the problem, technique, decision-maker (or analyst), and decision support system. Different decision situations (problems) have distinct characteristics (for instance, the type of decision problem, its scale, and the type of data available), which should match the technical requirements of methods applied to analyze and solve them. Techniques themselves differ in algorithms, preference information required from DM, solution properties, or ease of use. Also, DMs, who must provide the preference information, differ in their decision-making styles, cognitive capabilities, skills, and experience. The criteria related to the decision support system include the interface's usability that implements the MCDA methods, easiness, transparency, and the preferred way of interacting with DMs.

Some researchers propose taxonomies and recommendation systems based on criteria that focus primarily on the technical aspects of the problem and preference elicitation process. The first taxonomy of MCDA methods was introduced by MacCrimmon [78], who also proposed a choice rule based on a tree diagram. A similar approach was presented later by Hwang and Yoon [60]. As the new methods and techniques were designed, new taxonomies were proposed. Recently, Wątróbski et al. [132] provided a generalized framework in the form of rules for selecting MCDA methods for decision-making situations. They also offer an interactive web-based tool that allows them to set a series of filters to choose the one that fits the decision-making context best. Similarly, Cinelli et al. [30] proposed a taxonomy of characteristics for the multiple criteria decision analysis process that can be used in searching for the best fitting multiple criteria approach.

2.1.2. The behavioral criteria to evaluate MCDA methods

Some studies explicitly identify the criteria that address DMs' behavioral features. Gershon and Duckstein [47] proposed a compromise programming procedure to choose an appropriate MCDA technique based on 28 criteria, including characteristics describing the problem, the techniques, and DMs. Among the latter, they identified such criteria as DM's desire for interaction, technique knowledge, and evaluation of technique simplicity. They argued that a *thorough understanding of the technique helps the decision-maker to understand fully the meaning of the solution*. Similarly, Evans [43] and Ozernoy [91, 92] paid attention to DM's characteristics that should be considered when selecting MCDA methods. They include DM's acceptance of a particular method and the ability to provide the preference information required by this method. Leoneti [75] distinguishes six critical factors in choosing the MCDA method and suggests that besides comparing the axiomatic characteristic of methods, some other issues – more related to the decision-making context – should be considered. They are available time, the effort required, the importance of the accuracy of results, transparency of the analytic process, and the skills needed for using the method. Guitouni and Martel [53] explicitly address the DM's cognition, to which they include, among others, DMs' subjective perception of the comfort of work with the methods (i.e., if they prefer to compare alternatives pairwisely or in direct rating). Together with other authors [47, 59, 122], they also raise the importance of the algorithm's transparency, the interface's usability when implemented as a software tool, and ease of use.

The fact that MCDA tools are widely implemented in decision support systems [89, 101] may make the DMs evaluate the former through the prism of software evaluation. In this context, it is necessary to investigate what may affect the acceptance of applied systems and the usefulness of proposed decision support methods. Petter et al. [96] presented an extensive literature review of 180 studies from 1992 to 2007, dealing with various aspects of the success of information systems (IS). Applying DeLone and McLean (D&M) model, 90 empirical studies were examined, and results were summarized using the six dimensions — system quality, information quality, service quality, use, user satisfaction, and net benefits. It is worth noting that the TAM-based models are often implemented [5, 27, 104, 115] to consider the acceptance of different methods implemented in DSS.

Considering the aforementioned behavioral issues, a notion of the perceived functionality of the MCDA method may be defined. It relates to DM's subjective evaluation of this method and includes its ease of use [4, 47, 59, 122], time and effort requirements [47, 75, 122] evaluation of interface [47, 53], and perceived quality of the results when confronted with initial DM preferences [75]. Perceived functionality defined this way may depend on DM characteristics that describe their experience and skills in decision-making gained from their past professional activity, awareness of MCDA tools (knowledge of a technique), and DM's ability to provide the preference information required by this method. One may easily note that all the abovementioned issues define DM's general experience in decision-making with and without using MCDA techniques. Such experience is often considered a key factor when selecting an MCDA method for solving a particular problem [75, 91, 92]. Having a higher or lower decision-making experience, DM may vary from their colleagues in valuing the MCDA technique as an adequate, efficient, and useful tool. Therefore we formulate the following hypothesis:

H1: The decision-maker experience (DME) in decision-making impacts the perceived functionality (PF) of the MCDA technique.

2.1.3. The consistency of results obtained by MCDA methods

Many authors have already investigated how using different MCDA methods may affect the results of decision analysis (e.g., the differences in rankings) [22, 59, 83, 87, 133, 135]. As reported by Zanakis et al. [135], ranking methods might produce different rankings because: (1) they implement different weights calculation techniques used, (2) the algorithms differ in their approach to selecting the best solution, and (3) some algorithms introduce additional parameters that affect the chosen solution. Yeh [133] also claims that there is no best method for multiple criteria decision problems, and even for the same weighting vector, the rank order may vary depending on the method used, and this mismatch increases as the number of alternatives increases. Moshkovich et al. [87] concluded that *implementation of the same criterion weights and scale transformations for criterion values produced significant differences in the ranking of alternatives when two different methods were used for the aggregation of the preferential information.* Those results confirm the difficulty of selecting an appropriate multiple-criteria ranking method.

Hobbs [59] conducted an experiment that applied different methods to the same problem and tried to identify questions that may help DMs choose the method. He suggested that experiments that apply different methods to the same problem may help clarify the differences between the mechanisms used by those methods. Buede and Maxwell [22] conducted a series of simulation experiments using the Monte Carlo approach to study techniques inconsistency in rankings of alternatives (with a particular focus on top-ranked ones) obtained through a few different methods, i.e., additive scoring following MAVT principles, AHP, percentaging, TOPSIS, and fuzzy algorithm proposed by Yager. They found that, in general, MAVT and AHP seem to generate the most similar results; however, other issues might have a more significant impact on the consistency of final results than the choice between the computational algorithms of MAVT and AHP. There may be differences in structuring the problem and weights elicitation. Also, Mela et al. [83] compared six different methods within three cases from the field of building designs to find that the differences in the results may depend on the structure of criteria weights. They noted that *the degree of conflict of the criteria can have a significant impact on the behavior of the MCDM methods.* When similar importance of criteria was assumed, the methods generated fairly similar results. Contrary, when the conflict between criteria increases, the differences may occur significantly. It seems clear then that for adequately defined criteria weights, there are no obstacles for DMs who diligently use some MCDA techniques (at least those based on similar preference aggregation procedures) to obtain similar rankings of alternatives (coherent results). The higher the DM's experience in decision-making, the more they should be able to diligently use the MCDA techniques and elicit their preferences more coherently. Finally, the coherent results obtained from different MCDA methods should improve the DM's satisfaction and the acceptance of using them for solving problems. It allows us to formulate the following hypotheses:

H2: DM's experience (DME) in decision-making impacts their ability to use different MCDA methods (COH) coherently.

H3: DM's ability to use different MCDA methods coherently (COH) impacts the perceived functionality (PF) MCDA method.

2.2. Decision-making style and its impact on multiple criteria decision support

2.2.1. Decision-making style and its measures

Decision-making style, which is often considered as cognitive style, is defined as habitual behavior [37], learned, habitual reaction [114], and response pattern [123] in the decision-making situation. It can explain how the mind works [106] and how the information is used [107] when deciding. Thunholm [123] further notices that cognitive abilities such as information processing, self-evaluation, and self-regulation can have a consistent impact on the decision-making process, and *since decision-making style not only involves habit, it might have an impact on decision support systems.* Consequently, it may determine the DM's preferences regarding data presentation, how preferences are analyzed (e.g., qualitatively or quantitatively), and the DSS used [124]. There are many instruments used for measuring decision-making or cognitive styles, such as the Myers–Briggs Type Indicator Test (MBTI), General Decision-Making Style Inventory (GDMS), Cognitive Style Index (CSI), Kirton Adaption-Innovation Inventory (KAII). However, the Rational-Experiential Inventory (REI) [93] seems to be one most well-known and frequently used in practice [10, 17, 117]. It assumes the existence of two different and orthogonal information-processing systems – rational and experiential ones. The rational information processing system is slow, deliberative, rule-governed, and analytical. On the other hand, the experiential system is considered fast, operating automatically and holistically [41, 42, 93].

2.2.2. Decision-making style, decision-making experience, and their impact on the decision process

Armstrong et al. [6] comprehensively review cognitive style's theory, measurement, and practical relevance for business and management decision-making. However, along with the decision-making style, other behavioral characteristics, such as experience and skills, are also reported to impact individual decision-making substantially [21, 94, 95]. Abdelsalam et al. [1] investigated the relationship between the decision-making styles of Egyptian managers and several demographic variables. They showed that it is affected by gender, total years of experience, business type, and the total number of employees in the organization. In experimental studies, Bjork and Hamilton [17] showed that, with the nurses' service length, they were more likely to use an intuitive style of thinking rather than a rational (REI test). Baiocco et al. [12] found that higher school achievements were positively associated with the rational decision-making style (GDMS test). In contrast, the number of absences from school was positively related to spontaneous and avoidant styles. Bavolar and Orosová [14] showed that avoidant and spontaneous decision-making styles (GDMS test) are related to how the DMs would make decisions in real-life situations (declared in the A-DMC test). Other studies reported relationships between decision-making style (GDMS test) and indecisiveness and rationality in decision-making [32], job satisfaction, job search process [31], and decision outcomes [94], among others.

Stanovich et al. [119] argued that decision-making skills might be related to dispositional thinking styles (such as the need for cognition) associated with heuristic thinking overridden by analytical thinking. Empirical results [25, 84] generally confirm the view that some aspects of decision-making skills such as resistance to framing and sunk cost are related positively to the need for cognition (the extent to which people engage in and enjoy thinking) [24]. The results provided by Bruine de Bruin et al. [21], Parker and Fischhoff [95], and Mohammed and Schwall [84] suggest additionally that overall decision-making skills are related positively to the rational decision-making style and negatively to the spontaneous and avoidant decision-making styles.

As we see from the above, the literature suggests some relationship between experience and decision-making profile may occur. Hence, we formulate another hypothesis:

H4: DM's experience (DME) in decision-making impacts their decision-making style (DMS).

Considering different levels of engagement in information processing by DM with various decision-making styles, one may expect different results (in terms of quality) while using various MCDA techniques. For example, DMs with a high rational mode may more precisely impart information about their preferences in the preference elicitation protocol implemented by a particular method and avoid a series of errors or biases. The latter has already been proven to result in inaccurate scoring systems produced by MCDA techniques mismatching the DM's actual preferences in the negotiation context [69, 130]. Building on this research, we hypothesize that:

H5: DM's decision-making style (DMS) impacts its ability to use different MCDA methods coherently (COH).

2.2.3. Decision-making style and multiple criteria software decision support

Fuerst and Cheney [45] investigated the characteristics of DMs, the decision support system, and the implementation process that may affect the use of DSS. They studied eight systems and 64 subjects from the oil industry and found that the most important variables affecting decision support system usage were output accuracy, user training, relevancy of output, and the DM's experience. Davis and Elnicki [34] presented the results of an experiment investigating relationships between cognitive types, information presentation, and their effect on decision-making performance within decision support. Experimental results demonstrated significant differences in performance by cognitive types. Sensation-thinking DMs performed better with tabular data reports while intuitive-thinking – with graphical data reports. Green and Hughes [52] experimentally confirmed the interactions between decision-making style (MBTI test) and the type of training that influenced the initial use of DSS by DMs. They recommended seminars for heuristic DMs and hands-on workshop experiences for analytic DMs. They also found that training and decision-making style affect the time of the decision-making process, and they influence the amount of data used and the number of alternatives invented by DM in the decision-making process. The influence of experience, gender, intelligence, and decision-making style on DSS effectiveness was also highlighted by Ramamurthy et al. [99]. Chakraborty et al. [27] examined DM's acceptance of new technologies using the technology acceptance model [35]. They showed that cognitive style (KAII test) directly impacts perceived usability, perceived ease of use, and subjective standards. Both perceived usability, and subjective standards affect the actual use of technology. People with innovative cognitive styles are more likely to perceive new technology as useful and easy to use than those with adaptive cognitive styles.

Lu et al. [77] examined the acceptance of the Fuzzy Weighted Sum Model (FWS), AHP, and Linear Weighted Sum Model (WSM) that were implemented in DSS from the perspectives of DM's decision-making style, beliefs, and attitudes. The relationships between decision-making styles and DSS acceptance vary across methods. They show that perceived ease of use of those techniques does not directly affect willingness to use them in the future. The system should be flexible and adaptable for different users, as, for instance, those with higher intuitive modes may prefer to use the FWS model (though no significant relationships were found between its evaluation and perceived ease of use). Building upon empirical evidence that decision-making style can influence the use and perceived usability of DSS [27, 52], actual use of MCDA technique [77], and preferences towards information presentation [34], we predict that:

H6: The decision-making style (DMS) impacts the perceived functionality of MCDA tools (PF).

Summing up the previous considerations regarding the selection and use of MCDA methods (Section 2.1) and the behavioral criteria used to evaluate them (Section 2.2), we intend to answer the following question:

Q1: How do the behavioral factors identified above, i.e., decision-maker experience (DME), decision-making style (DMS), ability to use different MCDA methods coherently (COH), and perceived functionality of MCDA tools (PF), differentiate the DMs in their selections (recommendations) of the MCDA methods as the best suited for future use?

2.3. Structural model for relationships and consequent mediation relationships

The hypotheses H1–H6 defined above show the general relationships among three selected behavioral factors, i.e., decision-making experience (DME), decision-making style (DMS), and coherence in use of the MCDA methods (COH), affecting the perceived functionality of MCDA methods (PF). These relationships, when considered separately, define a series of direct causal impacts between the selected factors. However, when considered jointly, they build a complex structure within which, despite the direct impact, the indirect ones can also be observed, i.e., one factor may impact another via a mediating factor. For instance, the impact of DMS on PF may be measured directly but also indirectly through the mediator COH, reflecting the relationships defined through the hypotheses that DMS impacts COH and COH impacts PF. Hence, the hypotheses posed in the previous subsections can reflect general (total) causative effects between the factors and should be verified by considering a series of possible sequences of direct paths in the model. In Figure 1, we show all the paths (P) reflecting the direct relationships between the factors we considered.

We hypothesized that DME affects perceived functionality (PF) (H1). As shown in Figure 1, path P1 in the model depicts the direct relationship between these factors. However, DME also affects DMS (P4) and COH (P2), and both DMS and COH are hypothesized to affect PF (P6 and P3, respectively). Thus, the indirect effect of the relationship DME $\rightarrow$ PF is identified by the paths P4–P6 (DME $\rightarrow$ DMS $\rightarrow$ PF), P2–P3 (DME $\rightarrow$ COH $\rightarrow$ PF), and P4–P5–P3 (DME $\rightarrow$ DMS $\rightarrow$ COH $\rightarrow$ PF). Thus, the general hypothesis H1, defined previously in Section 2.1.2 and addressing a total effect of DME on PF, can be formulated in detail through two subhypotheses, H1a, and H1b:

H1: DM's experience (DME) in decision-making impacts the perceived functionality of the MCDA technique (PF).

H1a: DM's experience (DME) in decision-making directly impacts the perceived functionality of the MCDA technique (PF).

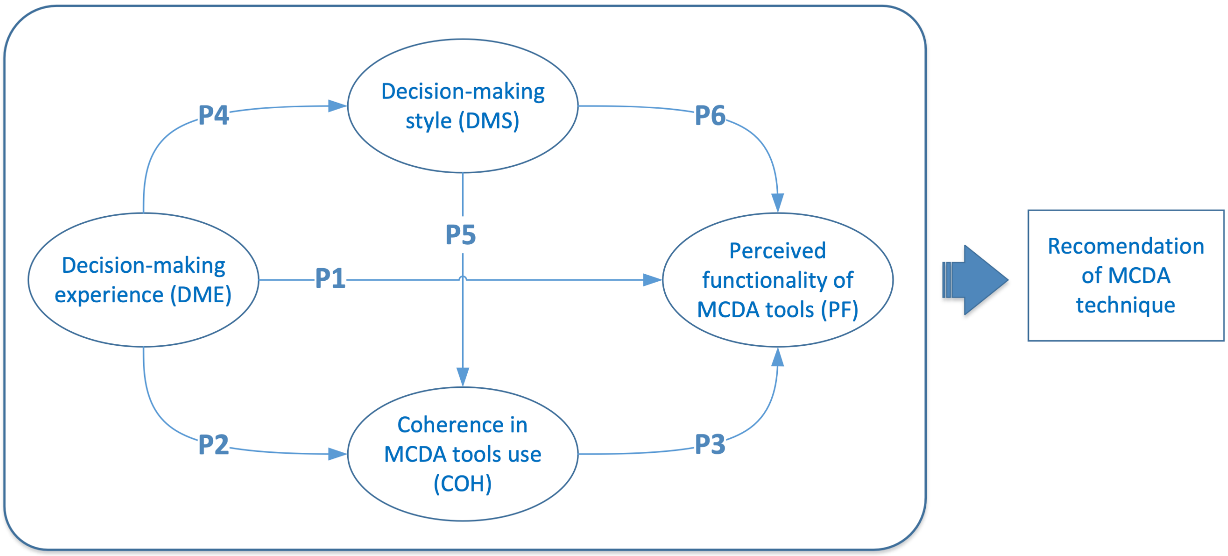

Figure 1. An overview of the model of behavioral relationships.

H1b: DM's experience (DME) in decision-making indirectly impacts the perceived functionality of the MCDA technique (PF) through the mediators DMS and COH.

Similarly, we have hypothesized that DME affects COH (H2). As shown in Figure 1, this relationship may be directly depicted by path P2. However, we should also consider that the indirect effect of the relationship DME $\rightarrow$ COH may be identified by the paths P4–P5 (DME $\rightarrow$ DMS $\rightarrow$ COH). Therefore the general hypothesis H2 can be provided through H2a and H2b:

H2: DM's experience (DME) in decision-making impacts their ability to use different MCDA methods coherently (COH).

H2a: DM's experience (DME) in decision-making directly impacts their ability to use different MCDA methods coherently (COH).

H2b: DM's experience (DME) in decision-making indirectly impacts their ability to use different MCDA methods coherently (COH) through DMS as a mediator.

Finally, a similar situation occurs when the effects of DMS on PF are to be verified. The direct effect may be measured through path P6 and the indirect one – through COH as a mediator (path P5-P3). Hence, hypothesis H6 can now be detailed as follows:

H6: The decision-making style (DMS) impacts the perceived functionality of MCDA tools (PF).

H6a: The decision-making style (DMS) directly impacts the perceived functionality of MCDA tools (PF).

H6b: The decision-making style (DMS) indirectly impacts the perceived functionality of MCDA tools (PF) through COH as a mediator.

Considering that the factors used to formulate the hypotheses are described quantitatively on strong scales, the structural equation model (SEM) can be used to test the aforementioned complex structure of relationships formally. Finally, answering Q1 aims to verify the choices of methods made by the decision-makers that differ in their cognitive profiles. Technically, the exogenous variable verified within Q1 is nominal and cannot be directly included in a classic SEM. Therefore, we will verify it by conducting a simple cluster-like analysis and testing the differences in values of behavioral variables using classical statistical significance tests.

2.4. The MCDA methods applied in the experiment

Nowadays, there is an abundance of MCDA methods and their modifications [111]. Each of them has its advantages and limitations. Therefore, when choosing the methods for our experiment, we focused on those reported to be the most frequently used in real-world applications. Additionally, we wished to compare the methods that operate with a similar preference model and preference aggregation philosophy to ensure that potential differences in results they produce are more related to the DM's behavioral characteristics than to the technical properties of the methods and their aggregation mechanisms. Undoubtedly, the techniques that satisfy these conditions are AHP [109], SMART [38], and TOPSIS [60]. They are widely described and applied in MCDA [15, 39, 72, 137] and different application areas [57, 136].

The SMART method is a part of the classical techniques, including Direct Rating, SAW, or Point Allocation [19, 29, 76]. In these approaches, decision-makers are responsible for assigning a direct rating to each of the alternatives or allocating a budget of points among the alternatives. These methods demonstrated their effectiveness within decision support systems and negotiation experiments [68]. Therefore, the decision to include the SMART method in the experiment was a natural one.

Even though in the literature, we observed the development of new or hybrid methods based on similar concepts like AHP (e.g., FUCOM, BWM, DIBR, OPA, LBWA), or TOPSIS (e.g., MABAC, MAROCS, VIKOR, MAIRCA), they are not as popular as those three selected to the experiment [11]. The bibliometric analysis of the multiple criteria decision-aiding methods from 1977 to 2022 provided by Basilio et al. [13] confirmed that researchers most frequently use AHP and TOPSIS. Zyoud and Fuchs-Hanusch [137] conducted a bibliometric-based survey describing the total research output of 10188 documents AHP and 2412 documents of TOPSIS. The authors also conclude that those methods are *highly active fields of research among the MCDA methods and they are a good representative example of the diverse applications of MCDA methods in conjunction with other disciplines*. Madzik and Falat [79] investigated $35,430$ documents retrieved from the Scopus database related to AHP and published between 1980 and 2021.

Concluding, many researchers argued that those methods are intuitive, logical, and easy to understand and to implement [127, 136]. Therefore, the comparative performance of AHP, SMART, and TOPSIS techniques is of fundamental importance and great interest from a theoretical and practical point of view. In our experiment, the difference between AHP, SMART, and TOPSIS methods concerns the way the preferences are elicited. In AHP, the alternatives are compared pairwisely using a 9-point linguistic scale. TOPSIS uses the notion of distances that automatically transform the quantitative description of alternatives into scores and only requires DM to provide the weights and evaluations of quantitative issues. SMART uses the direct rating mechanism, in which DMs assign numerical scores to options. The differences in preference information required by these techniques and the ways of imparting them may attract different types of DMs [77]. However, they still aggregate these preferences using the same additive preference model based on multi-attribute value theory (MAVT) [66], which accepts preference compensation and criteria preference independence.

3. Experimental setup and methodology

This section presents the experimental setup used to verify the research model. We define the main notions and operationalize the main concepts used in this model, the relationships between which we want to confirm, i.e., decision-making experience (DME), decision-making style (DMS), coherence in use of the MCDA methods (COH), and perceived functionality of the MCDA tools (PF). Finally, the participants of the experiment are described.

3.1. Description of the experiment

To reach the research goal, we organized the online multiple criteria decision-making experiment through the purposely designed online decision support system (ODSS). In the experiment, the participants faced a predefined MCDM problem, in which they acted as the DM who evaluated alternatives of flats to rent. The problem was well-structured in a decision matrix, including five alternatives and five evaluation criteria. The performance of the alternatives was described using various scales, depending on the criterion. For instance, a nominal scale was used to describe the equipment of the flats, while the intervals depicted the commuting time. The performances of all alternatives were chosen purposely to avoid evident dominance among them (see Table 1).

Table 1. Decision matrix in the ODSS experiment

Alternative	Rental costs [PLN]	Number of rooms	Size [m^2]	Equipment	Commuting time [min]
A	950	2 (1 room with a kitchenette)	35	fridge, washing machine, microwave	10–12
B	1200	3 (living room with a kitchenette)	54	fridge, washing machine, dishwasher, wireless internet	30–35
C	900	2 + kitchen (separate)	35	fridge, washing machine, cable internet	20–25
D	700	1 + kitchen	25	fridge, washing machine, TV, cable TV, cable internet	30–35
E	950	1 + kitchen	54	fridge, washing machine, cable internet	20–25

The experiment in ODSS consisted of four main phases presented in Figure 2.

In phase 1, the participants completed a pre-decision-making questionnaire, collecting personal and demographic data. The questionnaire also included items about the decision-making experience of users. In phase 2, they read the problem. Then, in phase 3, the participants determined the issue weights, and the alternatives were compared in a series of single-criterion analyses. Three decision support modules were implemented in ODSS to compare the alternatives, each using one MCDA technique, i.e., AHP, SMART, and TOPSIS. These modules were implemented in the experimental protocol in ODSS using a randomization mechanism, which was responsible for organizing the decision-aiding process using various sequences of methods displayed to subsequent respondents. It is a commonly used practice in experimental studies operating with repeated measures, which allows eliminating the learning or fatigue effect that might affect the conclusions when the order of measures is the same for all the participants [28, 120, 128]. The decision-aiding modules operated with different user interfaces that fit the

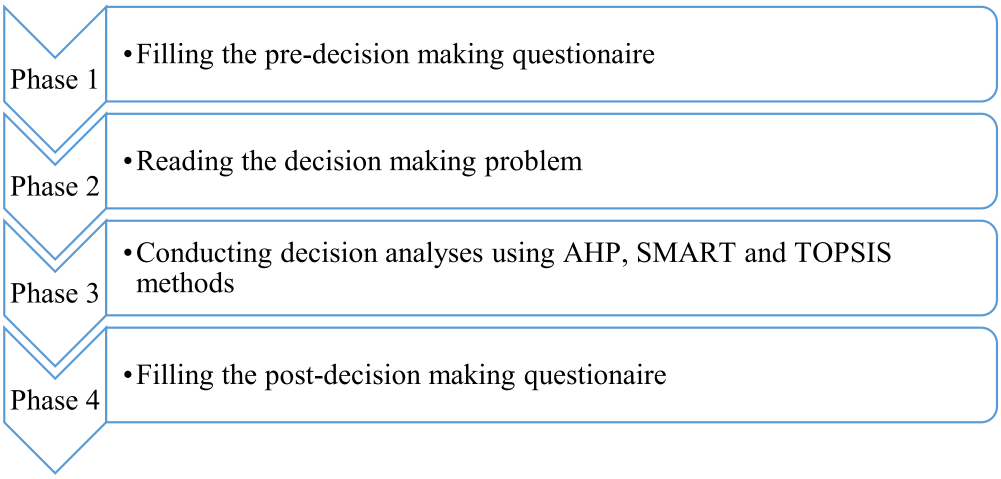

Figure 2. The phases of the ODSS experiment.

requirements of the algorithms of these methods. For the AHP method, the preferences are classically imparted using pairwise comparisons of options and a 9-point verbal scale. Therefore, the user interface in our AHP module operated with a series of sliders, with the accompanying linguistic description of the strengths of preferences. The usual mechanism of assigning the rating points for the SMART method was implemented, using a predefined scale from 0 to 100 points. Thus, the user interface operated with classic boxes to which DM typed the amounts of rating points for each option. Finally, the TOPSIS method performs the procedure automatically if the problem is quantitative, as options are assessed using distance measures. However, to assess the qualitative options, a mechanism for obtaining their numerical equivalents from the DM needs to be designed first. We used simple pictograms (stars of quality) often implemented on various internet websites. It allowed for avoiding the necessity to define preferences numerically. The examples of the interfaces are shown in Figure 3.

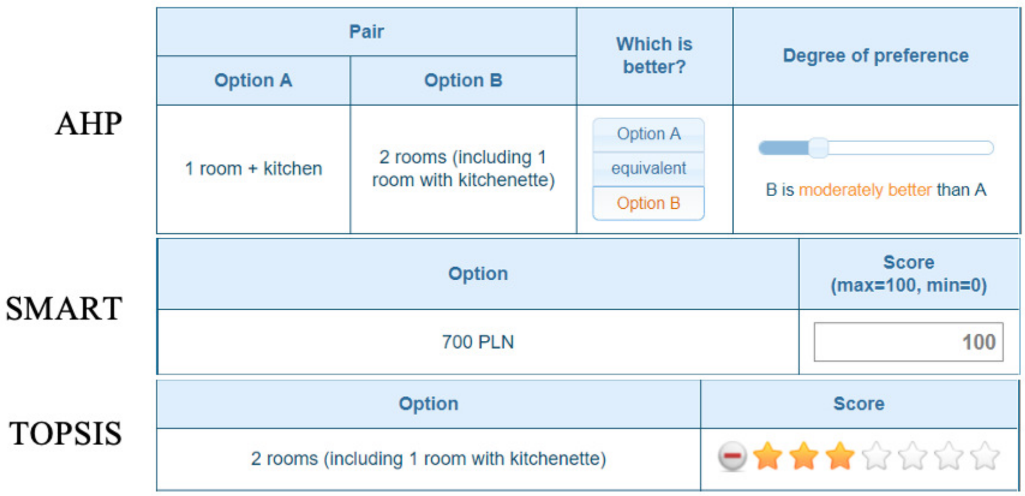

Figure 3. ODSS interfaces for AHP, SMART, and TOPSIS methods used for alternatives' evaluation.

Finally, in phase 4, the participants filled out a post-decision-making questionnaire, in which the REI test and the questions about the evaluation of decision support modules were included.

3.2. Methodology

In our model, four components are used to operationalize the main concepts, the relationships between which we want to confirm (Figure 1). These are decision-making experience (DME), decision-making style (DMS), coherence in the use of the MCDA methods (COH), and perceived functionality of the MCDA tools (PF). In this study, every component was measured in the following way:

- **Decision-making experience (DME)** was assessed using self-declared answers to three questions from the pre-decision-making questionnaire expressed on a 7-point Likert scale:
  1. How often in your professional life do you make multiple criteria business decisions? (from 1 (very rarely) to 7 (very often)).
  2. How would you rate your decision-making skills? (from 1 (I have extreme difficulties making decisions) to 7 (I have minimal difficulties making decisions)).
  3. How well do you know decision support methods? (from 1 (very poor) to 7 (very well)).

     We will refer to these items later in the manuscript and the figures by their names: [frequency], [skills], and [methods' knowledge], respectively.
- **Coherence in MCDA use (COH)** was measured using Kendall's tau correlation between the rankings of alternatives obtained from three implemented methods (AHP, SMART, TOPSIS). Kendall's tau coefficient is commonly used to verify the degree of similarity between rankings when the ordinal concordance should be considered [90, 116]. In our study, three coefficients were computed, one for every two rankings determined by two methods (AHP-to-TOPSIS, AHP-to-SMART, and TOPSIS-to-SMART). These coefficients described the coherence in the results obtained by the DM when using every two methods. To describe the DM's general coherence when using the MCDA techniques, we built a latent construct that reflects the series of coherences in pairwise comparisons.
- **Perceived functionality of the MCDA tools (PF)** was measured using subjective declarations of the method's functionality in the post-decision questionnaire. To formulate items that reflect functionality, we based on the criteria suggested by other researchers in earlier studies: simplicity of use [53, 58, 59, 92, 110], evaluation of interface [53, 92], reliable representation of preferences [110], and time required to perform the analysis [75]. Hence, the respondent evaluated the functionality of each method according to the following criteria using a 7-point Likert scale: ease of use (from 1 (simple) to 7 (difficult)), interface (from 1 (intuitive) to 7 (complicated)), preference representation (from 1 (preserving preferences well) to 7 (preserving preferences poorly)), and time (from 1 (fast) to 7 (time-consuming)). PF was determined for each method separately but we also built a second-level construct that described the global perceived functionality of MCDA methods.
- **Decision-making style (DMS)** was measured using an REI-20 instrument. REI is a psychometric measure based on the concept of dual-process developed by Pacini and Epstein [93] which assesses individual preference for rational and experiential thinking styles. These two thinking styles have been shown to predict behavior independently [42]. The original version of the inventory [93] was composed of 40 items. However, this test has some modifications, e.g., a shortened version of the REI-20 [98, 102] or the REI-A for adolescents [81]. The reason for introducing these reduced versions of REI tests was that for some types of respondents (such as adolescents in REI-A), the nuances of the meaning of some sentences describing their behavior might be indistinguishable.

To avoid similar problems in the Polish translation of the REI test, we used reduced REI-20, which contains 20 questions, all measured on a 5-point Likert scale (see Table A1 in Appendix A). We used three independent translations of the original REI-20 test and reconciled the translation differences to obtain a common text.

- The respondents provided **a recommendation for MCDA methods** in the post-decision-making questionnaire. They answered the following question:

> Which MCDA techniques (AHP, SMART, or TOPSIS) would you recommend as the best for supporting the multiple criteria decision analysis?

We categorized the respondents into three classes related to the recommendation of a particular technique. Then the differences in values of the behavioral characteristics were determined using non-parametric tests (Kruskal–Wallis and Mann–Whitney ones) to find which differentiated the classes significantly.

Note that all the general concepts mentioned above are operationalized as latent variables, according to the principles of SEM. They are obtained in a preestimation phase through a series of mixed E/CFA analysis [71]. Using latent constructs estimated this way has an advantage over implementing other measures that aggregate multidimensional data, e.g., an average value from multiple items (answers). First, it improves the interpretability of the results by allowing us to verify if the structure of relationships meets the philosophical requirements of the analysis (i.e., if the items assumed to form a construct reveal adequate loading values). Second, it allows for handling potential measurement errors that may occur from the empirical data. Finally, it can help identify and mitigate the problem of multicollinearity and redundancy that may be included in the model when an average value is determined without any reflection of the primary data.

3.3. Participants

The experiment was organized in a few sessions from 2016 to 2018. The participants were 753 students from five Polish universities who participated in academic courses in decision-making and operational research (University in Białystok, University of Economics in Katowice, Bialystok University of Technology, Medical University of Bialystok, and State Vocational University in Suwalki). They all obtained prior training during which they were solving various decision-making cases and learned decision-aiding techniques. In the experiment, we used a decision-making situation of evaluating several flats to rent. This is the problem students usually encounter before starting each semester. Therefore, we may assume that the participant's decision-making situation is typical of any decision-making situation in which DM (e.g., manager) makes a decision within their business domains (e.g., procurement negotiation) having previous experience and knowledge in that field. Furthermore, to increase the consequentiality of their participation in the experiment, students received extra points that affected their final course grades.

It is worth noting that researchers still argue about using students in experiments and surveys and how the results of such experiments may be generalized. However, some studies show that many questions and hypotheses may be effectively answered using datasets containing students' responses. For example, early studies by Remus [103] confirmed that when the line managers and the students make production-scheduling decisions, they do not differ significantly in cost efficiency. Furthermore, when analyzing negotiation experiments, the researchers found that students with some negotiation training and experience perform better than untrained ones and that professional negotiators do not significantly outperform them [56]. Despite contradictory opinions also occurring [8], we believe that by keeping the decision-making context familiar to the students, we ensure the problem's gravity and reality. Although it cannot be generalized to all decision-making situations, it may allow for building a more detailed theory within the boundary conditions assumed in our relationship model.

Finally, the dataset was verified for potential outliers. We followed the classical recommendations for CFA and SEM and identified them using a straightforward analysis based on the Mahalanobis multiple criteria distance measure (with the rigor of $p > 0.001$). As a result, ten students (1.3% of the sample) were removed from the sample. In further analyses, we used a sample consisting of 743 participants. The basic demographic and behavioral characteristics of the respondents are shown in Table 2.

Table 2. Selected characteristics of experiment participants

Characteristics	No. [%]
Demographic data	
Gender (females)	408 (54.9%)
Age (years)	
19 and less	312 (42.0%)
20–22	286 (38.5%)
23 and more	145 (19.5%)
Academic program	
Economics and management	271 (36.5%)
Computer science	270 (36.3%)
Mathematics	134 (18.0%)
Other (humanistic, art, natural science, etc.)	68 (9.2%)
Decision-making experience (from 1 to 7)[a]	Average (SD)
Frequency of decision-making	2.92 (1.69)
Skills in decision-making	4.75 (1.38)
Knowledge of decision-aiding methods	3.57 (1.45)

[a] 1 – extremely low, 7 – extremely high.

4. Results

This section presents the results obtained from the structural equation model and cluster analysis. According to SEM methodology, in the first step, we verify key constructs in the model through factor analysis. The measurement model is verified in the second step, and the structural model is tested. We finished with investigating recommendations of using different methods by using cluster analyses. When describing the results, we follow the classic recommendation of analyzing data and reporting results using the SEM approach [65, 113]. Three main stages are considered: the model setting stage (measurement of observed variables, measurement model setting, structural model setting), the model evaluation and modification stage, and the interpretation and reporting stage. The aforementioned three-stage procedure fulfills also the requirements of robust SEM analysis [134].

4.1. Analyzing the key constructs in the model

According to SEM methodology (see, e.g. [71]), before the structural regression (SR) model is estimated and validated, all comprising measurement models need to be verified (a two-step modeling). Usually, confirmatory factor analysis (CFA) is used to verify the measurement models developed earlier. However, if the original measurements were adopted or modified or a new measure is developed, it may be profitable to implement a combined exploratory/confirmatory factor analysis (E/CFA) [20, 63]. Alternatively, exploratory structural equation modeling (ESEM) may be used [9, 112]. Kline [71] also suggests four-step modeling as an alternative to the two-step approach, in which EFA models are built (step one) to verify the correct number of factors and item loadings. Following the suggestions above, we will verify our constructs using EFA before including them in a measurement model.

- **Decision-making experience.** As mentioned in Section 3, DME was measured as a single construct using self-declared answers to three questions. Initial verification of this construct through EFA (with principal component analysis) confirms the existence of a single factor (based on eigenvalues greater than 1), with factor loadings greater than 0.662 and $53.76\%$of variance explained. Bartlett's test confirms the significance of the correlation matrix at $p < 0.001$, and Cronbach's alpha equals 0.559.
- **Coherence in MCDA use.** The COH measure was developed out of three tau Kendall indexes, showing the similarity of the results obtained by the users operating with three different MCDA techniques. Here, the EFA analysis also produced a single factor, with loadings greater than 0.501, 63.94% of variance explained, and significant results of Bartlett's test ($p < 0.001$), and Cronbach's alpha equal to 0.717.
- **Perceived functionality of the MCDA tools.** PF was the construct designed to measure users' answers regarding the functionality of three MCDA techniques. We used EFA with principal component analysis and factor discrimination rule based on eigenvalues greater than 1. It allowed us to confirm that three factors adequately describe three separate subscales, each describing the perceived usefulness of a single MCDA technique (Figure 4). Such a model contains no cross-loadings greater than 0.2. The factor loadings are greater than 0.650, and 63.45% of the variance is explained (Bartlett's test significant at $p < 0.001$). Cronbach's alpha equals 0.732 for PF TOPSIS, 0.775 for PF AHP, and 0.809 for PF SMART.
- **Decision-making style.** DMS was based on the REI-20 test. Initial EFA analysis based on eigenvalues and varimax rotation (constructs are supposed to be orthogonal) recommended identifying four factors. However, we found many cross-loadings smaller than 0.2 for different constructs. For instance, for R19 (Table A1 in Appendix A), the subsequent loadings are 0.173, 0.280, 0.392, and 0.268, though – according to the original test – it should load solely to the ability to rational thinking. Therefore, we performed EFA with two fixed factors (Rationality and Experientiality, respectively) and the principal component to confirm the original structure of question loadings on the two REI modes. As a result, eight variables (R5, R7, R17, R19, E2, E4, E6, and E14) received factor lodgings below 0.5 and were removed from further analysis of the global measurement model. EFA confirmed the two-factor structure to explain 51.51% of the variance based on the twelve remaining variables, which is still far more than in the original REI test. No cross-loadings were observed, the

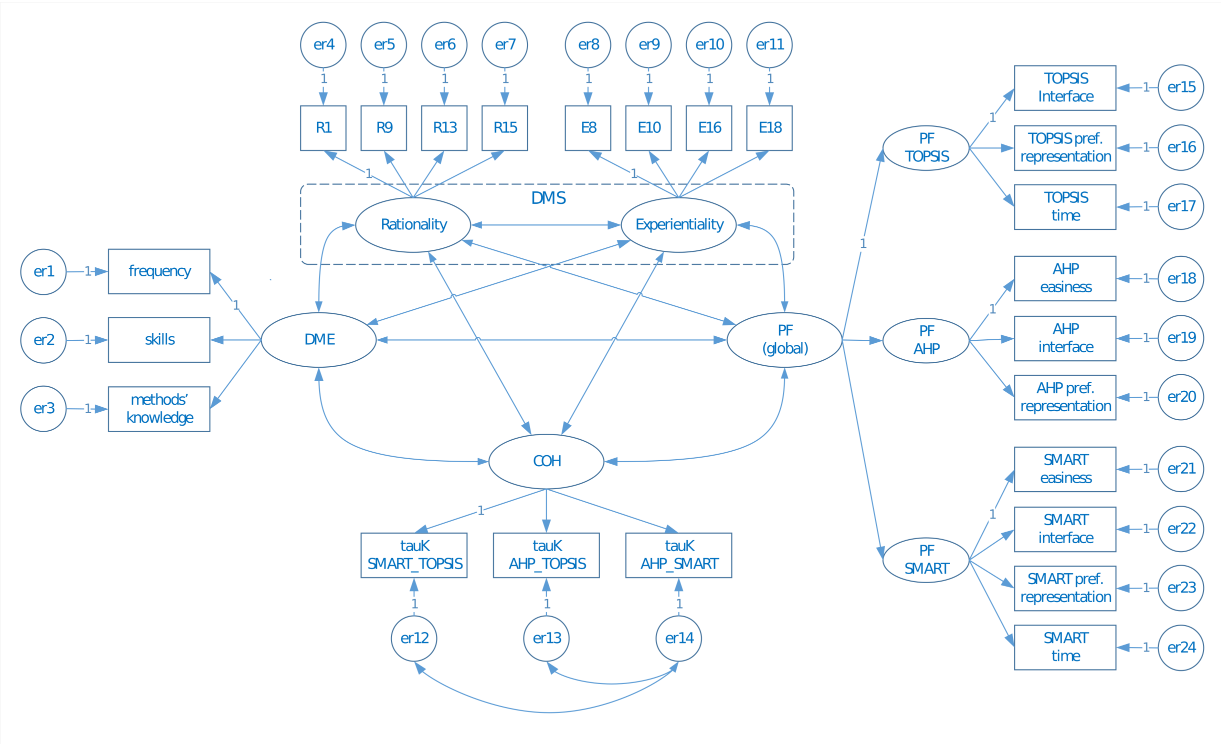

Figure 4. 5-factor CFA fitted measurement model.

loadings were no smaller than 0.617, and significance was confirmed by Bartlett's test ($p < 0.001$). Cronbach's alpha is equal to 0.721 for Rationality and 0.789 for Experientiality. As the REI's two thinking modes are considered orthogonal [93], we will include them in our model as two separate indicators of DMS.

4.2. Verification of the measurement model

Having pre-evaluated the single measures used in the model, we respecified our SR model into a CFA model to verify its measurement properties. The model was finally designed with five factors since DMS was operationalized using two orthogonal constructs. Due to the confirmed multivariate nonlinearity of data (kurtosis = 126.46, $c.r.$ = 39.581), the asymptotically distribution-free (ADF) method was used to estimate the model. However, ADF was criticized for requiring large samples [131], and recent recommendations suggest its use if a sample size exceeds the estimated parameters at least ten times [23, 100]. In our study, the initial 5-factor measurement model has 73 freely estimated variables; thus, with a sample size of 743, it just meets the recommended limits. The model estimation was performed in AMOS 20 software, and its basic statistics are shown in the first row of Table 3.

The initial 5-factor measurement model has a poor fit (χ^2_M(392)=1260.227, $p < 0.001$). Therefore, some modifications and respecifications are required to make it better represent the data sample. They are aimed at searches for cross-loadings and information redundancies [23]. Naturally, this post hoc model-fitting moves us back to exploratory analysis and needs to be performed using modification indexes (MI). It allowed us to identify the cross-loadings among the items within and between the five general constructs in our model. In most situations (for between-factor problems), we eliminated the items with cross-loadings instead of adding the residual covariances of no substantive interpretations. However, in

Table 3. Fits statistics for two-step testing of measurement and structural regression models

Model	χ^2_M	$df_M s$	χ^2_D	df_D	RMSEA	GFI	CFI
Measurement model							
5-factor standard CFA	1260.227	392			0.055	0.923	0.817
5-factor fitted CFA	470.697	237	789.53	155 $p < 0.001$	0.036	0.949	0.905
Structural regression model							
5-factor structural model (nine paths)	473.481	238	2.783	1 $p = 0.095$	0.037	0.948	0.905

the case of within-factor specification problems, high MIs may indicate the method effects [2, 82]. In our model, such a situation occurred for the COH factor, where the residuals for all three items produced high MIs. Therefore the error covariances were added to these items. The resulting final input data for the measurement model after respecification is shown in Appendix A (Table A2).

The resulting 5-factor fitted model was estimated with the ADF method. The results show a significant improvement in the model fit when compared to the initial 5-factor model with a chi-square difference $\chi^2_D(155) = 789.53$ and $p < 0.001$ (see Table 2, row 2). For our fitted model, RMSEA = 0.036, and GFI and CFI indexes equal 0.949 and 0.905, respectively. Although the chi-square difference is statistically significant, one needs to remember that for severely non-normal data samples, the chi-square value may not be reliably determined. It may be either increased or decreased [54]. Therefore corrected chi-square is also determined, e.g., using the Satorra–Bentler statistic or the Bollen–Stein approach that is claimed to control non-normality better. For our model, we used bootstrapping to determine Bollen–Stein statistics, which showed that the exact-fit hypothesis should not be rejected ($p = 0.338$). RMSEA also confirmed a good model fit (RMSEA = 0.036). The lower and upper bounds of RMSEA are equal to 0.32 and 0.41, respectively, with 90% confidence, which allows rejecting the poor-fit hypothesis. The comparative fit index slightly exceeds the 0.9 level, but we acknowledge an initial Bentler's recommendation that the acceptable threshold is 0.9 [2] (though others also exist [73]) and consider this model acceptable.

The 5-factor CFA fitted measurement model we designed is shown in Figure 4, and the corresponding factor loadings are listed in Table A2 in Appendix A. The standardized factor loadings for some factors, such as Experientiality, are relatively high and vary from 0.68 to 0.78. However, some other standardized loadings are low, such as 0.34 for the Kendall tau coefficient between the SMART and TOPSIS results for the COH factor. Therefore, the evidence for convergent validity is rather mixed. For all comparisons but one, the within-factor indicators' correlations are higher than the correlations of indicators between these factors. Therefore, the discriminant validity may be considered satisfied. Consequently, our 5-factor CFA fitted measurement model will test the hypothesized regression paths in Section 4.3.

4.3. Testing a structural model (SR) and interpreting results

The SR model should have nine causal paths reflecting the relationships between the latent constructs. One relationship is missing when compared to the CFA measurement model (Figure 4), as no causal link between Rationality and Experientiality exists within DMS. Such an operation does not deteriorate the model fit significantly, i.e., $\chi^2_D(1)$=2.783 and $p = 0.095$ (see Table 3, row 3). Therefore, we estimated our 5-factor 9-path SR model, obtaining the results shown in Figure 5 and Table 4. In the figure, the non-significant paths were depicted with dashed arcs (significant ones were denoted by * for $p < 0.05$ and ** for $p < 0.01$). The unstandardized and standardized (in brackets) regression coefficients depict each arc and R^2 values – each dependent construct.

Out of nine paths in the model, two were insignificant. Both describe the direct effect of a decision maker's experience (DME) on their ability to coherently use MCDA techniques (COH) and their evaluation of the functionality of the MCDA techniques (PF). Therefore the hypotheses H2a and H1a cannot be confirmed. However, all remaining direct effects are significant, at least at $p < 0.05$.

There is a moderate causal effect of DME on DMS. Both relationships, i.e., DME $\rightarrow$ Rationality and DME $\rightarrow$ Experientiality, are significant ($p < 0.001$). DME seems to affect DM's slow thinking mode (Rationality) positively. The relationship is nearly one-and-a-half times stronger (0.432/0.291 = 1.48) than the DME impact on fast-thinking abilities (Experientiality). Both effects are positive, meaning DME enhances the DM's ability to use both thinking modes, which confirms hypothesis H4. The significant effects of DME on DMS have a relatively small share in explaining the variance of both thinking modes, which is twice as high in the case of Rationality as for Experientiality (R^2 are equal to 0.187 and 0.085, respectively). However, it needs to be noted that such shares are not meaningless in social sciences. For example, the explained variance equal to 0.25 is often considered moderate, while a threshold as low as 0.04 is a practical minimum [44].

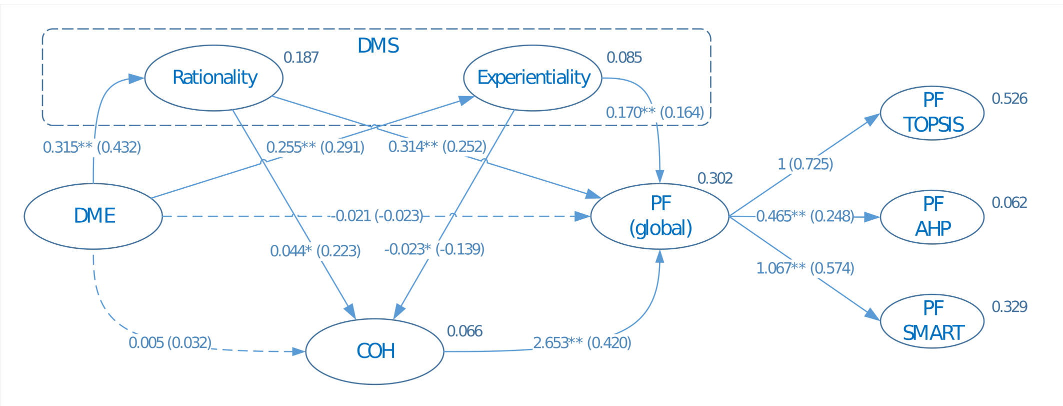

Figure 5. 9-path SR model.

Table 4. ADF estimated regression weights in the 5-factor 9-path SR model

Regression weights	Unstandardized	S.E.	P	Standardized	Hypothesis
DME $\rightarrow$ Rationality	0.315	0.045	***	0.432	H4 supported
DME $\rightarrow$ Experientiality	0.255	0.045	***	0.291	H4 supported
Rationality $\rightarrow$ COH	0.044	0.018	0.013	0.223	H5 supported
Experientiality $\rightarrow$ COH	–0.023	0.010	0.028	–0.139	H5 supported
DME $\rightarrow$ COH	0.005	0.011	0.661	0.032	H2a not supported
Rationality $\rightarrow$ PF (global)	0.314	0.086	***	0.252	H6a supported
Experientiality $\rightarrow$ PF (global)	0.17	0.057	0.003	0.164	H6a supported
COH $\rightarrow$ PF (global)	2.653	0.587	***	0.420	H3 supported
DME $\rightarrow$ PF (global)	–0.021	0.063	0.739	–0.023	H1a not supported
PF (global) $\rightarrow$ PF TOPSIS	1			0.725	
PF (global) $\rightarrow$ PF AHP	0.465	0.091	***	0.248	
PF (global) $\rightarrow$ PF SMART	1.067	0.149	***	0.574	

DMS seems to affect COH ($p < 0.05$) significantly. Both Rationality and Experientiality impact the scale of DM's ability to use various MCDA techniques coherently. These relationships are relatively weak, as the beta coefficients are only 0.223 and –0.139, respectively, and the total variance of COH, explained by the model, is equal to 7% only (0.066). However, as expected, Rationality affects COH positively, while Experientiality just opposed. It confirms our hypothesis H5. One may also observe a significant impact of both Rationality and Experientiality on PF, confirming hypothesis H6a. These impacts are similar in strength to COH ones (weak), but both are positive. Increasing Rationality and Experientiality makes the DM evaluate the MCDA methods functionality higher. Perceived functionality (PF) seems to be also impacted directly by COH. COH has the greatest effect on PF out of all other factors, with the standardized regression weight equal to 0.420 ($p < 0.001$). The higher the DM's ability to use different MCDA methods coherently, the higher their evaluation followed the decision-making process. Hence, we confirm hypothesis H3.

Although the direct effect of DME on COH occurred insignificant ($p = 0.661$), DME may impact COH indirectly through the mediator, which is DMS. Therefore the total unstandardized effect of DME on COH may be measured, which occurs to be equal to 0.013 (see Table 5). Mediation analysis requires analyzing two models of relationships between DME and COH, i.e., path relations DME → Rationality → COH (indirect standardized effect: $0.432 \times 0.223 = 0.096$) and DME → Experientiality → COH (indirect standardized effect: $(0.291 \times (-0.139) = -0.040)$. The impact of independent and mediating variables (Rationality and Experientiality) is statistically insignificant if a restrictive cut-off level of $p = 0.05$ is assumed ($p = 0.094$ in the ADF bootstrapping). Hence, we cannot confirm hypothesis H2b. The bootstrap analysis performed to determine the significance of the total effect does not confirm it to be significant even for a less restrictive level of $p = 0.1$ ($p = 0.180$). Hence, we cannot confirm hypothesis H2.

Table 5. Decomposition of four effects of the endogenous and exogenous variables for the 5-factor 9-path SR

Causal effect	Unstandardized	S.E.	P	Standardized	Hypothesis
DME → COH					
Direct	0.005	0.023	0.613	0.032	H2a not supported
Total indirect	0.008	0.011	0.094	0.056	H2b not supported
Total	0.013	0.020	0.180	0.088	H2 not supported
Rationality → PF (global)					
Direct	0.314	0.148	0.003	0.252	H6a supported
Total indirect	0.117	0.089	0.007	0.094	H6b supported
Total	0.431	0.155	***	0.346	H6 supported
Experientiality → PF (global)					
Direct	0.170	0.112	0.011	0.164	H6a supported
Total indirect	–0.060	0.058	0.014	–0.058	H6b supported
Total	0.110	0.093	0.070	0.106	H6 not supported
DME → PF (global)					
Direct	–0.021		0.668	-0.023	H1a not supported
Total indirect	0.176		0.002	0.194	H1b supported
Total	0.155		0.019	0.171	H1 supported

The model was obtained by ADF estimation with 3000 bootstrap samples of double size, $N = 2 \times 743$, 95% CI.

Rationality has a positive impact on PF of the MCDA tools, with a direct standardized effect equal to 0.252 and a total standardized effect (with mediation via COH) of 0.346 ($p < 0.001$). Experientiality also has a direct positive effect on PF, lower than Rationality and equal to 0.164. However, the indirect effect is negative and has, in general, a suppressing effect on how DMS impacts PF. The total standardized effect for Experientiality $\rightarrow$ PF remains positive and equals 0.106. Unfortunately, it cannot be considered significant ($p = 0.070$ in bootstrapping). Consequently, we may confirm hypothesis H6, that DMS affects PF, but this effect is related only to the DM's rational mode, and this impact is somewhat smaller than the COH $\rightarrow$ PF.

There are also interesting effects when the total impact of DME on PF is analyzed. Although the direct effect is insignificant (standardized regression coefficient is equal to –0.021, $p = 0.739$), the indirect effect occurs to be positive (0.194) and significant ($p = 0.002$). Thus we may observe a mediation effect of the DMS and COH on forming the total significant impact of DME on PF, which equals 0.171 ($p = 0.019$). In detail, such mediation may be computed from five models of indirect-only relationships between DME and PF. Three models consider one mediator: DME $\rightarrow$ Rationality $\rightarrow$ PF (indirect standardized effect: 0.432 $\times$ 0.252 = 0.109), DME $\rightarrow$ Experientiality $\rightarrow$ PF (indirect standardized effect: $0.291 \times 0.164 = 0.048$), and DME $\rightarrow$ COH $\rightarrow$ PF (indirect standardized effect: 0.032 $\times$ 0.420 = 0.013). Two other models include two mediators: DME $\rightarrow$ Rationality $\rightarrow$ COH $\rightarrow$ PF (indirect standardized effect: 0.432 $\times$ 0.223 $\times$ 0.420 = 0.040), DME $\rightarrow$ Experientiality $\rightarrow$ COH $\rightarrow$ PF (indirect standardized effect: 0.291 $\times$ (– 0.139) $\times$ 0.420 = –0.017). The total indirect effect of DME on PF (0.109 + 0.048 + 0.013 + 0.040 - 0.017 = 0.193) is statistically significant ($p = 0.002$). Concluding, we confirm hypotheses H1b and H1. All the impacts observed allow us to explain 30% of the variance of the PF. According to some thumb rules recalled from Ferguson's considerations [44], it can be regarded as a more than moderate effect.

As the PF was initially designed as a second-order latent variable, we may now analyze how the perceived functionality of MCDA methods loads on evaluating each of three MCDA techniques, i.e., AHP, SMART, and TOPSIS. We can see that the highest enthusiasm in evaluating the MCDA techniques was mainly linked to the satisfaction from using TOPSIS (standardized effect equal to 0.725). Interestingly, it was nearly three times greater than the satisfaction from AHP (of the standardized effect equal to 0.248). The global PF also explains twice as much the evaluation of the functionality of the SMART technique (standardized effect equal to 0.574) than the functionality of AHP.

The summary of hypotheses and their verification derived from the comprehensive analysis of effects identified in the SR model is shown in Table 6.

4.4. Recommendation of MCDA methods

The structure of responses to the last post-decision-making question Q1, and the mean values of behavioral characteristics of decision-makers obtained from the SEM model, are presented in Table 7. Almost half of the participants (47.8%) recommended TOPSIS as the most suitable for supporting their decisions in the decision-making problems they may face in the future. The second most recommended method was AHP (29.5%), while the least recommended was SMART (22.7%).

Answering question Q1, we found that, in general, those who recommended a particular method also evaluated its functionality best. For example, those who chose AHP evaluated its functionality best (and it was a significantly higher evaluation than the other methods, $p < 0.001$ in a series of M-W tests). Similarly, those choosing SMART evaluated it as the most functional, significantly more than

Table 6. Verification of hypothesis. Summary

Hypothesis	Supported
H1: DME in decision-making impacts the PF of the MCDA technique.	yes
H1a: DME in decision-making directly impacts the PF of the MCDA technique.	no
H1b: DME in decision-making indirectly impacts the PF of the MCDA technique through the mediators DMS and COH.	yes
H2: DME in decision-making impacts their ability to use different MCDA methods COH.	no
H2a: DME in decision-making directly impacts their ability to use different MCDA methods COH.	no
H2b: DME in decision-making indirectly impacts their ability to use different MCDA methods COH through DMS as a mediator.	no
H3: DM's ability to use different MCDA methods COH impacts the PF of the MCDA method.	yes
H4: DME in decision-making impacts their DMS.	yes
H5: DMS impacts its ability to use different MCDA methods COH.	yes
H6: DMS impacts the PF of MCDA tools .	yes (for Rationality only)
H6a: DMS directly impacts the PF of MCDA tools.	yes
H6b: DMS indirectly impacts the PF of MCDA tools through COH as a mediator.	yes

COH – coherence in use of the MCDA methods, DME – DM's experience, DMS – decision-making style, PF – perceived functionality.

Table 7. The recommendation of the MCDA method and the mean behavioral factors

Method	N [%]	DME	EXP	RAT	COH	PF	PF_A	PF _S	PF _T
AHP	219 (29.5)	2.249	2.371	2.488	0.207	3.239	4.693	4.568	4.777
SMART	169 (22.7)	2.310	2.283	2.608	0.220	3.467	4.216	5.347	5.096
TOPSIS	355 (47.8)	2.380	2.427	2.554	0.209	3.369	4.281	4.643	5.168
K-W test significance		0.017	0.049	0.032	0.307	< 0.001	< 0.001	< 0.001	< 0.001

AHP and TOPSIS ($p < 0.001$ is a series of M-W tests). Those who chose TOPSIS also considered it more functional than other techniques, yet the evaluation difference with SMART was insignificant ($p = 0.148$).

When we look at the differences in the general evaluation of the functionality of MCDA techniques, all three clusters of respondents differ significantly ($p < 0.001$). Those who decided on AHP considered MCDA techniques the least functional, while those who recommended SMART – as most functional. The evaluation of the general functionality of MCDA techniques is the only factor that differentiates significantly among all three clusters. It is the opposite situation to the coherency results in MCDA techniques, which did not differ significantly across the clusters.

The AHP adherents occurred least experienced and least rational. They differed significantly in their experience from those who chose TOPSIS, who were the most experienced ones (M-W test with $p = 0.006$), and in Rationality from the SMART choosers, who were the most rational (M-W test with $p = 0.006$). However, they did not differ in their Experientiality level from DMs from the other two groups. Finally, the TOPSIS choosers occurred to be the most experiential ones. They differed significantly in Experientiality levels only from the group that chose SMART (M-W test with $p = 0.018$).

5. Discussion

The results described in the previous section provide interesting insights into the relationship among the constructs in the model. The fundamental construct in the model is DME, a single exogenous variable. It reflects the DM's general experience and skills in solving decision-making problems gained from frequent encounters with MCDA problems in everyday business life, abilities to solve such problems, and knowledge of the MCDA techniques. Unexpectedly, it did not significantly directly impact DM's ability to operate coherently with three classic MCDA methods (COH) nor the subjective evaluation of the functionality of these techniques (PF). However, DME significantly affects the decision-making style (DMS), which is consistent with some earlier findings [55, 74] that the decision-making style is not fixed and can be changed in the long term, for instance, by improving skills and knowledge. This impact is two-way, as DME positively affects both Rationality and Experientiality; however, the former is impacted more (nearly 1.5 times). This finding is interesting and surprising at the same time. With increasing experience in decision-making (and awareness of MCDA techniques), one might expect that DMs become more sensitive to the dangers of cognitive biases and heuristics that result from fast thinking. Consequently, they will reduce the share of the experiential approach in their decision-making process and expose more analytical and diligent information processing behavior (negative effects on Experientiality). However, our data show that increasing decision-making experience makes DMs enhance rational and experiential skills, making them more versatile (high Rationality and high Experientiality). It is a favorable decision-making profile since versatile DMs better adjust to deploy the rational or experiential reaction in contextually appropriate ways [3, 121]. They can be analytical when needed but still use the approach based on intuition and association when solving a problem requires deriving from previous experience.

DMS significantly affects the DM's ability to use various MCDA tools coherently (COH). Both Rationality and Experientiality have individual yet opposite impacts on DMs' coherence. These findings are consistent with Kersten's previous study of the information processing style affecting the accuracy in defining the preferences by agents in principal-agent negotiations [70]. As expected, high Rationality makes the DMs more able to perform accurate decision analysis by employing a series of decision support tools. They can impart their preferences more consistently, build reliable scoring systems, and identify the solutions that align with their true preferences. Contrary, high Experientiality seems to disturb the process of reliable decision analysis. The effect is somewhat smaller than in the case of Rationality. Still, it shows a suppressing effect the high Experientiality has on the increasing ability of DMs to use MCDA tools reliably caused by their high Rationality. This suppressing effect is important in interpreting how versatile DMs perform. For them, a positive net effect may be identified ($0.223 \times 1 - 0.139 \times 1 = 0.084$), but it is more than twice as weak as for highly rational and slightly experiential DMs. We tested this joint effect of high Rationality and Experientiality of versatile DMs in bootstrapping to find if it can be considered non-zero's. Unfortunately, the bootstrap proved the effect insignificant (with lower and upper bounds equal to –0.238 and 0.363, respectively, and $p = 0.05$).

We should remember that our analytical tasks embraced a series of MCDA analyses conducted using three different support tools. Some of them, such as TOPSIS or AHP, required qualitative judgments or operating with a verbal declaration of preferences without any correspondence (at least at the elicitation stage and interfaces implemented in ODSS) to the qualitative scores. It involves subjective considerations regarding the meaning of some linguistic etiquettes that might be affected by the DMs' earlier experience in solving decision-making problems and considering options to be better or worse. As such judgments require some generalization and are not precise in defining the scale of differences in preferences, it may explain the negative effect of high Experientiality in our model.

One of the strongest direct effects in our model was determined for the relationship between COH and PF. Additionally, taking into account quite a large amount of variance explained for PF, we may conclude that the users mainly evaluate the functionality of the methods if they can see how consistent results they can produce. From the practical viewpoint, if we wish to ensure the future use of MCDA techniques in solving real-world problems, we should focus on explaining and showing DMs that these methods are trustworthy. As we can see from our experiment, this may be easily achieved by organizing training in the MCDA mechanisms during which their algorithms are explained to the DMs. Then they can confirm the methods' effectiveness by trying how they solve a simple numerical example based on the preferences DMs impart.

Both Rationality and Experientiality have a positive direct impact on PF; however, the influence of Rationality is stronger than Experientiality. This finding supports Epstein's consideration that decision-making is a complex process that dual-process theories can explain and requires defining two decision-making modes ([42, 93]). The versatile DMs are flexible in using MCDA methods, adjusting them to the situational context and their cognitive capabilities. Therefore, they are satisfied with using either the methods that require a precise definition of preferences through direct assignments of numerical scores or those utilizing a graphical user interface or linguistic, less precise definitions. On the other hand, indifferent DMs (with low Rationality and low Experientiality) evaluate the functionality of the MCDA methods lower. It is related to the characteristics of their style, i.e., they usually are not interested in investigating the problems themselves, and they base instead on the opinion of others. Moreover, the direct effect of DMS on PF is strengthened by the indirect one (through COH). It seems natural that being more able to do analytics (and having the additional information that one has just done these analytics practically well) makes one acknowledge better the added value DMs get from using MCDA tools. Experientiality also positively affects PF, but its indirect effect (through COH) plays a suppressing role. The total effect is also positive but with borderline statistics regarding its significance. It shows, however, that enhancing the versatility of DMs' information processing style makes them more positively perceive the MCDA techniques and, hopefully, willing to use them in the future.

Finally, our analyses give an interesting insight into what elements of MCDA tools implemented in ODSS comprise a general PF of MCDA methods. First, we can see that the biggest share in creating general PF has a PF of TOPSIS, almost twice as big as AHP's, with SMART's loading being 80% of the TOPSIS one. It may suggest that the issues such as time requirements and technical simplicity in imparting preferences using the method may play a key role in creating the subjective value of the functionality of the methods. A deeper insight into the loadings on the items within each method confirms this observation. The highest loading within each method is assigned to its interface design, from 0.81 for TOPSIS to 0.95 for AHP. Easiness seems to be the second important one (from 0.80 to 0.86), and time requirements the third one (average loading equal to 0.76). Moderate loadings are only identified for the ability of the method to represent the DM's preferences adequately. It clearly shows that there are other more important characteristics of the MCDA tool than its ability to process and reflect the initially imparted preferences well. Hence, the DSS engineers should focus on designing the user interface according to these recommendations. However, it is worth mentioning that a quick and easy approach does not always have to lead to an exact solution, as shown in [130].

Analyzing the final impact of the behavioral factors on the DMs' subjective recommendation regarding the suitability of MCDA techniques in supporting multiple decision-making processes, we confirmed what might be derived from the general characteristics of the decision-making profiles. For instance, we identified that the most rational people tend to choose the technique that requires the most analytical and quantitative approach in defining their preferences, i.e., SMART. On the other hand, the most experiential ones, i.e., those who process information quickly and operate with holistically defined categories, chose the TOPSIS technique, which required defining their preferences through the series of colored stars without even any verbal description of their meaning. Additionally, those who chose AHP occurred to be the least experienced in decision-making. It fits the opinion of the researchers and practitioners who recommend this method as easy and does not require particular skills from DM as it provides logical rigor of analytical procedure that everyone can comfortably follow [33].

The results mentioned above may be used to suggest the best-fitting and most accurate method for the DM of a particular behavioral profile. Technically, it requires identification of the DMs experience and decision-making style through the test we used in our experiment and then classifying her/him into one of the clusters identified experimentally by us (see Table 7). The classification mechanisms, here based on the notion of distances, would recommend:

- AHP to DMs with a meager decision-making experience, low Rationality but average Experientiality,
- SMART to DMs with average experience, high Rationality, and low Experientiality,
- TOPSIS to DMs with high experience, average Rationality, and high Experientiality.

6. Conclusions and future research

Many approaches have been proposed to solve multiple criteria decision-making problems in the literature. The choice of the MCDA methods depends on the problem under consideration, the algorithm's requirements, and the available decision support system. The MCDA method should also meet users' needs, expectations, and cognitive abilities.

This study aimed to examine the direct impact of DM's experience in making multiple criteria decisions and decision-making style on the ability to use various MCDA techniques coherently and on the perceived functionality of these techniques. It also investigated the indirect influence of DM's experience and decision-making style on the perceived functionality of MCDA methods. Therefore, we used the SEM model to test six different hypotheses based on the result of the online experiment. Additionally, we verified the relationship between the identified factors and the DMs' subjective recommendations regarding the most suited MCDA technique (question Q1). It makes our approach comprehensive and different from earlier studies, where some of the relationships among these behavioral characteristics were only considered individually.

The main contribution of this paper is the descriptive findings regarding behavioral characteristics and their impact on the perceived functionality of multiple criteria methods. Applying the structural equation model, we confirm that

- using MCDA techniques coherently is related to DM's behavioral profiles described by DM experience and information-processing style,
- the ability to coherently use the MCDA methods has the strongest positive impact (among considering behavioral characteristics) on their perceived functionality,
- the decision-making experience has an indirect impact through style on the perceived functionality of multiple criteria methods,
- decision-making profile has both direct and mediatory impact (through the ability to use the MCDA methods coherently) on the perceived functionality of MCDA methods.

The experiment results confirm that training may be required to show DMs that they can efficiently use MCDA tools and produce reliable and consistent results. Training enhances their subjective valuation of the functionality of MCDA techniques, which, in turn, differentiates the choice of the method they would be willing to use. We additionally showed that DMs with particular levels of selected behavioral factors might differ in selecting the MCDA method. These findings may be used to build cognitive multiple criteria decision support systems that better meet DM's expectations regarding preference analysis in decision support systems as well as their cognitive limitations.

Finally, some limitations of this study need to be addressed. First, the study is focused on the three selected MCDA methods: AHP, SMART, and TOPSIS. Our choice of methods used in the study was not accidental. Although they operate with different user interfaces (fitting the requirements and specificities of the algorithms), they still aggregate preferences using the same classic additive preference model. Moreover, these methods are claimed to be cognitively easy [109, 136] and may be perceived as the first choice when implemented in DSS. Naturally, selecting another set of methods, e.g., those deriving from the disaggregation paradigm, could produce different results. It would then be interesting to implement our analytical setup for another set of methods to conduct a multi-group SEM analysis and test the stability of the results depending on the changing cognitive demand of MCDA tools.

Secondly, the REI test revealed shortcomings in our study that confirm the problems raised earlier by other researchers [18, 81, 88, 105]. REI was identified to indicate the weak percentage of variance explained and, consequently, the need to modify the questionnaire. Modifications were also required in our study, and we needed to remove a few items from the original REI test to ensure its validity. It might be interesting to check if other inventories could produce more informative results, e.g., based on the concept of five styles defined by the GDMS inventory [114]. Another issue that may be considered while defining decision-making style is its stability over time. It is worth remembering that the REI test describes the general DM's attitude to problem-solving. It does not capture the context-dependent nuances in how people may act while solving a particular problem, being affected by some situational factors that may force them to change the usual way they behave as described by the decision-making style. Therefore, some researchers suggest using other tests to discover the actual information processing style adapted to the situation DM finds herself/himself in [88]. Implementing such an inventory might allow us to confirm some findings, e.g., that the versatile DMs exploit only their rational abilities to solve problems when facing analytical tasks and/or find other dependencies.

When answering question Q1, we used a straightforward approach that identified the behavioral differences for the clusters of DMs that differ in their recommendation of MCDA techniques. Some other causative relationships could be found if a regression-based approach were implemented. For instance, a multinomial logistic regression could be used here to find the potential linkages and consider the differences in the strength of the impact of the behavioral characteristic on the DM recommendations.

One also needs to bear in mind that our findings were derived from the analysis based on a particular sample comprised of students taking part in the academic coursed in decision-making. This group received prior training in decision-making and may reveal a specific decision-making profile typical to young adults, not necessarily similar to the one revealed by the representative group of DMs. The latter may also differ from our students' DM experience and skills. Thus, some broader research could be designed to prove the universality of our findings and their significance for other groups of DMs in the specific cultural, demographic, and behavioral context.

In summary, our future work will test the previous relationships for other MCDA methods. We would further focus on redesigning the inventory to determine the information-processing style (also considering its contextual character). Finally, we will try to build a causal model for identifying clear recommendation rules on which method should be implemented for supporting DM of a particular decision-making style and experience.

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A. Appendix

Table A1. Rational experiential inventory (REI-20)

No.	Symbol	Item
		RAT: Rationality subscale (reversal)
1	R1	I try to avoid situations that require thinking in depth about something. (–)
3	R3	I'm not that good at figuring out complicated problems. (–)
5	R5	I enjoy intellectual challenges.
7	R7	I am not very good at solving problems that require careful logical analysis. (–)
9	R9	I don't like to have to do a lot of thinking. (–)
11	R11	I enjoy solving problems that require hard thinking.
13	R13	Thinking is not my idea of an enjoyable activity. (–)
15	R15	I am not a very analytical thinker. (–)
17	R17	Reasoning things our carefully is not one of my strong points. (–)
19	R19	I don't reason well under pressure. (–)
		EXP: Experientiality subscale (reversal)
2	E2	I like to rely on my intuitive impressions.
4	E4	I don't have a very good sense of intuition. (–)
6	E6	Using my gut feelings usually works well for me in figuring out problems in my life.
8	E8	I believe in trusting my hunches.
10	E10	Intuition can be a very useful way to solve problems.
12	E12	I often go by my instincts when deciding on a course of action.
14	E14	I trust my initial feelings about people.
16	E16	If I were to rely on my gut feelings, I would often make mistakes.
18	E18	I don't like situations in which I have to rely on intuition. (–)
20	E20	I think it is foolish to make important decisions based on feelings. (–)

(–) denotes reverse coding of item.

Table A2. Input Data (correlations, standard deviations) for analysis of a structural regression model

No.	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	frequency	1											
2	skills	0.207**	1										
3	method's knowledge	0.306**	0.389**	1									
4	R1	0.046	0.284**	0.112**	1								
5	R9	0.081*	0.220**	0.151**	0.454**	1							
6	R13	0.063	0.161**	0.089*	0.454**	0.420**	1						
7	R15	0.156**	0.235**	0.118**	0.309**	0.279**	0.451**	1					
8	E8	0.025	0.069	0.141**	-0.042	-0.015	-0.039	-0.036	1				
9	E10	0.011	0.076*	0.113**	-0.060	-0.023	-0.079*	-0.047	0.546**	1			
10	E16	0.022	0.119**	0.128**	0.052	0.102**	0.054	0.049	0.443**	0.465**	1		
11	E18	0.005	0.184**	0.185**	0.063	0.118**	-0.002	0.030	0.417**	0.494**	0.542**	1	
12	tauK AHP_SMART	-0.018	0.008	-0.008	0.092*	0.089*	0.124**	0.055	-0.035	-0.032	-0.018	-0.066	1
13	tauK AHP_TOPSIS	-0.035	0.030	-0.016	0.116**	0.093*	0.154**	0.088*	-0.002	-0.015	-0.004	-0.027	0.780**
14	tauK SMART_TOPSIS	0.030	-0.017	-0.035	0.014	-0.012	0.069	0.070	-0.048	-0.009	-0.054	-0.031	0.304**
15	TOPSIS interface	-0.002	0.045	-0.013	0.137**	0.147**	0.144**	0.114**	-0.008	-0.028	-0.040	-0.036	0.120**
16	C TOPSIS pref. representation	0.037	0.065	0.037	0.057	0.119**	0.102**	0.012	0.053	0.024	0.061	0.092*	0.058
17	TOPSIS time	-0.013	0.106**	0.012	0.090*	0.119**	0.087*	0.049	0.025	0.000	-0.016	0.037	0.140**
18	AHP easiness	-0.055	0.004	-0.005	0.007	0.032	-0.002	-0.034	0.055	0.012	-0.006	0.037	-0.025
19	AHP interface	0.012	-0.014	-0.020	-0.013	0.043	0.004	-0.010	0.030	-0.019	-0.008	0.013	-0.018
20	AHP pref. representation	-0.016	-0.019	-0.003	-0.064	-0.007	-0.013	-0.001	0.000	-0.006	-0.032	-0.009	0.054
21	SMART easiness	-0.033	0.036	0.021	0.112**	0.092*	0.116**	0.084*	0.033	0.016	0.046	0.035	0.049
22	SMART interface	0.023	-0.013	-0.003	0.089*	0.086*	0.103**	0.082*	0.022	0.011	0.054	0.019	0.081*
23	SMART pref. representation	0.054	0.039	0.019	0.054	0.016	0.109**	0.124**	0.046	0.096**	0.067	0.046	-0.044
24	SMART time	0.017	0.020	0.023	0.095**	0.099**	0.120**	0.124**	0.039	-0.010	0.050	0.024	0.073*
	SD	1.687	1.378	1.455	0.980	1.126	1.015	0.998	1.027	1.067	1.028	1.150	0.548

* – significant at p <0.05; ** – significant at p < 0.01

Table A3. Input data (correlations, standard deviations) for the analysis of a structural regression model

No.	Variable	13	14	15	16	17	18	19	20	21	22	23	24
13	tauK AHP_TOPSIS	1											
14	tauK SMART_TOPSIS	0.198**	1										
15	TOPSIS interface	0.155**	0.132**	1									
16	TOPSIS pref. representation	0.074*	0.065	0.448**	1								
17	TOPSIS time	0.147**	0.108**	0.578**	0.428**	1							
18	AHP easiness	0.017	-0.032	0.144**	0.147**	0.184**	1						
19	AHP interface	0.004	0.012	0.177**	0.123**	0.124**	0.725**	1					
20	AHP pref. representation	0.095**	-0.021	0.127**	0.126**	0.175**	0.407**	0.471**	1				
21	SMART easiness	0.100**	0.038	0.262**	0.159**	0.206**	0.192**	0.142**	0.087*	1			
22	SMART interface	0.100**	0.067	0.308**	0.185**	0.153**	0.193**	0.229**	0.130**	0.686**	1		
23	SMART pref. representation	0.010	0.041	0.217**	0.156**	0.147**	0.106**	0.125**	0.142**	0.445**	0.460**	1	
24	SMART time	0.111**	0.022	0.178**	0.168**	0.205**	0.095**	0.095**	0.120**	0.608**	0.549**	0.373**	1
	SD	0.537	0.333	1.171	1.397	1.306	1.642	1.594	1.606	1.609	1.497	1.623	1.813

⋆: significant at $p < 0.05$; ⋆⋆: significant at $p < 0.01$

Table A4. ADF estimates of factor loadings for a 5-factor CFA measurement model

Effect	Factor loading			Measurement errors		
	Unstand.	S.E.	Standard.	Unstand.	S.E.	Standard.
frequency ← DME	1		0.430	2.264	0.105	0.815
skills ← DME	1.176	0.118	0.669	0.876	0.073	0.553
method's knowledge ← DME	1.312	0.123	0.658	1.158	0.078	0.567
R15 ← Rationality	1		0.564	0.580	0.037	0.682
R1 ← Rationality	1.076	0.086	0.635	0.462	0.030	0.596
R9 ← Rationality	1.368	0.104	0.670	0.618	0.041	0.551
R13 ← Rationality	1.325	0.091	0.735	0.404	0.038	0.460
E8 ← Experientiality	1		0.683	0.475	0.031	0.534
E10 ← Experientiality	1.122	0.051	0.738	0.436	0.029	0.455
E16 ← Experientiality	1.188	0.062	0.779	0.380	0.036	0.393
E18 ← Experientiality	1.178	0.061	0.690	0.634	0.034	0.524
tauK SMART_TOPSIS ← COH	1		0.337	0.090	0.005	0.886
tauK AHP_TOPSIS ← COH	2.878	0.728	0.612	0.160	0.026	0.626
tauK AHP_SMART← COH	2.627	0.629	0.537	0.197	0.021	0.712
AHP easiness ← PF AHP	1		0.806	0.816	0.076	0.350
AHP interface ← PF AHP	1.170	0.062	0.951	0.218	0.103	0.095
AHP pref. representation ← PF AHP	0.631	0.040	0.511	1.711	0.085	0.739
SMART interface ← PF SMART	1		0.859	0.523	0.054	0.262
SMART pref. representation ← PF SMART	0.683	0.037	0.535	1.713	0.083	0.714
SMART time ← PF SMART	1.064	0.046	0.755	1.258	0.092	0.430
SMART easiness ← PF SMART	1.096	0.036	0.858	0.632	0.056	0.263
TOPSIS interface ← PF TOPSIS	1		0.815	0.414	0.036	0.335
TOPSIS pref. representation ← PF TOPSIS	0.812	0.049	0.558	1.199	0.065	0.689
TOPSIS time ← PF TOPSIS	1.036	0.058	0.755	0.665	0.061	0.430
PF TOPSIS ← PF	1		0.731	0.383	0.074	0.466
PF AHP ← PF	0.464	0.090	0.249	1.422	0.111	0.938
PF SMART ← PF	1.046	0.145	0.571	0.992	0.096	0.674

All unstandardized estimates were significant at $p < 0.001$.
Standardized estimates for measurement errors are proportions of unexplained variance.