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The validity of concept mapping: let's call a spade a spade

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Abstract
Concept Mapping (CM) is promoted as a research method suitable for interdisciplinary and international research, "… best suited to applications where diverse or wide-ranging opinions need to be gathered and made sense of." Our study does not support this claim in practical applications when data are analyzed as prescribed by the same literature. Neither the conventional analytic approach in CM nor alternative clustering algorithms appear to be able to reveal meaningful attributes when these attributes vary between different sorters. CM may be appropriate to use when groups can be assumed to be homogeneous, but CM cannot test this assumption. Furthermore, proposed methods for data reduction obscure the discovery of meaningful attributes even when groups are homogeneous. However, we demonstrate by means of proof of principle experiments, that if the general approach to concept mapping data is mediated such that (1) steps to identify possible heterogeneity of the sorters are taken, (2) the modeling approach to attribute identification uses the full distance (or co-occurrence) matrix of statements instead of a two-dimensional reduction by multi-dimensional scaling, and (3) appropriate visualization methods of the cluster analysis are used, Concept Mapping can produce meaningful results.

Keywords Concept mapping · Multidimensional scaling · Cluster analysis · Interdisciplinary research

1 Introduction

Concept maps are versatile cognitive tools used across disciplines to improve understanding, teaching, brainstorming, and organization of information (Novak and Cañas 2006; Trochim 1989a, b). Concept maps, originally developed by Joseph Novak, are graphical representations that demonstrate the relationships between ideas and concepts (Novak and Gowin 1984). Concept mapping has been applied in various domains. For example, concept maps have been used to study the opinions of practitioners on medical care for people with

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intellectual disabilities (Breuer et al. 2022); to identify opportunities for the food bank and local agencies to better help food insecure clients (Shannon et al. 2021); to examine, from the perspective of the community, the impact of drugs on people's lives and neighborhoods (Windsor 2013).

Concept mapping (CM) is an exploratory research method that is 'inherently integrative' in its use of qualitative and quantitative procedures in a structured conceptualization process (Dixon 2009; Burke et al. 2005), thus producing a representation of reality or an interesting suggestive map meant for planning and evaluation purposes. Since the introduction of CM in the 1980s, its participatory character has been recognized as an important and attractive characteristic (Burke et al. 2005) and useful in the development of participatory community research programs (Windsor 2013). Trochim (1989a) found applications of CM ranging from the identification of multicultural awareness goals of 4 staff members for a day camp, to the production of a map as an organizing device for long-range planning efforts of the Cornell University University Health Services (with between 50 and 75 participants), to the development of a framework for designing a training program for volunteers to work with mental patients (number of participants not given) (Trochim 1989b). Concept mapping has been used in public health-oriented research, human services, biomedical research, social science research, and business and human resources research (Rosas and Kane 2012). Concept mapping is promoted for interdisciplinary and international research, as it is "purposefully designed to integrate input from multiple sources with differing concept expertise or interest" (Kane and Trochim 2007). Because of the use of CM in a wide range of academic disciplines, and our combined experience working in interdisciplinary research (e.g., Tobi and Kampen 2018) we were eager to learn more about the usefulness of CM in interdisciplinary settings.

The aim of our study is to investigate the validity of CM by means of a thorough assessment of the procedure, and a series of experiments simulating an interdisciplinary research setting. We first present a brief overview of the whole CM procedure based on Kane and Trochim (2007). The described CM procedure raised a number of questions on how technical procedures are done exactly, why it is done that way and what the consequences of these methodological choices are for applied research. We propose alternative methods to counter these problems, and we present a proof of principle experiment illustrating these problems and showing effectiveness of our proposed remedial measures. We conclude with a discussion of the validity of CM in interdisciplinary setting and possible alterations.

2 A brief review of the procedure of concept mapping

2.1 Phase 1: Preparation

The initial phase and crucial foundation of CM is fundamentally centered on preparation. According to Kane and Trochim (2007), this stage involves meticulously defining the issue under examination, establishing clear goals, and delineating the desired outcomes. This preparatory phase is essential for aligning the focus of the research with the needs and expectations of the stakeholders involved, and the selection and invitation of facilitators and participants are pivotal. The facilitators must be adept at guiding the discussion and helping participants navigate through the process of categorizing and linking concepts effectively.

The participants, ideally, should be stakeholders or individuals with a vested interest or expertise in the topic at hand. This composition of the panel is critical as it directly impacts the breadth and depth of the concept mapping exercise.

Kane and Trochim emphasize the suitability of CM for exploring a range of research questions pertinent to planning and evaluation projects. Example questions include:

- "What are the issues in a planning or evaluation project?"
- "Do the stakeholders have a common vision of what they are trying to achieve that enables them to stay on track throughout the life cycle of a project?"
- "Can stakeholders link program outcomes to original expectations or intentions to see if they are achieving what they set out to achieve?"

These questions highlight the potential of CM to facilitate a shared understanding among stakeholders, thereby fostering a collaborative environment conducive to addressing complex project challenges.

The preparation phase also involves logistical arrangements such as scheduling, selecting appropriate methods for data collection and analysis, and preparing materials that will be used during the mapping sessions. The careful planning of these elements ensures that the subsequent phases of concept mapping can proceed smoothly and efficiently, with all participants fully equipped to contribute meaningfully to the discussions and analyses. Thus, the preparation phase is not merely administrative but strategic, setting the stage for a structured and goal-oriented exploration of key project themes and stakeholder perspectives. This systematic approach to preparation not only enhances the procedural integrity of the CM process but also significantly contributes to the robustness and relevance of the findings generated through this methodological framework.

2.2 Phase 2: producing statements

Phase 2 of the concept mapping process, as described by Kane and Trochim (2007) in their seminal work, involves the critical task of producing statements that form the core material for subsequent mapping activities. This phase starts with the panel being presented with a specifically designed question that is both relevant to the research objectives and sufficiently open-ended to elicit comprehensive and informative responses from the participants. This question is pivotal as it sets the direction for the type of information that will be collected, thereby shaping the entire concept mapping exercise.

During this phase, participants engage in what is typically a brainstorming session, either individually or in groups. This session aims to generate a wide array of responses that reflect the participants' thoughts, perceptions, and insights related to the posed question. The spontaneity and free-form nature of brainstorming allow for the capture of a diverse set of ideas, making it a potent technique for gathering qualitative data.

However, the initial set of statements generated from the brainstorming session is often too voluminous and varied to be useful in its raw form. As such, a critical editing process follows, where these primary statements are meticulously reviewed and refined by the researchers. Kane and Trochim highlight the importance of this process, noting that the statement set must be reduced and edited to ensure uniqueness, relevance, clarity, and comprehension. This step is crucial because it eliminates redundancy, clarifies ambiguities, and ensures that each statement is distinct and comprehensible to future participants who will engage in the sorting and rating phases.

The editing process provides substantial room for interpretation, a characteristic common in qualitative data reduction. Researchers must apply their judgment to balance between retaining the original intent of participants' contributions and making the statements clear and relevant for the subsequent mapping exercises. This phase, therefore, requires a keen understanding of the thematic material, a deep engagement with the concept, and an ability to foresee how these statements will interact in later stages. Moreover, as researchers refine the statements, they must remain vigilant about introducing biases that could skew the mapping results. Each decision to include, exclude, or modify a statement carries implications for the types of themes and relationships that will be discernible in the final concept map. Hence, this phase not only serves as a bridge between the initial exploratory input from participants and the structured analysis that follows but also as a filter that enhances the quality and utility of the information to be mapped.

The production and refinement of statements in Phase 2 are fundamental to the integrity and success of the concept mapping process. This phase requires careful design of the initial questions, a facilitative approach to brainstorming, and rigorous, thoughtful editing to craft a final set of Q statements that are primed for effective mapping.

2.3 Phase 3: sorting statements

Next, each participant is asked to sort the Q statements in the final statement set in piles or stacks, on the basis of similarity between the statements. The sorting task gives no guidance to the panel members other than that piles must have a minimum of two statements and may not place all statements on a single pile. No information is supplied about the attributes to sort on, nor on the number of piles to aim at. After the sorting tasks, participants rate the Q statements on importance or priority on an ordinal scale (Kane and Trochim 2007; Chap. 4).

As the sorting task does not steer in any way, each participant can make a different number of piles based on a different set of attributes and (perceived) meaningful commonalities and differences on these attributes. Therefore, one would expect the data to contain plenty of variation. Intuitively we would assume that two statements j and k are more similar (i.e. conceptually close) to one another than to statement h when more sorters put statements j and k on the same stack, than either statements j and h or statements k and h. This principle brings us to the core of Concept Mapping.

2.4 Phase 4: the core of the analysis

At this point we assume a sample of N participants who have sorted all statements s_j, $j = (1,\ldots,Q)$. A basic representation of these CM data consist of an $N \times Q(Q-1)$ matrix S with binary entries indicating for each participant whether or two statements s_j and s_k were placed together or not. So, S consists of rows corresponding to respondents, and columns consisting of zeros and ones denoting if statement s_1 was placed on the same pile as statement s_2, if statement s_1 was placed on the same pile as statement s_3, and so on, all the way to the column denoting if statement s_{Q-1} was placed on the same pile as statement s_Q.

The data in S provide the information to construct a total of N square $Q \times Q$ sorter level co-occurence matrices X_i, with elements (see e.g., Leydesdorff and Vaughan 2006; Kruskal and Wish 1978):

$$x_{ijk} = \begin{cases} 1 \text{ if } s_j \text{ and } s_k \text{ were put in the same pile by participant } i \\ 0 \text{ if } s_j \text{ and } s_k \text{were put in different piles by participant } i \end{cases} \tag{1}$$

$i = (1,\ldots,N)$ and j, $k = (1,\ldots,Q)$. The more frequently statements j and k are put on the same pile, the larger their perceived similarity and the smaller the distance between the statements. If all sorters sort statements based on the same attributes (the default in the traditional approach to concept mapping), the joint co-occurrence matrix defined by

$$C = \sum_{i=1}^{N} X_i. \tag{2}$$

is transferred into a $Q \times Q$ (Euclidian) distance matrix D where (Leydesdorff and Vaughan 2006):

$$d_{jk} = \sqrt{\sum_{h=1}^{Q} (c_{jh} - c_{kh})^2}. \tag{3}$$

The conventional approach to Concept Mapping (Trochim 1989a, p. 8) uses the distance matrix as input for multidimensional scaling (MDS), whose 2 strongest dimensions are subjected to K-means cluster analysis using Ward's method and userdefined number of clusters k. The initial number of clusters is somewhere between 3 and 20 (Trochim 1989a), while (Rosas and Kane 2012) pooled study analysis showed that final solutions on average present 9 clusters and range between 6 and 14 clusters. Some researchers have used hierarchical cluster analysis (HCA) instead of K-means clustering (e.g. Shannon et al. 2021).

The cluster solution can be displayed in a so-called point cluster map (Miller et al. 2018, p. 172), which depicts the statements in the two-dimensional plane defined by the 2 MDS dimensions, where statement IDs are colored by cluster membership. Eyeballing the point cluster map may lead to redefining the number of meaningful clusters, leading to a final cluster solution. The attractive visualisation of the statements in the point cluster map is the starting point to interpretation of attributes in Phase 5.

2.5 Phase 5: interpretation of the clusters

In the final phase of concept mapping, the interpretation of the clusters, a critical evaluative process takes place where the results of the clustering analysis are assessed and understood in depth. According to Kane and Trochim (2007), in Chap. 6 of their guide, this stage involves a detailed examination of the point cluster maps that were generated during analysis.

During this phase, either participants who provided the input or researchers themselves review the clustered maps of statements. These clusters are then interpreted and named, often relying on "anchor statements" which serve as representative or pivotal points within each cluster. Anchor statements help in providing clarity and focus, acting as a basis around which other statements are grouped and understood. This process of naming and interpreting clusters is essential as it translates the abstract groupings of data into coherent themes that can be easily communicated and applied in further research or practical applications.

The interpretation session also provides an opportunity for discussing consensus across different groups of participants or examining the consistency of the results. This discussion can highlight whether different subgroups see the world similarly or if there are distinct perspectives that need further exploration. Such insights are valuable, as they can inform whether the concept mapping has successfully captured a comprehensive understanding of the issue at hand or if further iterations are necessary.

This final phase is not just a process of naming and knowing but is also a reflective practice where the validity and reliability of the results are scrutinized. It ensures that the concept map produced is not only a reflection of participant inputs but also a robust tool that can be used to inform decision-making, policy formulation, or further research. Thus, the interpretation of the clusters is a decisive step that solidifies the entire concept mapping process, providing meaningful insights that are grounded in the systematic analysis of qualitative data.

3 Issues in analysis and our proposed solutions

3.1 Assumed homogeneity of sorters

The default paradigm in Concept Mapping assumes that all participants use the same attributes of the statements to compose the stacks. To illustrate how this is assumption is unrealistic, consider three very simple statements "London", "Frankfurt" and "Berlin", and three sorters. A possible outcome of the sorting exercise is:

sorterID	Statement	stackID
resp1	London	Capital city
resp1	Frankfurt	City
resp1	Berlin	Capital city
resp2	London	1
resp2	Frankfurt	2
resp2	Berlin	2
resp3	London	A
resp3	Frankfurt	B
resp3	Berlin	A

We see that 2 sorters (resp1 and resp3) put "London" and "Paris" together while "Frankfurt" defines a separate stack (apparent attribute "capital city versus city"), while another sorter (resp2) clusters statements "Berlin" and "Frankfurt" together and "London" separately (apparent attribute "German versus UK"). When it is not reasonable to expect that all sorters sort on the basis of the same attributes, or when one wishes to verify this assumption, an intermediate step is required to discover and produce clusters of sorters using identical attributes. A cluster analysis of *S* will identify groups of identical sorters, and each sorter cluster produces its own co-occurence matrix that must receive separate analysis. Of course, when 2 or more sorter clusters are identified, interest may be placed in which statements receive different treatment, that is, end up in different stacks due to different attributes used for classification. A cross-cluster map can be instructive for comparing clusters from two different clusters.

3.2 Overkill in data reduction

The decision to scale the distance matrix of statements down to just 2 dimensions was originally motivated by Kruskal and Wish (1978) who said that "it is generally easier to work with two-dimensional configurations than with those involving more dimensions." The coordinates of each statement in the resulting two-dimensional plane are used to identify meaningful clusters of statements by means of K-means cluster analysis using Ward's method, as it "generally gave more reasonable and interpretable solutions than other approaches such as single linkage or centroid methods" (Trochim 1989a, p. 8). While it is true that the human mind can comprehend two dimensions better than higher amounts of dimensions (at least when displayed on paper), the twodimensional solution may not adequately reflect distances between statements in the Q dimensional space and may therefore distort interpretation. Therefore, Péladeau et al. (2017) propose to first conduct cluster analysis and then MDS, as "clusters created on the original matrix demonstrate, consistently, a better representation of the original pairings made by participants than clustering made on the MDS coordinates" (p. 60).

We developed two alternative, and in our experience more effective, methods to discover patterns and consistency in the way that statements were paced on piles. The first alternative is straightforward and applies K-means clustering directly to the distance matrix *not applying MDS anywhere in analysis*. This method has the advantage that it uses all information on distances between items, rather than using just the two main dimensions from MDS. The results may be visualized as a heatmap of the co-occurrence matrix and dendrograms of clustered statements (see Wilkinson and Friendly 1987).

The second alternative deviates from existing procedures more radically and approaches the sorting problem as a form of network analysis (Scott 2012), where "nodes" correspond to statements and "connections" correspond to the number of times statements ended up on the same stack. This method also uses the raw distance matrix as main input, but is more informative because in addition to visualizing major stacks in a so-called network plot, it also shows the degree to which statements are (mis)placed on different stacks. The number of meaningful clusters in network analysis can be detected by the Louvain method (see Blondel et al. 2008).

4 Showing the validity of different approaches to analysis of concept mapping data

4.1 Simulating concept mapping data

Researchers investigating concept mapping face several challenges when trying to simulate the sorting of statements based on thematic similarities. The inherent complexity of human thought processes and the subjective interpretation of thematic categories can make it difficult to create a standard simulation that accurately reflects how individuals group and perceive different statements. Additionally, ensuring that participants understand and engage with the abstract concepts represented in the statements requires careful design and clear instructions.

We used a standard deck of cards to offer a novel and effective way to mimicking these complexities. Each card in a deck, much like each statement in concept mapping, carries distinct attributes that can represent different thematic elements. For example, suits in a deck (such as clubs, diamonds, hearts, and spades) can be designated to correspond to broad thematic categories like technology, health, finance, and education, respectively. The two colors in a deck, red and black, can further differentiate between subjective and objective types of statements. And so on.

During the simulation, (virtual) participants are given a deck of cards and are tasked to sort these cards into piles based on perceived thematic similarities (e.g., color, suit, rank, odd versus even numbers). This mirrors the concept mapping process, where individuals or groups categorize statements according to shared themes. Analyzing the outcomes of this card-sorting activity provides valuable insights into how information is processed during analysis, similar to the analysis in traditional concept mapping studies. Researchers can examine the consistency of categorization among participants, identify dominant grouping patterns, and assess the clarity of thematic boundaries. This study takes advantage of the inherent features of a deck of cards to simulate and study the cognitive and perceptual processes involved in thematic categorization.

When we recognize the important similarities between sorting statements by theme and sorting cards by their attributes, designing a simulation study verifying validity of the proposed analytical techniques used in Concept Mapping is relatively straightforward. A series of simulation studies was designed on the model of sorting one standard deck of $Q=54$ cards with numbers 2 through 10, Jack, Queen, King and Ace of Spades, Clubs, Hearts and Diamonds, and 2 Wildcards. The cards allow for several attributes for classification, of which we selected:

1. *Suits*, resulting in 5 piles: Spades, Clubs, Hearts, Diamonds, and Wildcards.
2. *Ranks*, resulting in 11 piles: Ace, 2, 3, …, 10, and Picture cards (i.e. Jack, Queen, King, and Wildcard).

We assumed that each participant classified cards according to 1 (and just 1) attribute. In order to introduce some random noise in the data, we further assumed that within a selected attribute for classification, respondents had a high probability to correctly classify (90%), and any wrongly classified card had an equal probability to end up in one of the other piles. Note that a high probability of correct classification prevents the need for replication. Finally, we assume that all participants sorted all statements (so that $n_{jk} = n$ for all j, k). The simulation produced 54×54 co-occurrence matrices that were input for further analysis i.e. the MDS as prescribed in CM with two dimensions followed by a K-means clustering using Ward's method (Everitt 1980, p.65). We set $k=10$ to mimic the usual analytic procedure in CM; an alternative is to use the so-called silhouette method to determine the number of clusters (see Rousseeuw 1987; Charrad et al. 2014). Data simulation as well as Concept Mapping analyses where conducted in *R* using the cmAnalysis package (Hageman and Kampen 2025). The script to run our simulations is available in the supplementary materials.

4.2 Heterogeneity of sorters: proof of principle

We did a simulation where half of the sample ($n=20$) used Suit, and half of the sample ($n=20$) used Ranks for sorting. Inspection of the point cluster map (Fig. 1) and the dendrogram (Fig. 2) supports the interpretation that cards are ranked by Suit, but at no point would one conclude that Rank played a role in sorting. However, a K-means cluster analysis of *S* where the number of clusters was determined by the silhouette method (see Rousseeuw 1987) correctly revealed two distinct clusters of sorters (see Fig. 3). Other simulations (results not printed to save space) used mixtures where sorters used upto 4 different attributes for sorting (Suit, Rank, Color, and odd vs. Even) and cluster analysis proved effective in splitting up the total sample of sorters into its subgroups. Figure 4 gives a cross-cluster map of the two sorter clusters. This plot reveals that one group of sorters used Suit (left-hand) and another group used rank (right-hand) as sorting attribute.

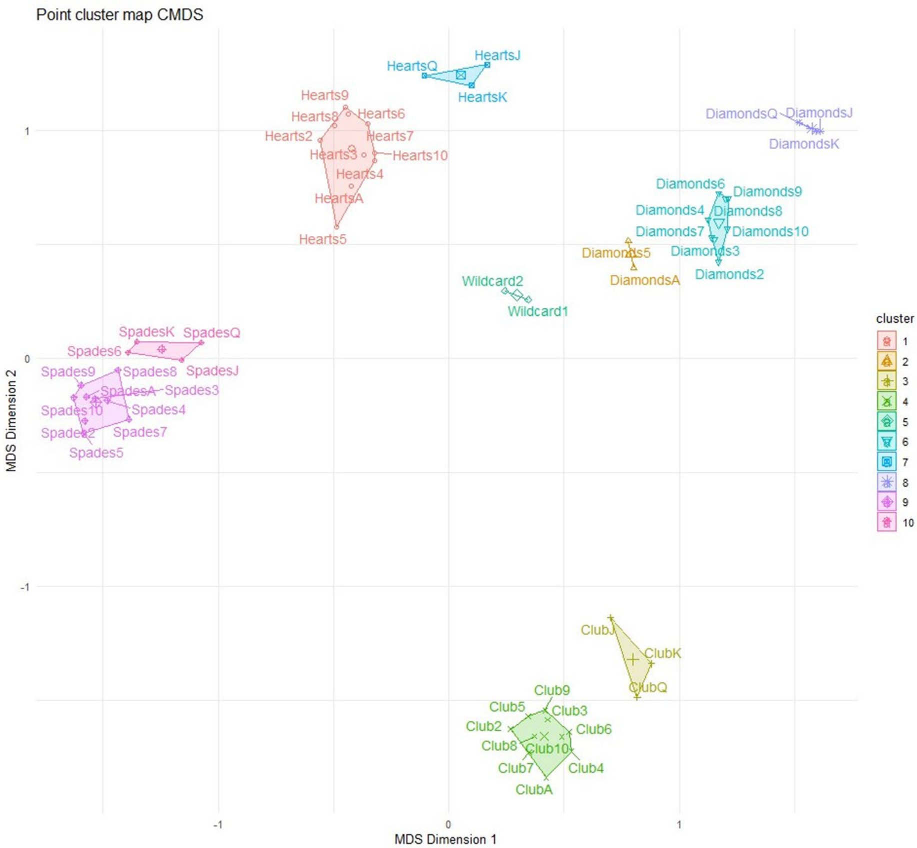

Fig. 1 Point cluster map for a simulation where half of the sample ($n=20$) used Suit, and half of the sample ($n=20$) used Ranks for sorting

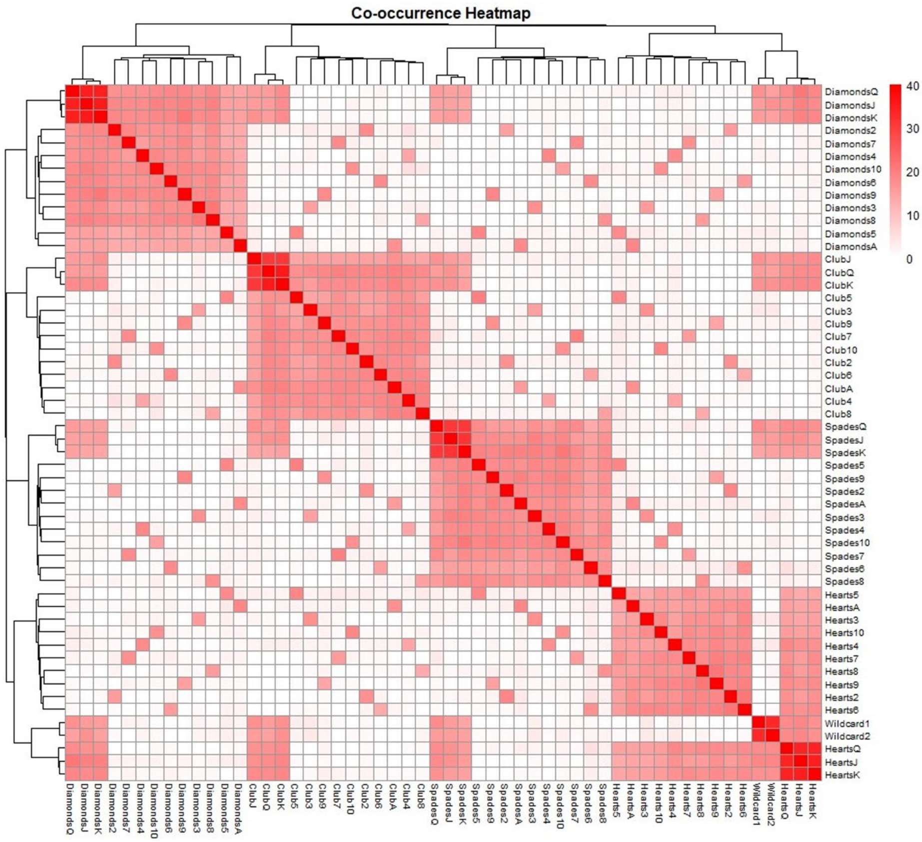

Fig. 2 Heatmap and dendrogram for a simulation where half of the sample ($n=20$) used Suit, and half of the sample ($n=20$) used Ranks for sorting

4.3 Data reduction: proof of principle

When we analyse the second sorter cluster identified in Fig. 4 (purposively selected because it corresponds to the most complicated data structure using Ranks as attribute), the conventional approach to Concept Mapping, inspecting K-means clusters of 2 MDS dimensions with k arbitrarily defined to equal 10, still fails to facilitate identifying the underlying 11 cluster structure (see Fig. 5). The configuration suggests a 4 cluster solution rather than the 10 cluster solution forced on the data (let alone the 11 cluster solution which would be correct). On the other hand, direct analysis of the complete distance matrix by hierarchical cluster analysis using Ward's method clearly reveals presence of 11 clusters of statements (see Fig. 6). Another revealing way of visualizing the results in an attractive manner is the network plot applying the Louvain method for cluster identification (Fig. 7). The network plot correctly depicts the 11 meaningful clusters, for instance, the cluster of rank 2 and rank 4, the cluster of picture cards, and so on. It further provides an indication of the frequency of alternative placements of statements on different piles. The two alternative visualizations,

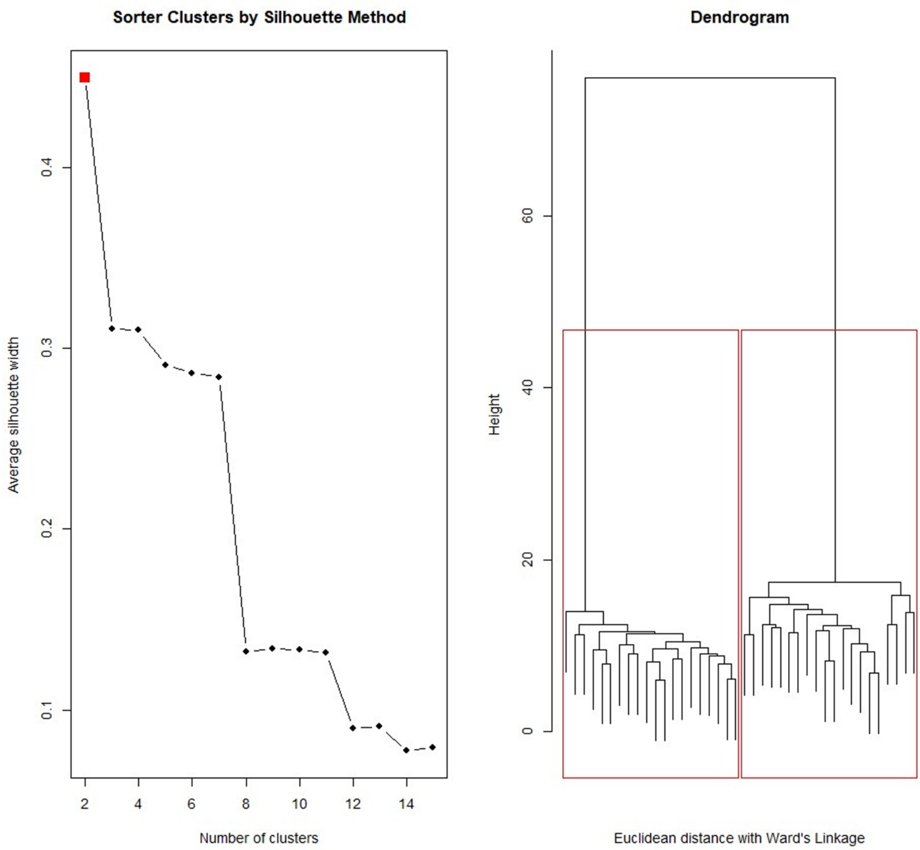

Fig. 3 Silhouette plot and dendrogram for a simulation where half of the sample (n=20) used Suit, and half of the sample (n=20) used Ranks for sorting

the heat map and the network plot, appear more effective to depict the degree to which statements ended on the same pile than the point cluster map.

5 Conclusions

We explored the usefulness of CM in an interdisciplinary setting in which one would expect heterogeneity of sorting strategies of participants. To that end, we created a highly simplified situation where the same statements were sorted on 2 different attributes, and found that both traditional CM analysis and HCA failed to reveal both attributes. Kane and Trochim consider so-called bridging values important in determining the concepts of clusters, but that will not help in un-mixing mixed sets of used attributes (e.g., in Fig. 1 we would wrongly arrive at 5, perhaps 6 clusters corresponding to meaningless attributes). In such situations, any analytic method leads at best to identification of the attribute with the lowest number of piles, but in practice to some (non-existing!) hybrid of attributes. Our first conclusion is therefore, that in any application of CM where the attributes for sorting statements

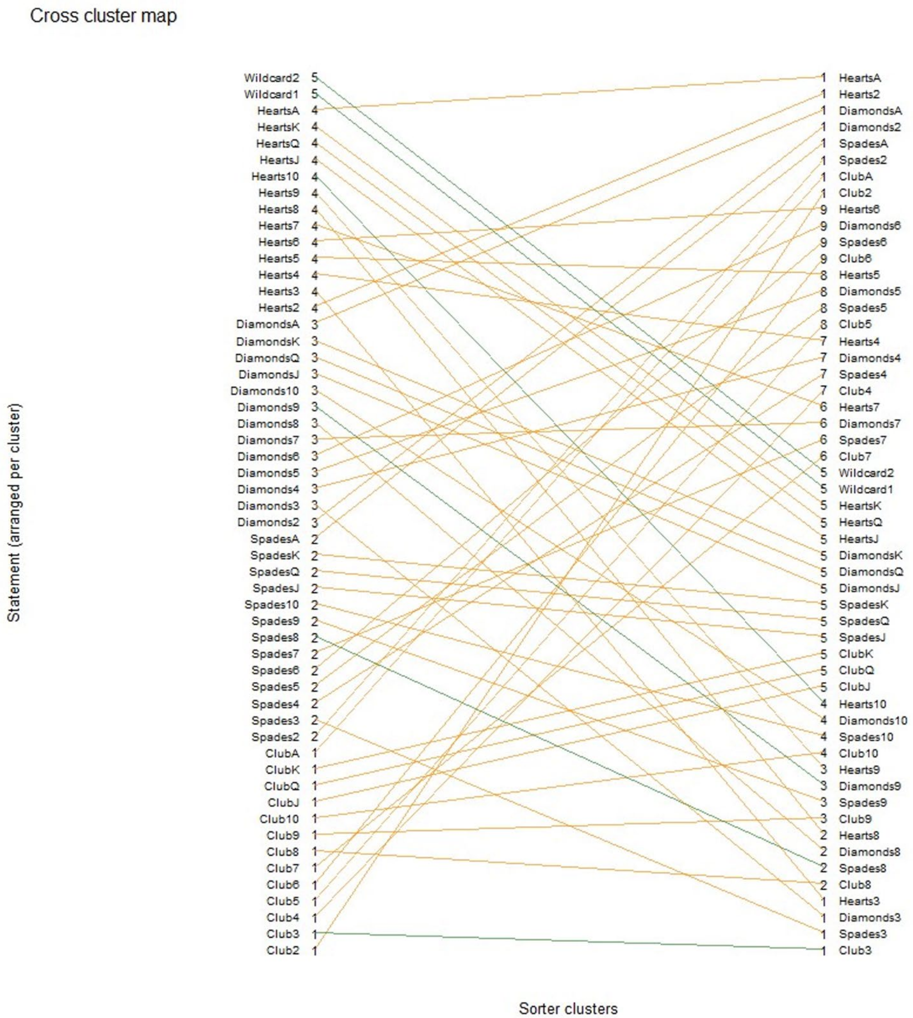

Fig. 4 Cross-cluster map for a simulation where half of the sample ($n=20$) used Suit, and half of the sample ($n=20$) used Ranks for sorting

are unknown and the analysis aims to identify these attributes, sorting data must be preprocessed by identifying clusters (or groups) of similarly sorting individuals before proceeding with separate analyses of sorting data within each identified group. The second conclusion is that skipping MDS did not come at a cost. On the contrary, dendrograms and network plots applied to the complete distance matrix are more accurate as well as easier to interpret than point cluster maps and do not require the assumption that the dimensionality of the problem can be reduced from Q to 2. This leads to the third conclusion, that the different visualizations of the sorting data presented in this article suggest that heatmaps, dendrograms and network plots are significantly more useful to interpret the clusters of statements than point cluster maps.

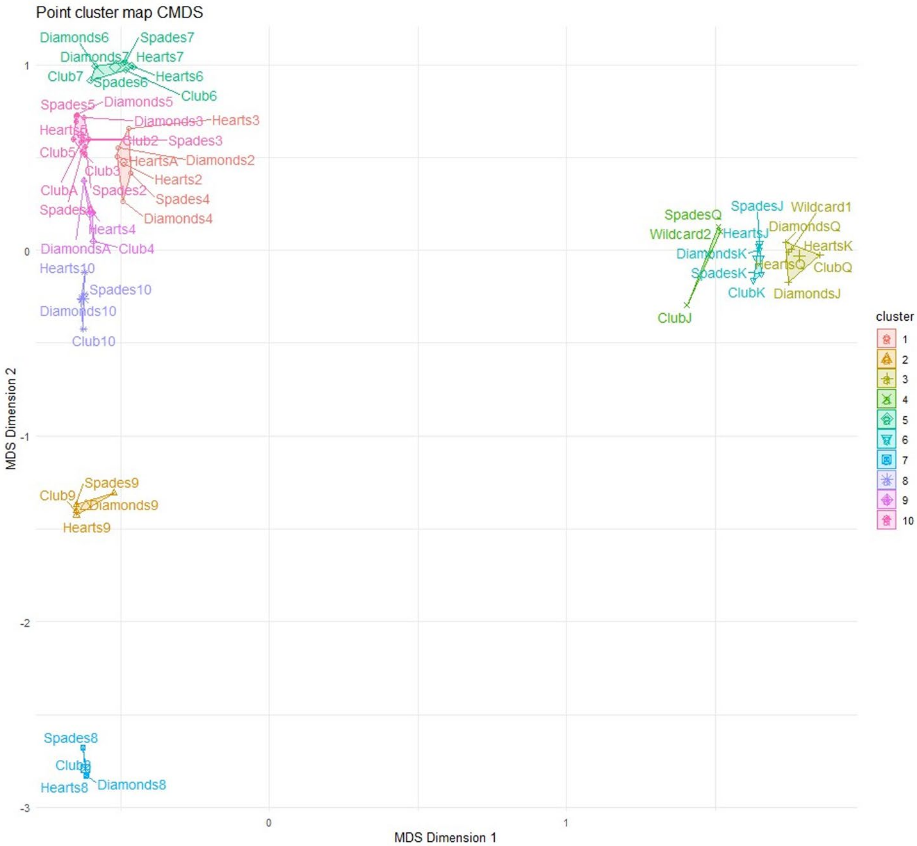

Fig. 5 Point cluster map for a simulation where the subsample ($n=20$) used Ranks for sorting

It might be argued that the use of simulated data to support broad claims about human cognitive capability in statement sorting is unconvincing and methodologically unsound, particularly as it neglects the nuanced and productive ways in which CM can be combined with qualitative methods such as thematic analysis or focus groups. However, analytic methods that produce demonstrably incorrect groupings of statements cannot yield meaningful, valid, insights into thematic sorting or the cognitive processes involved. Therefore, CM *in its present form* is not suitable for interdisciplinary research or other instances where the choice of attributes between sorters must be assumed to vary (and interest may be exactly in that variation). That said, pending 3 adjustments in the conventional procedure for analysis of Concept Mapping data, we do see merit and use of the method. These adjustments are:

1. Concept Mapping data must be tested for existence of different clusters of sorters who must receive separate analyses;
2. Analysis must take into account the complete co-occurrence matrix (and so MDS must be abolished);
3. Heatmaps, dendrograms and network plots of statements deserve preference to point cluster maps in visualizations used to aid interpretation.

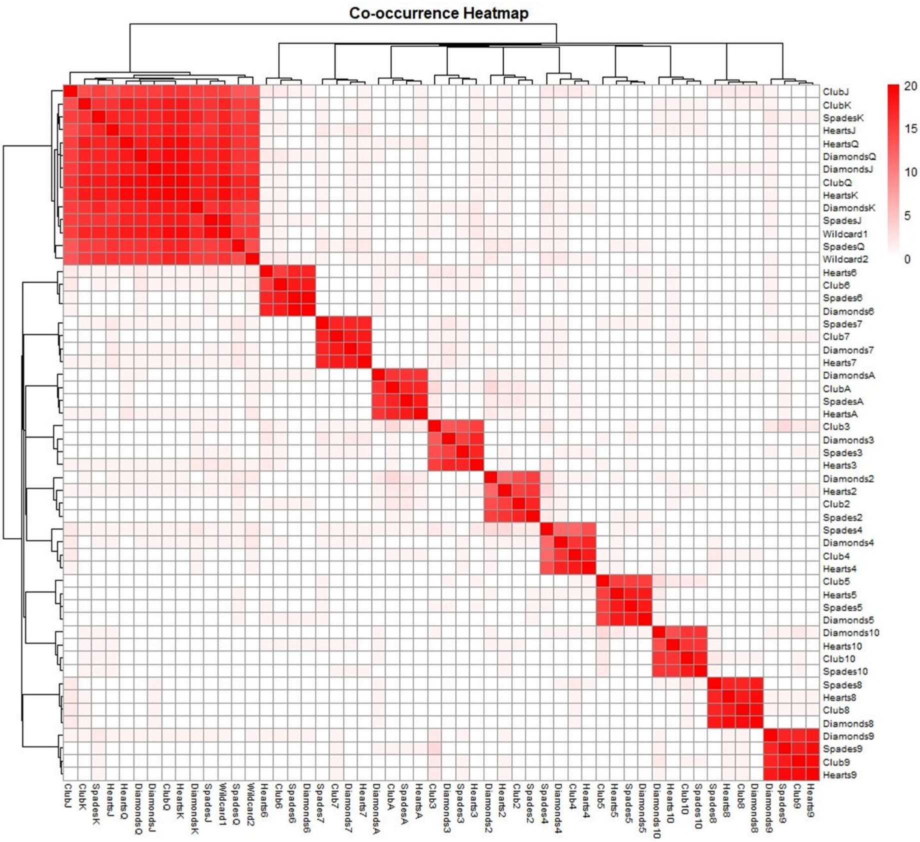

Fig. 6 Heatmap and dendrogram for a simulation where the subsample ($n = 20$) used Ranks for sorting

Given these adjustments in analysis, Concept Mapping is able to call a spade a spade.

6 Supplementary Information

The results in this paper were obtained using R (ver. 4.4.2) with package cmAnalysis (ver. 1.0.0) which is available from the Comprehensive R Archive Network (CRAN) at url CRAN.R-project.org. Our study did not require an ethical board approval because it did not directly involve humans or animals.

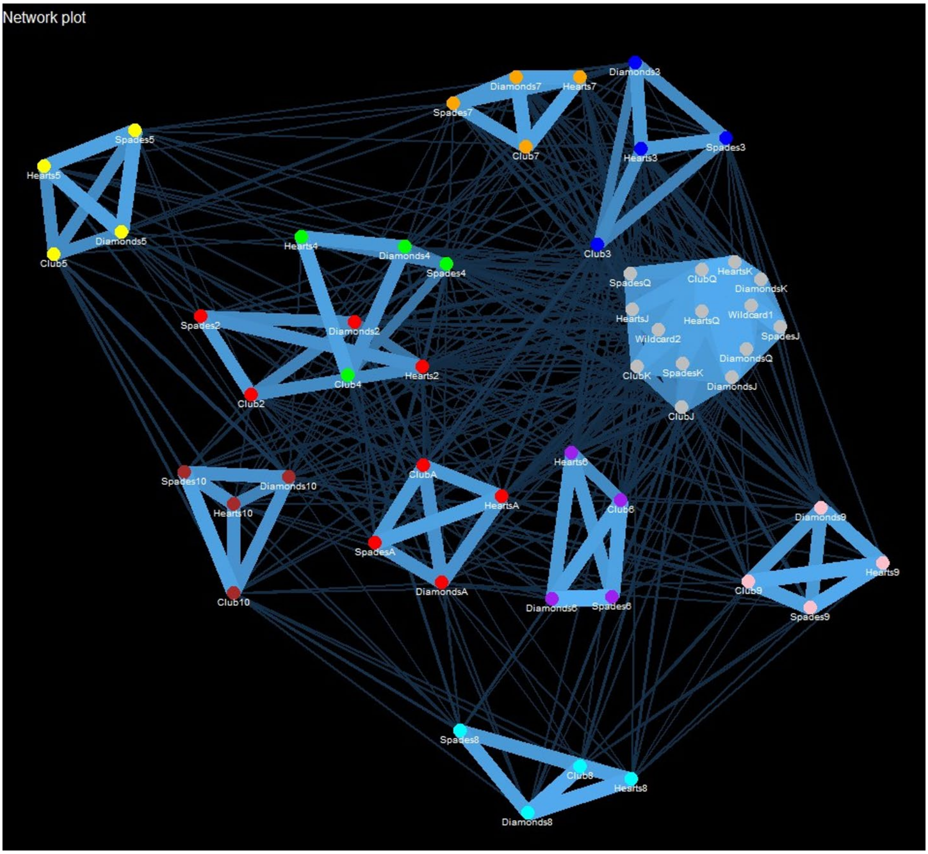

Fig. 7 Network plot for a simulation where the subsample ($n=20$) used Ranks for sorting

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