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Abstract
This article seeks to overcome the problem of structuring multi-criteria decision problems in a scientifically valid way. For this purpose, we theoretically and empirically compare two techniques which can be used for the purpose of structuring problem domains: card sorting procedures and statistical web mining. Based on two empirical test cases we assess whether decision structuring is reliable regarding the applied structuring method and whether the resulting hierarchies are valid representations of the decision problem at hand. The results indicate that the two techniques lead to quite different goal-criteria hierarchies and that web mining does not produce useful problem representations. In contrast, card sorting seems to be a valid structuring technique. We explain these results by the fact that card sorting procedures are interpretive techniques which are able to deal with vague concepts (criteria) while web mining, as a purely statistical approach, does not work well with ambiguous concepts.

Keywords
Problem Structuring, Multiple Criteria Decision Analysis, Concept Mapping, Semantic Analysis, Web Mining

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1. Introduction

Research into decision support seeks to improve human decision making, either from a normative, descriptive or prescriptive perspective (Smith & Winterfeldt 2004). While these views provide many different approaches in decision support, a common element underlying most approaches is to decompose and structure the decision problem at hand. The structuring of decision problems is an integral part of decision support because it provides essential tools to enhance human decision making. Structured representations of decision problems (e.g. hierarchies composed of decision objectives and criteria) increase the decision maker's (DM) understanding of the problem and capacity to process information (Aschenbrenner et al. 1980; Forman & Gass 2001). Furthermore, such structures are useful for the implementation of so-called “divide-and-conquer” strategies, where a decision problem is divided into its components which are separately evaluated and then put back together to derive an overall solution for the decision at hand (Shanteau 1988). The basic idea underlying problem decomposition is that smaller parts of the problem can be handled more easily by human information processing capabilities than the entire problem at once. This allows decision makers to increase their information frame and thus their decisions. “Divide-and-conquer” strategies are not only used by human experts (Shanteau 1988), but also in normative decision making (Saaty 1990). In both cases, the structuring of the decision problem keeps the decision process transparent and manageable. Furthermore, normative decision models based on pairwise comparisons (e.g. the analytic hierarchy process) usually rely on hierarchical structures to ensure that only comparable concepts are contrasted with each other. This is necessary to guarantee that the measurement of the DM's preferences is valid (Saaty 1994).

Due to these reasons, the first steps of multi-criteria decision making (MCDM) are typically the decomposition and the structuring of the decision problem at hand. These initial activities of MCDM are of particular importance for the accuracy (quality) of the resulting decision (Winterfeldt 1980; Saaty, 1990) because all subsequent process steps of MCDM are based on the initial structuring of the decision problem. Hence the structuring step has a significant effect on the outcome of the MCDM process (Brownlow & Watson 1987; Borcherding & Winterfeldt 1988; Brugha 1998). Although the structuring is usually considered as the most important, valuable and also difficult step in MCDM (Lindley 1986), the question how one can reliably derive a valid representation of the decision problem at hand does not receive much attention within the MCDM literature. Most methods for the structuring of decision problems have been criticized for being “artistic” and for lacking methodical accuracy (Winterfeldt 1980).

A potential solution to overcome the problems associated with decision structuring is offered by the research in semantic analysis. Based on large databases (usually the World Wide Web) and automatic information processing, semantic analysis aims at providing semantic information of useful quality at low costs. In the context of MCDM, semantic analysis combined with clustering procedures allows the automatic and thereby unbiased construction of hierarchical decision representations while keeping the decision effort low. As semantic analysis potentially provides improvements in both dimensions relevant to humans for the selection of an appropriate decision strategy, namely decision accuracy and effort (Todd & Benbasat 1991; Payne et al. 1993), it might also offer a substantial improvement in the acceptance of MCDM.

In this paper, we compare semantic analysis with more conventional tools, that is card sorting procedures, to evaluate their appropriateness for the construction of hierarchical problem representations in the context of MCDM. We add to literature by providing two empirical test cases which are examined in terms of face validity and reliability. In the following Section we shortly introduce the theoretical foundations underlying decision structuring, card sorting procedures and semantic analysis. Section 4 provides two empirical test cases and a discussion of our results. Finally, we summarize the findings and identify further research issues in the last Section.

2. Theoretical foundations

In this Section we give a short overview on the structuring of decision problems. Firstly, we introduce a process for the hierarchical bottom-up structuring of decision problems which will serve as basis for the empirical test cases in the next Section. Secondly, we briefly discuss card sorting procedures and semantic analysis which can be used within this process to reveal the structure of the decision at hand.

2.1 Hierarchical structuring of decision problems

Based on the work of Trochim (1989), we introduced a process for the hierarchical structuring of decision problems in Maier and Stix (2012), which was designed with the goal of finding a good compromise between methodical accuracy and practical applicability. Its main characteristic is the seamless integration of group techniques, quantitative data analysis and algorithmic data processing for the semi-automatic construction of goal-criteria hierarchies. The process is structured in five process steps which are usually conducted within workshops of ten to twenty participants. In the following, we will shortly discuss each process step (the description is based on Maier and Stix (2012), which also provides more details on our process and its underlying principles).

Step 1 – Preparation: The first step covers all activities related to setting up the subsequent process steps and workshops. This includes the selection of a qualified facilitator who guides the process of hierarchy construction, the selection of workshop participants and the preparation of a short brainstorming focus statement, which describes the decision problem as well as the intended contributions of the participants.

Step 2 – Identification of criteria: The second process step is dedicated to the generation of a list of criteria relevant for the decision at hand along with short statements describing each criterion in more detail. For this purpose brainstorming is usually used, but other techniques like document analysis or electronic brainstorming can be used as well.

Step 3 – Structuring of criteria: The third process step aims at structuring the finalized list of criteria by constructing a distance matrix D which reflects the pairwise relatedness between all criteria. There are several techniques which can be used to construct such a distance matrix. In this paper, we concentrate on card sorting procedures and on semantic analysis which are discussed in Section 2.2 and 2.3.

Step 4 – Automatic construction of a preliminary hierarchy: In this process step a preliminary hierarchical representation of the decision problem is constructed based on *D*. To avoid conflicts between participants and to enable a seamless process, we use a two-stage cluster algorithm to build the hierarchical representation of the distance matrix. This algorithm is based on Ward's variance minimizing approach for hierarchical clustering (Ward 1963) to assign criteria to clusters and to build layers of semantically similar distant clusters (for more details see Maier and Stix (2012)). The only input required from the user is a target average cluster size, which the algorithm tries to maintain. Usually, the cluster size is set to a rather low value (4 to 7) to ease the interpretation of the resulting hierarchy.

Step 5 – Finalization of the hierarchy: This process step finalizes the hierarchy by refining the raw structure. That is, the participants are asked to inspect and discuss the raw structure to identify cluster names and inappropriate assignments of criteria to clusters. The output of this process step is the final and agreed-on hierarchy, which can be utilized in the subsequent MCDM process-steps.

2.2 Card sorting procedures

Card sorting procedures are easy to use techniques for structuring a domain of interest, which are commonly utilized in areas like user interface design of IT-systems or to structure menus and linkage of websites (Capra 2005). They are typically based on a set of cards with related terms and participants who are asked to form piles of cards based on their "relatedness" or "similarity". Usually, each term is accompanied by a short statement which clarifies the respective concept. The reason for this is that simple keywords are often rather vague or ambiguous (such as the criteria listed in Table 2). To give an example, the concept "local supply" in the context of selecting an apartment for rental might be accompanied by the following statement: "Are shops providing essential consumer items nearby the apartment or not?". The rules of card sorting are rather flexible. For example, closed card sorting is based on predefined categories while open card sorting allows the subjects to create their own categories. Furthermore, it is possible to explicitly specify the sorting dimension (e.g. "importance" or "semantic relatedness") or to allow the subjects to assign cards to multiple groups which is especially useful for the construction of fuzzy or overlapping clusters (Capra 2005). However, the resulting sorting serves as a measure of psychological distance which can be used in multivariate analysis like clustering and multi-dimensional scaling (Rosenberg & Kim 1975). While there are more accurate ways to measure psychological distances, the main advantage of card sorting is its ease of use and economy, especially if the number of items is large (Rosenberg & Kim 1975). In our context, card sorting can be used as a procedure to structure the list of criteria in process step three.

2.3 Semantic analysis

Semantic analysis is a machine learning approach for the automatic analysis of text corpora, which can be used, among other things, for assessing the semantic relatedness of terms. According to Turney et al. (2001), semantic analysis can be broadly classified into two groups of techniques: unsupervised learning based on statistical procedures and learning facilitated by hand-built lexical databases. The former approach greatly benefited from the raise of the World

Wide Web. As a giant database, the World Wide Web enables the automatic extraction of information on word similarities of useful quality (Cilibrasi & Vitanyi 2007). The statistical measures to capture semantic relatedness are usually based on counting the number of documents within the corpus where the words of interest co-occur. If the World Wide Web is used as database, search engines can be utilized to determine the page count of single terms and of groups of words, and thereby to calculate similarity measures. For example, the web-based version of the classical Jaccard index is given by the following formula (adapted from Bollegala et al. (2007)):

$$WJ_1(P,Q) = \frac{H(P \cap Q)}{H(P) + H(Q) - H(P \cap Q)} \quad (1)$$

where *P* and *Q* are two terms of interest and where *H(P)* refers to the page count returned by a search engine with input term *P*. This web-based Jaccard index comes with the disadvantage that it does not account for the specific context of the decision domain. That is, keywords might have different meanings or different relative frequencies in different contexts. Thus, a similarity measure which does not account for the context might lead to biased results. An approach to avoid this problem is to define a list of keywords which specifies the context of the decision problem and to use the list to narrow the web search (Turney et al. 2001). Based on this approach, we adopted the web-based Jaccard index to yield the following context-specific similarity measure:

$$WJ_2(P,Q,C) = \frac{H(P \cap Q \cap C)}{H(P \cap C) + H(Q \cap C) - H(P \cap Q \cap C)} \quad (2)$$

where *C* is a set of keywords specifying the context of the search query.

In the context of structuring decision problems, such measures of semantic relatedness can be used as an alternative way to structure the list of criteria within step three of our process. From a theoretical perspective, web mining promises some advantages over card sorting procedures: as a fully automated procedure, web mining is time efficient and does not require manual input which avoids biases due to the current perspective of the workshop participants. However, to our knowledge, no empirical research exists addressing the question whether web mining is indeed useful for the structuring of multi-criteria decision problems or whether classical techniques, like card sorting, are still the better alternative. This research gap will be addressed in the following Section.

3. Empirical testing

To test the appropriateness of card sorting procedures and of statistical web mining for the structuring of decision problems, we will examine two questions within in this Section: Firstly, does it matter which technique is used within the overall process of structuring decision problems (see Section 2.1)? This question asks for the reliability of the overall process regarding changes in the underlying measurement technique. The second question is which of the structuring methods is superior regarding the construction of hierarchies reflecting the “true” structure of the decision domain. This question asks for the validity of the structuring procedures.

3.1 Method

To answer the questions related to the reliability of the overall process and to the validity of the measurement technique, we conducted two empirical test cases. The goal of each test case was to construct two goal-criteria hierarchies for a multi-criteria decision problem. One hierarchy was constructed based on card sorting data and the other was build on web mining data. We followed the instructions given by step one and two of the conceptualization process described in Section 2.1 to generate two sets of criteria: The first set included criteria relevant for selecting a job offer from several vacancies (set one) and the second set covered criteria relevant for choosing one of several apartments for rental (set two). Set one contained 26 criteria and set two contained 33 criteria (note that we used German as working language and that the criteria were translated to English only for the purpose of publication).

The card sorting procedure was conducted with students of the Vienna University of Economics and Business. To ease the sorting task and data gathering, a computer-assisted card sorting procedure was used. The participants (set one: 30 students; set two: 26 students) where asked to sort the criteria into piles of semantically related criteria, following the rules given by Trochim (1989): 1) each card can only be placed in one pile; 2) there have to be at least two piles; and 3) at least one pile needs to have more than one card. We explicitly specified the sorting dimension (semantic relatedness) to yield high data quality by preventing participants from applying and mixing several dimensions (e.g. semantic relatedness and importance for decision, see Maier and Stix (2012)). Multiple uses of cards were not allowed because we were interested in constructing non-overlapping hierarchical structures. We aggregated the individual sortings by constructing a similarity matrix S, where s_{ij} gives the number of participants who sorted criterion i and criterion j into one pile. No consensus building technique was used for aggregating the sorting because this is covered by the later process step five which was not within the scope of this analysis.

Semantic analysis was based on the context-specific Jaccard index given in Equation (2). The API version 2.2 for Microsoft's search engine Bing (Microsoft, 2011) was used to gather page count data. Before data gathering, all criteria were checked for synonyms and the most common terms (highest page count) in the respective context were used for data analysis. The keywords “job” (set one) and “apartment” (set two) served as context-specifying terms. The information on the pairwise similarities of criteria was used to build a similarity matrix.

The similarity matrices obtained from card sorting and from semantic analysis were transformed into distance matrices, which served as inputs of step four (algorithmic data analysis). We omitted process step five and simply used the raw structures resulting from step four as the basis of the analysis presented here. This was necessary because after the card sorting session there was no follow-up meeting to discuss the resulting raw structures.

To test the reliability of the overall process we used two measures. Firstly, Mantel tests (Mantel 1967) with 25000 permutations (based on the recommendations of Jackson and Somers (1989)) were used to test the distance matrices resulting from card sorting and from web mining for significant differences. Secondly, Mantel tests were also used to compare the hierarchies resulting from the web mining data and from card sorting data. For this purpose, the hierarchies were represented as distance matrices, where D_{ij} = shortest path from i to j within the respective hierarchy. We used Mantel test for both measures because distances are not independent of each other which precludes significance testing based on simple correlation coefficients (Mantel 1967). To test the validity of the resulting hierarchies we followed a face validity approach. That is, we discussed the constructed hierarchies to identify inappropriate subtrees and to determine the structuring method which leads to better hierarchical representations.

3.2 Results and discussion

Table 1 summarizes the results of both test cases. The outcomes of the Mantel tests are presented as a dyad consisting of the correlation coefficient and the p-value simulated by the permutation-procedure. The first dyad tests the distance matrices resulting from the card sorting procedure and from the web mining approach for independence. The following Mantel tests compare the hierarchies resulting from these distance matrices for cluster sizes S from four to seven (see the automatic construction of hierarchies in Section 2.1). As we can see from Table 1 the p-value of the first dyad for test case one is 0.065 and for the second test case 0.012. Thus, we reject the null hypothesis that the distance matrices resulting from card sorting and from web mining are independent. However, the correlation coefficients are rather low (0.084 for case one and 0.145 for case two). Based on the interpretation of this measure as a kind of inter-method reliability, we argue that the two methods lead to structures which differ from each other to a large extent. The other Mantel tests from S = 4 to S = 7 do not allow the rejection of the null-hypotheses that the distance matrices resulting from card sorting and from web mining lead to different hierarchical representations. Thus, the algorithm which constructs the hierarchies does not preserve the correlation of the underlying distance matrices. This indicates that the algorithm is susceptible to the structuring method. Nevertheless, test case one (and to lesser extent also case two) confirms the results reported by Maier and Stix (2012) that the structuring algorithm is relative stable regarding changes in the specified cluster size.

Test case	corr	p-value	corr S = 4	p-value S = 4	corr S = 5	p-value S = 5	corr S = 6	p-value S = 6	corr S = 7	p-value S = 7
1	0.084	0.065	-0.018	0.671	-0.018	0.666	-0.018	0.671	-0.018	0.670
2	0.145	0.012	0.025	0.246	0.025	0.248	-0.022	0.651	-0.016	0.557

Table 1: Results of the Mantel tests

Figure 1 combined with Table 2 presents the hierarchies resulting from the card sorting procedure and from the web mining approach of test case two and cluster size five (note that we do neither present nor discuss more hierarchies due to length constraints). A visual inspection shows that the hierarchy resulting from the card sorting procedure is well partitioned and clearly arranged. Furthermore, the groupings of criteria are, to a large extent, reasonable and allow the identification of meaningful cluster names. For example, the criteria “local supply” (20), “proximity to public transportation” (21), “leisure activities” (22), “distance to workplace” (23) and “distance to family and friends” (24) are grouped together and the resulting goal could be labeled as “location” or “logistic issues”. In comparison to those results, the semantic analysis approach leads to a rather complicated and less easily interpretable hierarchy. This visual complexity results from a relative large number of criteria not placed on the lowest level of the hierarchy (eleven criteria) and from a comparatively high variance of cluster sizes. Furthermore, many groupings of criteria seem to be unreasonable. While it makes sense to group “monthly costs” (14) together with “one-time costs” (15) and maybe with “rental agreement” (19), it is not reasonable to cluster “purchase option” (17) and “local supply” (20), especially if one considers the descriptions of these two criteria given in Table 3. In sum, the semantic analysis approach leads to more inappropriate clusters of criteria than the card sorting procedure, and therefore also to less valid goal-criteria hierarchies. Furthermore, the hierarchies resulting from semantic analysis are not clearly arranged which might offset some advantages offered by hierarchical problem representations like increased information processing capabilities of the DM.

1. floor covering	12. age (of building)	23. distance to workplace
2. interior (kitchen & bath)	13. heating installation	24. distance to family & friends
3. furnishings	14. monthly costs	25. leafy area
4. aesthetics	15. one-time costs	26. outdoor area (balcony)
5. size of apartment	16. rental period	27. neighbors
6. level of apartment	17. purchase option	28. noise exposure
7. number of rooms	18. landlord/owner	29. social environment
8. room layout	19. rental agreement	30. garage
9. quality of apartment	20. local supply	31. basement storage room
10. brightness	21. prox. to pub. transp.	32. infrastructure (of building)
11. condition of apartment	22. leisure activities	33. pet policy

Table 2: Criteria of test case two

purchase option	Does the renter have the right to buy the apartment after the rental period has expired?
local supply	Are there supermarkets and/or similar shops in the vicinity of the apartment?

Table 3: Descriptions of two criteria used in test case two

Although we expected that the two structuring approaches do not lead to identical results, we did not expect such large differences. Notably, we were surprised by the low face validity of the hierarchies resulting from semantic analysis, which is not in line with the results reported in the literature on semantic analysis (see Section 2.3). A possible explanation for this finding can be found by comparing the terms used in this study with the terms used in other studies on mining the web for relatedness. For example, Cilibrasi and Vitanyi (2007) used, amongst others, titles of books to test their measure of relatedness. In such a context, each term (title) unambiguously identifies a specific concept (book). In contrast, the concepts (criteria) used within MCDM are often much more vague (such as the criteria of test case two, see Table 2). Thus, there are usually no specific terms or names which unambiguously identify the criteria. In the case of card sorting procedures, it is easy to overcome this problem by providing short statements which describe the criteria in more detail. These descriptions allow humans to construct meaningful mental representations of the criteria, and thereby to form groups of related concepts. By contrast, web mining for relatedness is based on statistics which does not account for meaning. Hence, if there are no specific terms which unambiguously identify the concepts of interest, web mining for relatedness reaches its limits. One approach to cope with this shortcoming is to describe each criterion in more detail by a set of unspecific keywords. But there is no way to guarantee that a website containing all keywords of such a set is indeed about the concept of interest. Thus, the keyword search might return biased page count data. Furthermore, this approach comes with other disadvantages, like low or no page hits or more laborious preparation of keywords.

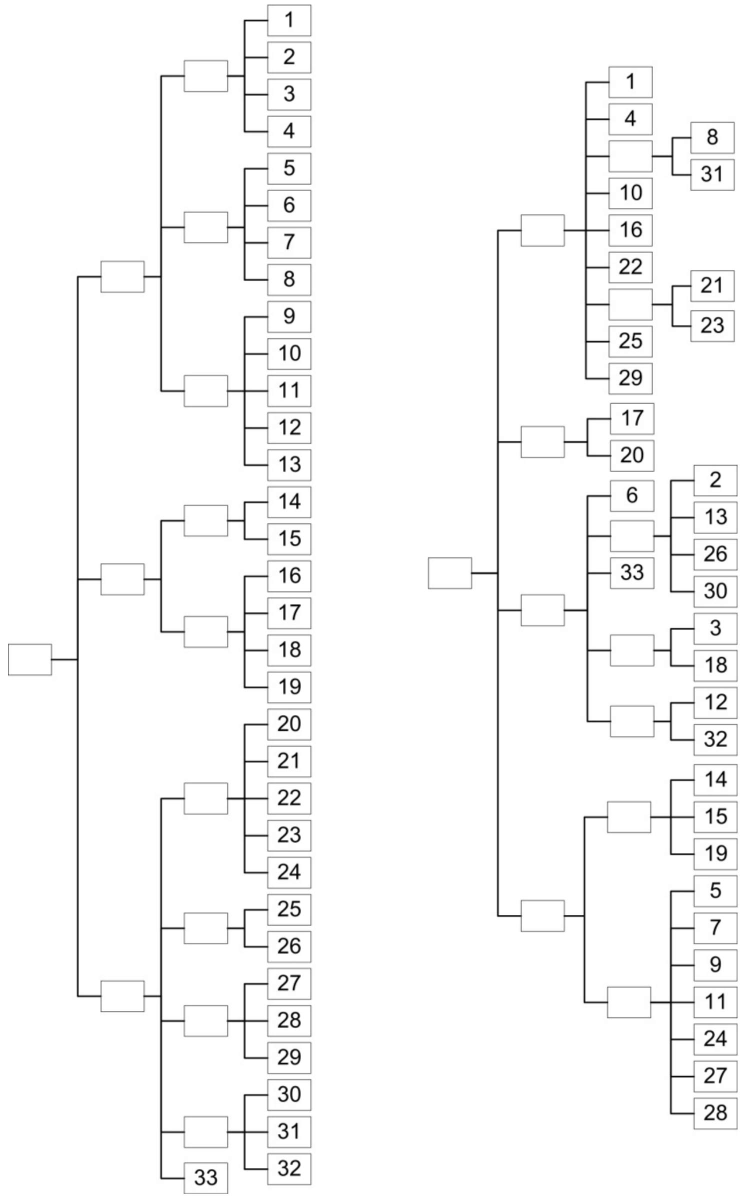

Figure 1: Results of test case two with cluster size four. The hierarchy on the left is based on card sorting data; the hierarchy on the right is based on web analysis data.

4. Conclusion

In this article, we analyzed two techniques regarding their adequacy for the hierarchical structuring of decision problems: semantic analysis via statistical web mining and card sorting procedures. As an automated procedure, semantic analysis theoretically offers time savings and unbiased results. In contrast, card sorting procedures are based on human information processing and offer the advantages that the resulting data reflects the participants' thinking of the decision at hand and that the structuring dimension can be easily changed. We conducted two empirical test cases to determine whether the two techniques lead to similar results and to examine the face validity of the resulting goal-criteria hierarchies. Pertaining to the former, we found that the two approaches lead to different but not completely unrelated distance matrices and to significantly different hierarchical structures. Pertaining to the validity, the card sorting procedure led to meaningful and interpretable hierarchies while the web mining approach led to less intuitive hierarchies. We offered a possible explanation for this result by discussing that web mining is not an interpretative but a statistical procedure. We argued that such statistical procedures are not well suited to deal with concepts which lack specific identifiers (names) and which therefore require short statements to exactly specify the concepts' meanings. Based on the two test cases we conclude that card sorting seems to be a valid and easy to use technique in the context of multi-criteria decision analysis while web mining suffers from some drawbacks. However, this result should be carefully interpreted because our face validity analysis is based on a qualitative assessment of the hierarchies which potentially suffers from subjective biases. Our next step is to address this limitation by testing the validity of the structuring techniques in a more objective fashion. For example, this could be done by asking a random sample of people which of the resulting hierarchies better reflect their mental structures. Also the time needed to name clusters of criteria or tests based on the number of criteria recalled by individuals after seeing a hierarchy might be used to measure the validity of the hierarchy-generating processes. Finally, we want to note that we followed a rather simple web mining approach which left many research opportunities unconsidered. For example, to test more complex similarity measures, to account for synonyms while calculating the number of page hits, to replace simple keywords searches by the statements used in card sorting or to verify our results in a broader range of decision domains would probably lead to valuable research outcomes. In the long run, such an effort might result in a web mining approach useful for constructing valid structures of decision problems. This would definitely represent a major advancement in the field of multi-criteria decision analysis.

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