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Information Architecture: Using Best Merge Method, Category Validity, and Multidimensional Scaling for Open Card Sort Data Analysis

Sione Paea[a], Christos Katsanos[b], and Gabiriele Bulivou[a]

[a]School of Information Technology, Engineering, Mathematics and Physics, The University of the South Pacific, Suva, Fiji; [b]Department of Informatics, Aristotle University of Thessaloniki, Thessaloniki, Greece

ABSTRACT
Open card sorting is a widely used method in HCI for the design of user-centered Information Architectures (IAs). This article proposes a new algorithm that combines the best merge method (BMM), category validity technique (CVT), and multidimensional scaling (MDS) to explore, analyze and visualize open card sort data. A study involving 20 participants and 41 cards explored the IA redesign of a university's website. The collected data were analyzed using two popular methods employed in the quantitative analysis of open card sort data (i.e., hierarchical clustering, *K*-means) and the proposed algorithm. It was found that the latter provides increased IA insights compared to the existing methods. Specifically, the proposed algorithm can expose hidden patterns and relationships amongst cards and identify complexities. We also found that the proposed algorithm produces better initial clusters, which have a direct effect on the final clustering quality.

1. Introduction

Card sorting is an important method in HCI research and practices for designing or evaluating information architectures (IAs) (Rosenfeld et al., 2002; Spencer, 2009). The IA of an interactive system describes the way its content is organized and labeled. A common assumption is that navigation structures are most efficient when content is organized congruent with the common user's mental model of the domain at hand. Card sorting is a widely used method to elicit such mental models and therefore usability designers commonly use it in the process of creating navigation structures (Katsanos et al., 2014; Puerta Melguizo et al., 2012; Schmettow & Sommer, 2016).

There are two main variations of card sorting: open and closed. In an open card sort, each participant organizes the same cards into categories that make sense to them. Participants are also asked to label their categories. By contrast, in a closed card sort, the researcher provides participants with a list of concepts and a list of categories; participants then sort the cards into the predefined categories. The focus of this article is on the analysis of open card sort data.

Analysis of open card sort data typically employs clustering algorithms (Nawaz, 2012; Ntouvaleti & Katsanos, 2022; Righ et al., 2013; Spencer, 2009; Wood & Wood, 2008). Clustering represents one of the most popular data mining techniques due to its usefulness in the wide variations of real-world applications (Grabmeier & Rudolph, 2002; Toda et al., 2007; Xiong et al., 2012). In the context of card sort data analysis, clustering organizes a set of cards into clusters so that items within a given cluster have a high degree of similarity and those of different clusters have a high degree of dissimilarity (Huang, 1998; Ozdal & Aykanat, 2004; Pampoukidou & Katsanos, 2021; Śmieja et al., 2019). The similarities/dissimilarities amongst data cards are estimated based on the attribute values using distance measures.

The most popular clustering techniques are hierarchical clustering-based methods and *K*-means-based methods. Hierarchical methods can be agglomerative (Guha et al., 2000; Karypis et al., 1999) or divisive (Chavent, 1998; Guénoche et al., 1991). Agglomerative methods yield a sequence of nested partitions, starting with trivial clustering. Each card is in a unique cluster and ends with a clustering in which all cards are in the same cluster (Davidson & Ravi, 2009; Zhao et al., 2005). A divisive method starts with all cards in a single cluster and performs a splitting procedure until a stopping criterion is met, usually upon obtaining a partition of singleton clusters (Xiong et al., 2012). The *K*-means algorithm (Bickel & Scheffer, 2004; MacQueen, 1967) is a widely-used partitional clustering algorithm. Here, data is mapped onto a dimensional metric space, and a distance function between data points is defined. The aim of the algorithm is to partition the data into k clusters such that the distance of each data point to the mean of its cluster is minimized. Both hierarchical and *K*-means algorithms are used to cluster card sort datasets (Capra, 2005; Nawaz, 2012; Paea & Baird, 2018; Paea et al., 2021).

This article proposes a new algorithm for open card sort data analysis. The proposed algorithm adopts the hierarchical clustering technique definition (starting with trivial

CONTACT Sione Paea sione.paea@usp.ac.fj School of Information Technology, Engineering, Mathematics and Physics, The University of the South Pacific, Suva, Fiji

clustering) using the best merge method (BMM) based on the strongest pairs. Then, it applies the category validity technique (CVT) with the highest participants' agreement in defining similarity between cards in the similarity matrix. The similarity matrix is a simple representation of pair combinations. It provides insight into the cards that participants paired together in the same group the most often in card sorting. The proposed algorithm provides a natural way of defining clusters that are not restricted to spherical shapes (or any other type of shape) and groups the data so that cards in the same cluster are more self-affine among themselves than cards in other clusters. This is the motivation of the proposed algorithm compared to existing approaches.

Fränti and Sieranoja (2019) mentioned that the K-means method depends a lot on good initialization. Poor initialization can cause the iterations to get stuck into an inferior local minimum. An efficient initialization technique reduces the computational complexity and achieves a better local minimum. The initialization of a method is heavily involved in determining the clustering solution (He et al., 2004). The proposed algorithm employs a new systematic initialization approach, which is expected to result in better final clustering results compared to existing approaches. This is another motivation for the proposed algorithm.

The article is structured as follows: Section 2 describes the methods. Section 3 presents the approaches and experiment results obtained from using the proposed algorithm on a real-world open card sort dataset. Section 4 discusses the application of existing techniques on our open card sort dataset and the obtained results. Section 5 compares the proposed and existing techniques, and Section 6 concludes the article and provides suggestions for future research.

2. Open card sorting study: Methods

This section describes a card sorting study conducted to collect a dataset for clustering. The participants were staff members and students of a regional university. The card sort study goal was to redesign the institution's research website.

2.1. Materials and procedures

Open card sorting can be conducted in groups and/or individuals. The current study used individual card sorting. However, the proposed algorithm can also be used for group card sorts. A typical step-by-step roadmap to effectively apply the open card sorting method is described in Righ et al. (2013).

This study involved a total of 41 cards (refer to Figure 4 or Appendix 2). Each card had a name on it, which represented a feature or function of the University's research office webpage. These card names were drawn from the contents of the existing website. Several discussions between the research team and users of the website, both staff members and students, were also undertaken to get their perceptions. This collaboration has helped in creating a list of card names relevant to the needs and expectations of current and future users.

Before the day of their participation in the study, a card sorting demonstration video and an information sheet were sent to participants. This was done to provide participants with relevant information about the research objectives, how to do card sorting, and how it would affect them during and after the study.

Face-to-face card sorting was conducted with participants using physical cards in the researcher's presence. This study took place while the COVID-19 pandemic hadn't reached Fiji, so no specific measures were required to protect participants' health. Researchers were made available to support participants in terms of questions and clarifications. On the day of card sorting, the researcher undertook the following steps:

- Prepared relevant resources (e.g., cards, camera, and consent forms) for individual card sorting sessions;
- Welcomed participants, facilitated introductions, and acknowledged participants' time and contribution;
- Briefed participants about the project and the procedures to protect the confidentiality of their personal information and data;
- Invited participants to seek clarification before signing the consent form;
- Assured participants that there were no wrong or correct answers and that they had the opportunity to organize the provided cards into groups and provide names for their groups as they saw fit;
- Informed participants that if they could not find a logical group for a specific card, they should set the card aside and continue the sorting process;
- Refrained from direct prompting or coaching of participants but was available for dialogue with participants on the rationale behind the groups that they created and named;
- Allowed free brainstorming and never discouraged an idea from a user even if the researcher thought the idea was not in the right direction;
- Thanked participants, de-briefed key lessons learnt, sought participants' experience during the process, and shared future activities that might be important for participants to be aware of.

The actual session time for card sorting varied from 30 to 70 min.

2.2. Participants

The target population was staff members and students of the institution who were typical users of the chosen website. This study recruited 20 (10 men and 10 women) participants who were working and/or studying at the University. The sample age range varies from 25 to 45 ($M = 31$ and $SD = 6.8$). Some participants created just four categories while others created more complex classifications involving up to 11 categories ($M = 7$, $SD = 1.5$). There were no significant (ns) differences between the number of categories formed by male ($M = 7$) and female ($M = 7$) participants. We run a t-test for the number of categories created by males and females to compare their respective means. Our analysis shows that p-value = 0.89 is greater than the standard significance level of 0.05. This shows no significant difference between the means of categories created by males and females. The number of categories formed was also unrelated to age ($r = -0.25$, ns).

There are two known articles (Lantz et al., 2019; Tullis & Wood, 2004) addressing how many participants are needed for card sorting studies. Tullis and Wood (2004) found that the number of participants for a card sorting study to achieve reliable results should lie between 20 and 30 participants. The study by Lantz et al. (2019) found that a relatively smaller number of participants (i.e., 10–15) is needed for card sorting methods. The current study uses 20 participants, a sample of adequate size based on the existing literature.

Participants were recruited through a variety of means, including personal contacts, referrals, and voluntary. Participants were also recruited using an informal snowball process (O'Leary, 2014) that was based on researchers' cultural knowledge and skills in recruiting participants through networking and relationship building (Paea et al. 2021). This type of recruitment is essential for building trust and respect between participants and the researcher. People can willingly partake when they trust the researcher and know their contribution is recognized and valued (Paea et al. 2021). Careful selection of potential users of a website provides real-world validation of ideas from sponsors, stakeholders, and team members (Spool et al., 1999).

2.3. Data analysis methods

2.3.1. Number of clusters

One important challenge that arises in quantitative analysis of open card sort data is deciding the number of clusters. In the initial solution, the number of clusters is equal to the number of cards included in the study, that is 41 cards (see Figure 5). This article uses the approach by Katsanos et al. (2008) based on the widely used eigenvalue-one criterion (Hatcher & O'Rourke, 2013) to identify the optimal, in terms of variance explained, number of clusters. Every cluster has an eigenvalue representing the amount of variance accounted for by a given cluster.

Table 1 presents the eigenvalue and percentages of variance associated with each factor. These values are also summed and expressed as a cumulative eigenvalue and percentage of variance. Usually, the first variables have the greatest eigenvalues. The method identifies the optimal number of clusters in terms of variance explained by implementing an eigenvalue analysis of the similarity matrix (Figure 5) and keeping only the eigenvalues greater than 1 (see Table 1). Table 1 shows that only the first six principal components (PCs) have an eigenvalue greater than 1 (Kaiser, 1960). So based on this proposal, six factors explaining 70.973% of the total variance must be retained for our open card sort dataset. However, the seventh eigenvalue $\lambda_7 = 0.823$ is approximately close to 1, so the first seven PCs can be retained to explain up to 72.979 percent of the total variability (Gulumbe et al., 2012). Using the eigenvalue-one criterion has been criticized for overestimating the number of factors to retain (Lance et al., 2006), leading to results that can be justified on the mathematical level but with no interpretable meaning at the conceptual level.

Another popular existing method for determining the number of factors to retain is the scree plot (Cattell, 1966) or elbow criterion, which involves the visual exploration of a graphical representation of the eigenvalues for breaks or discontinuities. The number of data points above the break (not including the point at which the break occurs) is the number of factors to retain. In other words, the significant factors are disposed like a cliff, having a big slope, while the trivial factors are disposed at the base of the cliff. Inspection and interpretation of a scree plot involve two steps (see Figure 1(a)): (a) draw a straight line through the smaller eigenvalues where a departure from this line occurs. This point highlights where the debris or break occurs. If the Scree is messy and difficult to interpret, additional manipulation of data and extraction should be undertaken, (b) the point above this debris or break (not including the break itself) indicates the number of factors to be retained.

Figure 1(a) shows that the scree plot inspection for our dataset produced a departure from linearity coinciding with a 6-factor result. In Table 1, this break occurs at component 7; thus, the number of factors to retain is six. The percentage of variance was also plotted and explained against the number of clusters (Figure 1(b)), which indicated any value between 6 and 12 can be used for our case. This article keeps the seven clusters as the optimal number based on the

Table 1. Eigenvalues, percent of variance, and cumulative percent of variance for our card sort dataset.

	Initial Eigenvalues			Extraction sums of squared loadings		
Component	Total	% Of variance	Cumulative %	Total	% Of variance	Cumulative %
1	10.760	26.244	26.244	10.760	26.244	26.244
2	5.495	13.401	39.645	5.495	13.401	39.645
3	5.018	12.240	51.885	5.018	12.240	51.885
4	3.871	9.441	61.326	3.871	9.441	61.326
5	2.325	5.670	66.996	2.325	5.670	66.996
6	1.631	3.977	70.973	1.631	3.977	70.973
7	0.823	2.006	72.979	0.823	2.006	72.979
8	0.798	1.947	74.926			
•	•	•	•			
•	•	•	•			
•	•	•	•			
41	0.000	0.000	100.000			

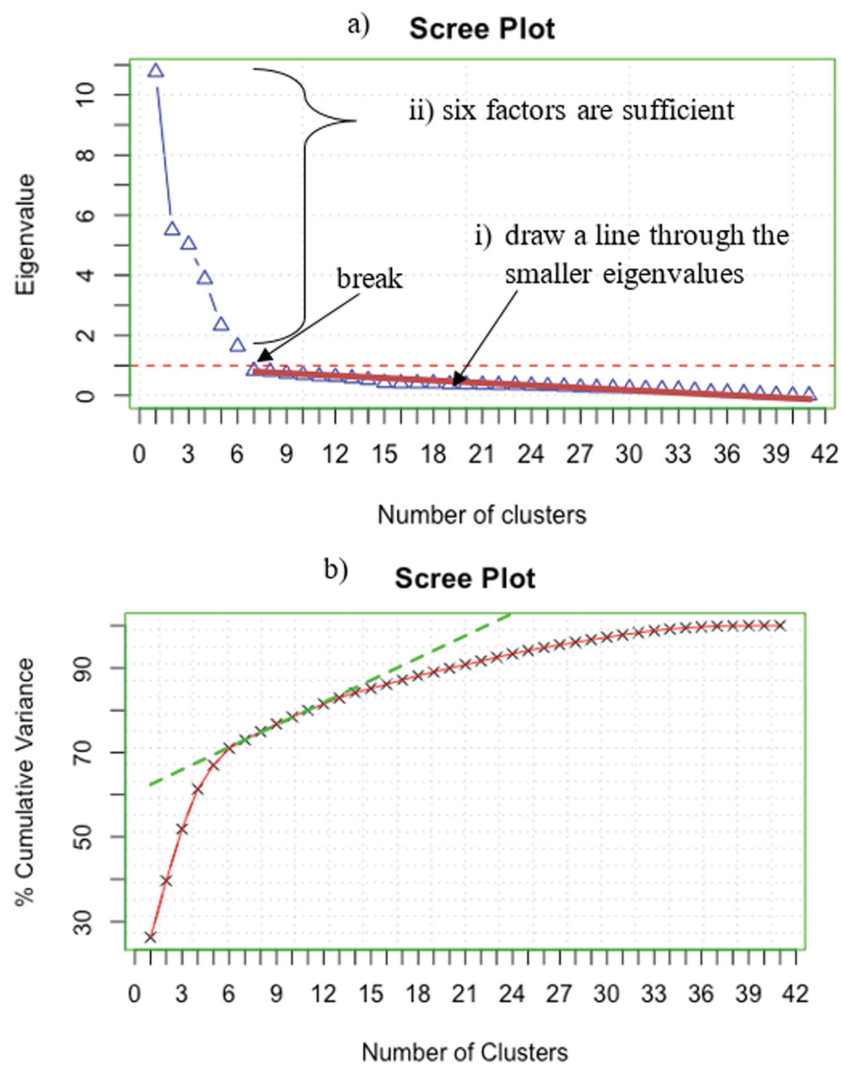

Figure 1. Determining the optimal number of categories for our card sort dataset. (a) The scree plot for the initial variables. (b) The scree plot for the cumulative variance.

other approaches. However, this method is very subjective because the curve's cut-off point is not always very clear (e.g., see Figure 1(b)).

Tibshirani et al. (2001) proposed another method for deciding the number of clusters called gap-statistic. This method compares intra-cluster variance with the expected values under the dataset's null reference distribution. After clustering the dataset for different values of k (number of clusters), we get the intra-cluster variance for the observed dataset as well as the reference dataset (uniform random reference datasets over the range of the observed data are generated), and then calculate the gap-statistic for r clusters C_r as:

$$\mathrm{Gap}_n(k) = E_n^*[\log W_k] - \log W_k,$$

where $n_r = |C_r|$, $W_k = r\sum_{r=1}^{k} \frac{1}{2n_r} D_r = \sum_{r=1}^{k} \frac{1}{2n_r} \sum_{i,i' \in C_r} d_{ii'}$ is the total intra-cluster distance d, across all r clusters C_r and $E_n^*\{.\}$ denote the expectation under a sample of size n from the reference distribution. To estimate the gap statistic and find the number of clusters via

$$\hat{k}_G = \text{smallest}\, k \text{ such that } Gap(k) \geq Gap(k+1) - S_{k+1},$$

where S_k is the standard error from the estimation of $Gap(k)$. Tibshirani et al. (2001) examined both a uniform distribution approach and a principal component construction as the reference dataset. In many cases, the uniform distribution performed better, and this is also used for our dataset. Using the gap statistic method, the optimal number of clusters k is seven. Figure 2 visualizes the distribution of the $Gap(k)$ values against the number of clusters k.

We compare the results from Table 1 and Figures 1 and 2 with the 3D Cluster View (3DCV) algorithm used in OptimalSort (Optimal Workshop), a popular online card sorting tool. 3DCV calculates the optimal number of clusters simply by taking the average (mean) of the number of categories created by participants in the survey. In agreement with the findings in Figures 1 and 2, the 3DCV algorithm also provides seven clusters for this dataset.

Table 2 summarizes the number of clusters provided by all the aforementioned methods. Based on these results, the authors chose seven clusters for the dataset in this study. The decision is also based on Figure 4; when the threshold is 60%, seven groups have two or more cards.

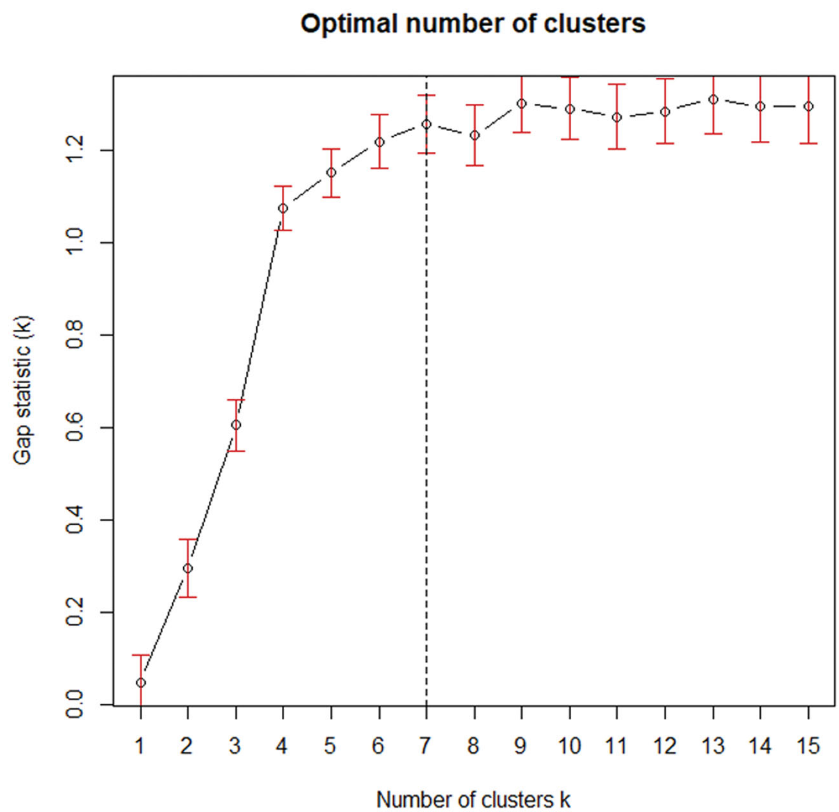

Figure 2. Determining the optimal number of clusters *k* for our open card sort dataset using the gap statistics method.

Table 2. Optimal number of clusters from five methods for our open card sort dataset.

Number	Name	Number of *k*
1	Eigenvalue-one criterion	7
2	Scree plot (eigenvalue)	6
3	Scree plot (percentage of variance)	7
4	Gap statistics method	7
5	Average of the number of categories	7

Table 3. The numerical fit indexes for the MDS analysis of our card sorting dataset.

Number of dimensions	Stress	*R*-squared
1	0.651	0.516
2	0.484	0.742
3	0.336	0.886
4	0.264	0.911
5	0.224	0.924

2.3.2. Multidimensional scaling (MDS) and goodness of fit

Card sort data can be quantitatively analyzed using multidimensional scaling (MDS) (Paea & Baird, 2018). One challenge that arises in this context is deciding the appropriate number of MDS dimensions. MDS is a technique that translates a table of similarities between pairs of cards into a map where distances between the points match the similarities as much as possible (Groenen & van de Velden, 2005), expressing all combinations of pairs within a group of cards. MDS aims to transform the participant judgments of similarity into distances represented in multidimensional space, resulting in the perceptual maps to show the relative positioning of all cards (Paea & Baird, 2018). Hence, MDS moves cards around in the space defined by the requested number of dimensions and checks how well the new configuration can reproduce the distance cards. In more technical terms, it uses a function minimization algorithm that evaluates different configurations intending to maximize the goodness of fit.

The goodness of fit of the MDS results for our card sort dataset was determined by stress values and squared correlation (*R*-squared), as displayed in Table 3 and Figure 3. The stress numbers drop to 0 and *R*-squared increases to 1 with the increasing number of dimensions. The numerical index of stress ranges from 0 (the best possible fit) to 1 (the worst possible fit). *R*-squared is perceived as the amount of variance in proximities in the data matrix. A higher numerical *R*-squared index indicates a better fit of the dimensionality (Davison & Sireci, 2000; Stalans, 1995). To select the best fitting model data, the fit values of stress and *R*-squared were examined. For any given configuration, the stress indicates how well that configuration matches the data. MDS literature suggests that lower stress values are preferred and reflect better congruence between the raw data and the processed data (Davison et al., 1983). The stress value (0.336) in the three dimensions is lower than the stress value (0.484) in the two dimensions for the output shown in Figure 3(a). However, the stress value (0.264) for the four dimensions is even lower.

The *R*-squared (R^2) against the number of dimensions was plotted to assist us in choosing the best number of dimensions. Figure 3(b) shows that as the number of dimensions increases from three to four, the *R*-square value increases. The three dimensions squared correlation (*R*-squared) value (0.886) approaching 1 (100%) indicates that the MDS model

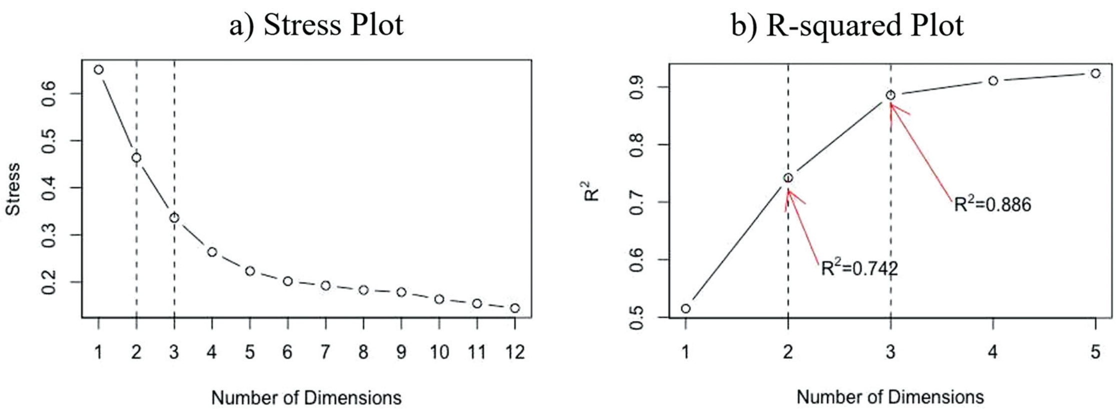

Figure 3. The graph of stress against the number of dimensions (a) and R^2versus the number of dimensions (b) for our open card sort dataset.

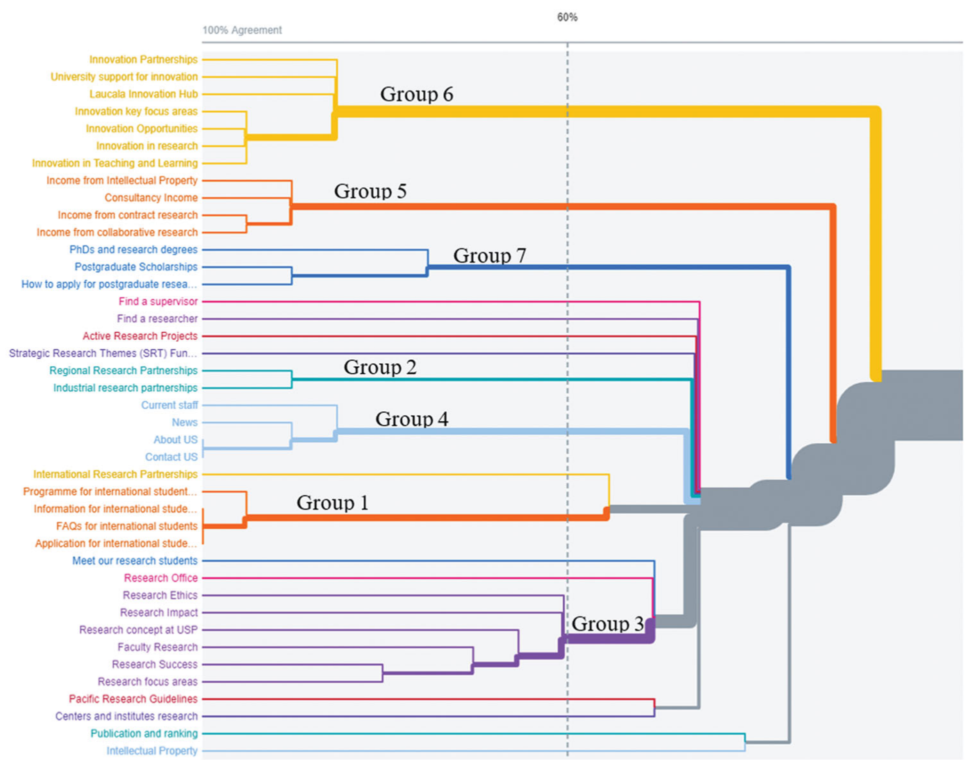

Figure 4. The BMM dendrogram (OptimalSort). The scores show that 60% of participants agree with this grouping. The thicker the lines, the more cards are merged together. The results are from the dataset of this study involving 20 participants who completed an open card sort with 41 cards.

can be characterized as good (Redell, 2019; Seok, 2009). Thus, the three-dimensional solution was chosen as the appropriate model for our card sort dataset. Note that more than three dimensions are rather difficult to both visualize and understand visually. When we refer to dimensions at this point, we are considering the number of coordinate axes in the multidimensional space. The position of a card in a space is specified by its coordinates on each dimension. When we use MDS, we prefer three dimensions because there is a substantial improvement over two, reducing the difficulty of interpretation. Because MDS techniques do not have any built-in procedures for labeling the dimensions, we suggest the coordinate axes as the first place to look at for the purpose of labeling dimensions. Paea and Baird (2018) support our claim. Their study found that the three-dimensional solution is a good fit for card sort data analysis.

3. Proposed algorithm and experiment results

This section discusses the proposed algorithm for open card sort data analysis.

3.1. Proposed techniques for open card sort data analysis

Cluster analysis itself is not a specific algorithm but a general task to be solved. It can be achieved by various algorithms that differ significantly in understanding what constitutes a cluster and how to find them efficiently. Popular notions of clusters include groups with small distances between cluster members, dense areas of the data space, intervals, or particular statistical distributions that have been used.

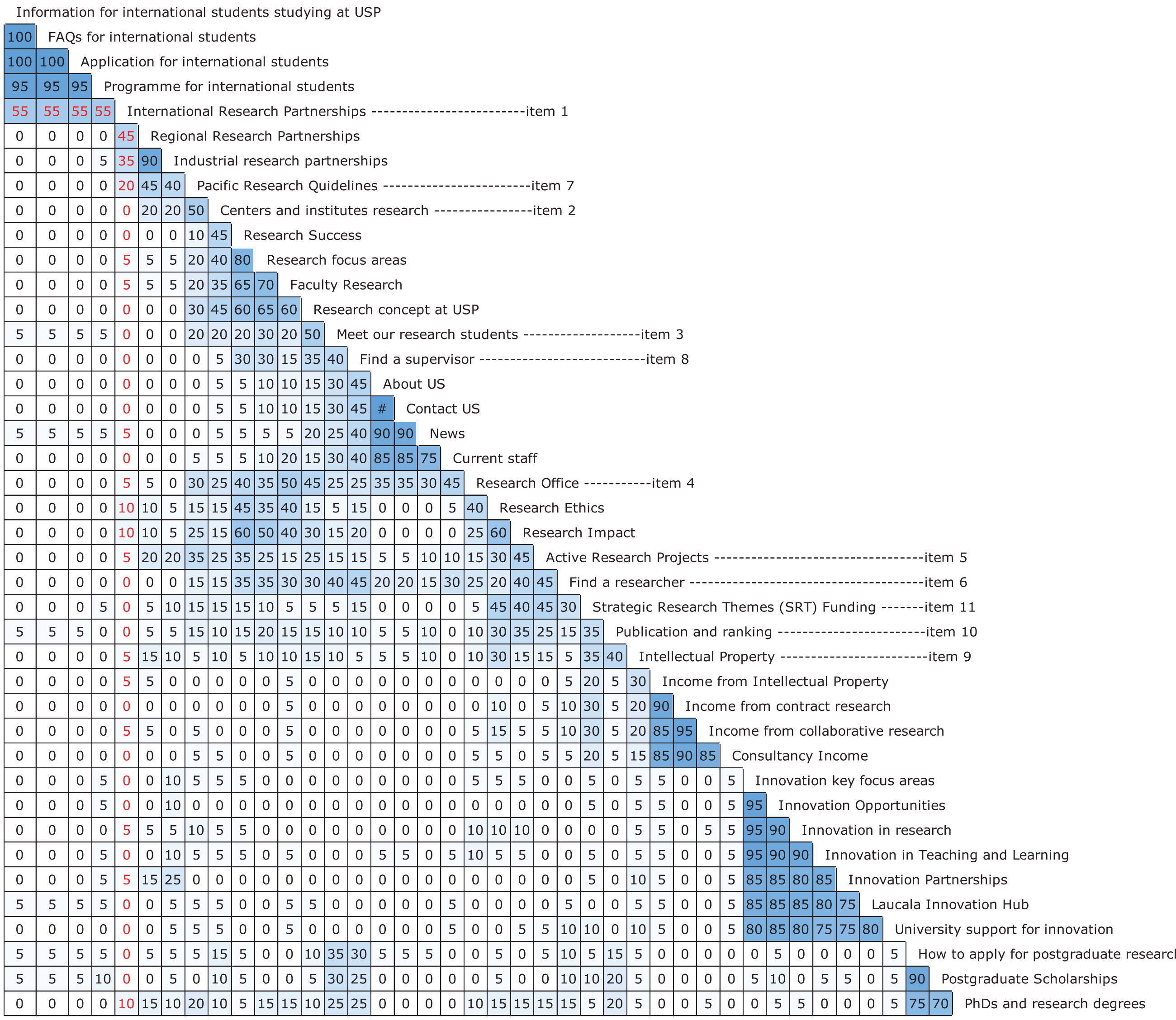

Figure 5. The similarity matrix displays how many participants agree with each pair combination of cards. The algorithm attempts to cluster similar cards along the right edge of the similarity matrix. The results are from the dataset of this study involving 20 participants who submitted valid results from a total of 41 cards.

This section describes the proposed algorithm called the Best Merge Category Validity Multidimensional Scaling (BM-CV-MDS) algorithm, which combines the best merge method (BMM) and the category validity technique (CVT), and then visualizes the results using multidimensional scaling (MDS). This study uses the similarity matrix algorithm and the BMM created by OptimalSort. The BM-CV-MDS algorithm is divided into three parts.

3.1.1. Part 1: Dendrogram: Best merge method (BMM)

Deriving information structures from card sorting data can be a challenge. Various quantitative analysis techniques have been proposed in the literature, such as factor analysis, *K*-means, and multidimensional scaling (Capra, 2005; Nawaz, 2012; Paea & Baird, 2018). However, hierarchical cluster analysis remains the most widely used technique for this purpose (Katsanos et al., 2019; Paul, 2014; Tullis & Wood, 2004; Villalonga-Gómez & Mora-Cantallops, 2021).

This article employs the method reported in (Paea & Baird, 2018), the BMM (OptimalSort). BMM is a dendrogram tree graph that can be used to examine how clusters are merged in hierarchical cluster analysis (Everitt & Dunn, 2001; Timm, 2002). It can provide insights into high-level topics (Righ et al., 2013). BMM is a technique based upon similarity matrixes and is the industry standard (Nawaz, 2012).

The basic process of BMM is composed of the following steps (Paea et al., 2021):

i. Let $\mu_1, \mu_2, \ldots, \mu_k$ be the cards to be sorted. We have μ_k categories with a card each.
ii. Produce combinations of two cards in a category (called the based pairs) for all cards. For instance, $[\mu_1, \mu_2]$, $[\mu_1, \mu_3]$, $\ldots$, $[\mu_1, \mu_{k+1}]$, $[\mu_2, \mu_3], \ldots$, $[\mu_2, \mu_{k+1}]$, $\ldots$, $[\mu_{k-1}, \mu_k]$. The order of the cards is not important, so $[\mu_1, \mu_3] = [\mu_3, \mu_1]$.
iii. The based pair with the highest score is locked in as a new category.

iv. The process in (iii) repeats, and when a pair is locked in intersects with an existing locked category, the former is agglomerated with the latter.
v. All subsets of this new category are eliminated.
vi. The algorithm stops when all the cards are merged into a single category for incidence $[\mu_1, \mu_2, \mu_1, \mu_2, \ldots, \mu_k]$.

An example is provided to help explain the calculations better (see Appendix 1).

Figure 4 presents the dendrogram produced for our card sort dataset based on BMM results. The dendrogram has 41 leaves, each representing a single card name. The leaves are spaced evenly along the vertical axis at 100% agreement. The horizontal axis gives the distance (or dissimilarity measure) at which any two clusters are joined. At 0% agreement, all the cards are merged as a single group. The thicker the lines, the more cards are being merged together in a single group.

One important challenge that arises in quantitative analysis of card sort data is where to cut the line in the dendrogram. This decision greatly affects the final navigation scheme (Katsanos et al., 2019; Ntouvaleti & Katsanos, 2022; Pampoukidou & Katsanos 2021). We employed the five methods reported in Table 2 to overcome this challenge. It was found that for our dataset, a total of seven clusters was required. A threshold t of 60% agreement of cards across participants was used to cut the dendrogram and produce seven clusters. The vertical grey line in Figure 4 shows the 60% threshold. This means that 60% of participants placed together at least two cards of each of the seven clusters in Figure 4. This also suggests that 60% of participants created the 11 single-card clusters in Figure 4. Below are a couple of criteria that the algorithm applied when selecting the threshold t in Figure 4.

1. The choosing of a threshold t value:
   The algorithm will look at a t value (Figure 4) that contains the optimal number of clusters k presented in Section 2.3.1 for the dataset using the following steps:
   i. The algorithm starts by moving the dashed vertical line (threshold) from the right (0% agreement) to the left (100% agreement) side of the dendrogram in Figure 4;
   ii. While moving the line, the algorithm is searching for the clusters that contain two or more cards using the equation below

$$k = \sum_{i=0}^{n} k_{n-i},$$

   where n is the highest number of cards in a cluster, k_n represents one cluster with maximum n cards, and k is the optimal number of the clusters at a t value.
   iii. Repeats the process in steps (i) and (ii) and stores the results in memory until the dashed line reaches 100% participant's agreement;
   iv. Compares all the calculated k values in (iii) and chooses the k value that each cluster contains the highest number of cards. Following the steps (i) to (iv) in this dataset, seven clusters lead to a threshold $t = 60\%$ participant's agreement with two or more cards in each cluster (Figure 4 and Table 4);
   v. Suppose step (iv) contains more clusters than the calculated k value due to more similar clusters of the same lowest number of cards. In this case, the algorithm will include a cluster with the closest next merge to t value (dashed vertical line) from the right side. The new cluster must not be part of any previously chosen clusters.
2. The chosen clusters must equal the number of k presented in Section 2.3.1.

Table 4. There are seven possible groups obtained from Figure 4.

Group	Card name (30 cards)
1	4 cards • Information for international students studying at USP • FAQs for international students • Application for international students • Programme for international students
2	2 cards • Regional research partnerships • Industrial research partnerships
3	6 cards • Research success • Research focus areas • Faculty research • Research concept at USP • Research ethics • Research impact
4	4 cards • About us • Contact us • News • Current staff
5	4 cards • Income from intellectual property • Income from contract research • Income from collaborative research • Consultancy income
6	7 cards • Innovation key focus areas • Innovation opportunities • Innovation in research • Innovation in teaching and learning • Innovation partnerships • Laucala innovation hub • University support for innovation
7	3 cards • How to apply for postgraduate research • Postgraduate scholarships • PhDs and research degrees

Table 4 presents the findings from Figure 4 on participants' preferences for IA in seven clusters. The BMM analysis shows that for 30 (73.2%) out of 41 cards, 60% of participants or more agreed to place the cards in the same cluster. A single card is included only if at least 60% of the participants have decided to group that card in the same cluster. The participants organized cards in seven clusters, with an average of 4 cards in a single group. BMM shows that participants substantially concurred that 11 cards (26.8%) on which the study participants did not meet the threshold of at least 60% agreement or belong to one of the seven clusters. These 11 cards are shown in Table 5. Even though these cards will be grouped at a later stage by BMM, it is suggested that these card names might have puzzled our participants and need careful scrutiny.

BMM algorithm is used to determine the initial core clusters. In clustering algorithms, the quality of initial clusters is extremely important and it has a direct effect on the final clustering quality (Barbará & Chen, 2003).

3.1.2. Part 2: Category validity technique (CVT)

CVT is a technique based upon similarity matrixes. Figure 5 demonstrates the findings from the current study dataset in a similarity matrix to illustrate the proposed method. Accordingly, the strongest pair is positioned at the top left corner, grouping them with the next associated strongest pair that either of those cards has, and then the process is repeated for that new pair. This way, groups of cards that are strongly related to each other appear together in the same shade of blue on the similarity matrix. The darker the blue shaded areas where two cards intersect, the more often they were paired together by the participants. A percentage of 100% indicates that all participants agree to pair two cards together, and 0% shows that no participant placed those two cards together.

There are 11 cards (26.8%) out of 41 in Table 5, which need to be grouped in a category. The primary purpose of CVT is to combine Tables 4 and 5 by distributing the 11 cards of Table 5 into the seven clusters of Table 4 such that cards within a given cluster have the highest degree of similarity. CVT conducts an individual analysis of each card in Table 5, and different steps need to be followed:

1. Create agreement levels: The authors subsequently display the data positioned along the right edge in Figure 5 as a line graph (Figure 6) to identify the 11 cards in Table 5. The line graph in Figure 6 is being layered in black lines. Level 1 includes the cards that are located at 60% or over. Level 2 includes the cards in the range of 55 and 59%. The rest of the levels lower the agreement threshold by 5% per level.
2. Pick a card to cluster: The algorithm starts at level 2 by looking at the card with the highest percent of participant's agreement. If two cards have the same percentages, the algorithm will pick the card in the order they appear, as shown in Figure 6. The process continues up to the final level.

Table 5. Cards on which the participants of the study did not attain the threshold of 60% agreement or higher.

Card name (11 cards)
• International research partnerships
• Pacific research guidelines
• Centers and institutes research
• Meet our research students
• Find a supervisor
• Research office
• Active research projects
• Find a researcher
• Strategic research themes (SRT) funding
• Publication and ranking
• Intellectual property

3. Assign a card to a cluster: A similarity matrix is a square $m \times m$ matrix, where m represents the number of cards. Each cell $c_{i,j}$ represents the number of times the card i and the card j have been categorized into the same group. Given a partition of the elements (calculated, for instance, with the BMM algorithm), we can calculate for each card the category validity using the following formula:

$$h(k \subset A) = \frac{\sum_{i \neq k}^{I \subset A} C_{k,i}}{n \sum_{i \neq k}^{I \subset M} C_{k,i}} = \frac{\beta_k}{\alpha_k} \ ,$$

where $h(k)$ is the category validity of the card k, $I \subset A$ are the cards that belong to the same A category of k (except k itself) and $I \subset M$ are all the cards (except k itself category), and n is the number of cards in A category (Bussolon, 2009) including the newly added cards. The algorithm, therefore, sums all the cells of a given k row (except the diagonal value $c(k,k)$), all the cells of the cards which belong to the same category of k (except, again, the diagonal value $c(k,k)$), then divides the latter value with the former. The formula reaches its maximum value (1.0) when an card has been categorized, by all the participants, with the cards of its category and never with the other cards.

For instance, let's find a cluster for card 1 circled in black color in level 2 (Figure 6) and indicated in Figure 5; card 1 is "International Research Partnerships." The red color in Figure 5 displays the row and column of all other cards participant's agreement related to card 1. The algorithm calculates the category validity for card 1 in each of the seven groups indicated in Table 4. In the following, we present examples of the calculations for groups 1, 2, and 3.

For group 1 (see Table 4).

$$\sum_{i \neq 5}^{I \subset A} C_{5,j} = \beta_5 = C_{5,1} + C_{5,2} + C_{5,3} + C_{5,4} = 55 + 55 + 55 + 55 = 220,$$
$$\sum_{i \neq 5}^{I \subset M} C_{5,j} = \alpha_5 = 4C_{5,1} + C_{5,2} + C_{5,3} + C_{5,4} + \ldots\ldots + C_{5,41} = 400,$$
and $n = 5$.
Then, $h(5 \subset A) = \frac{\beta_5}{\alpha_5} = \frac{220}{5(400)} = 0.11.$

The category validity of card 1 in group 1 is therefore 0.11.

For group 2 (see Table 4)

$$\sum_{i \neq 5}^{I \subset A} C_{5,j} = \beta_5 = C_{5,6} + C_{5,7} = 45 + 35 = 80,$$
$$\sum_{i \neq 5}^{I \subset M} C_{5,j} = \alpha_5 = 4C_{5,1} + C_{5,2} + C_{5,3} + C_{5,4} + \ldots\ldots + C_{5,41} = 400,$$
and $n = 3$.
Then, $h(5 \subset A) = \frac{\beta_5}{\alpha_5} = \frac{80}{3(400)} = 0.067.$

The category validity of card 1 in group 2 is therefore 0.067.

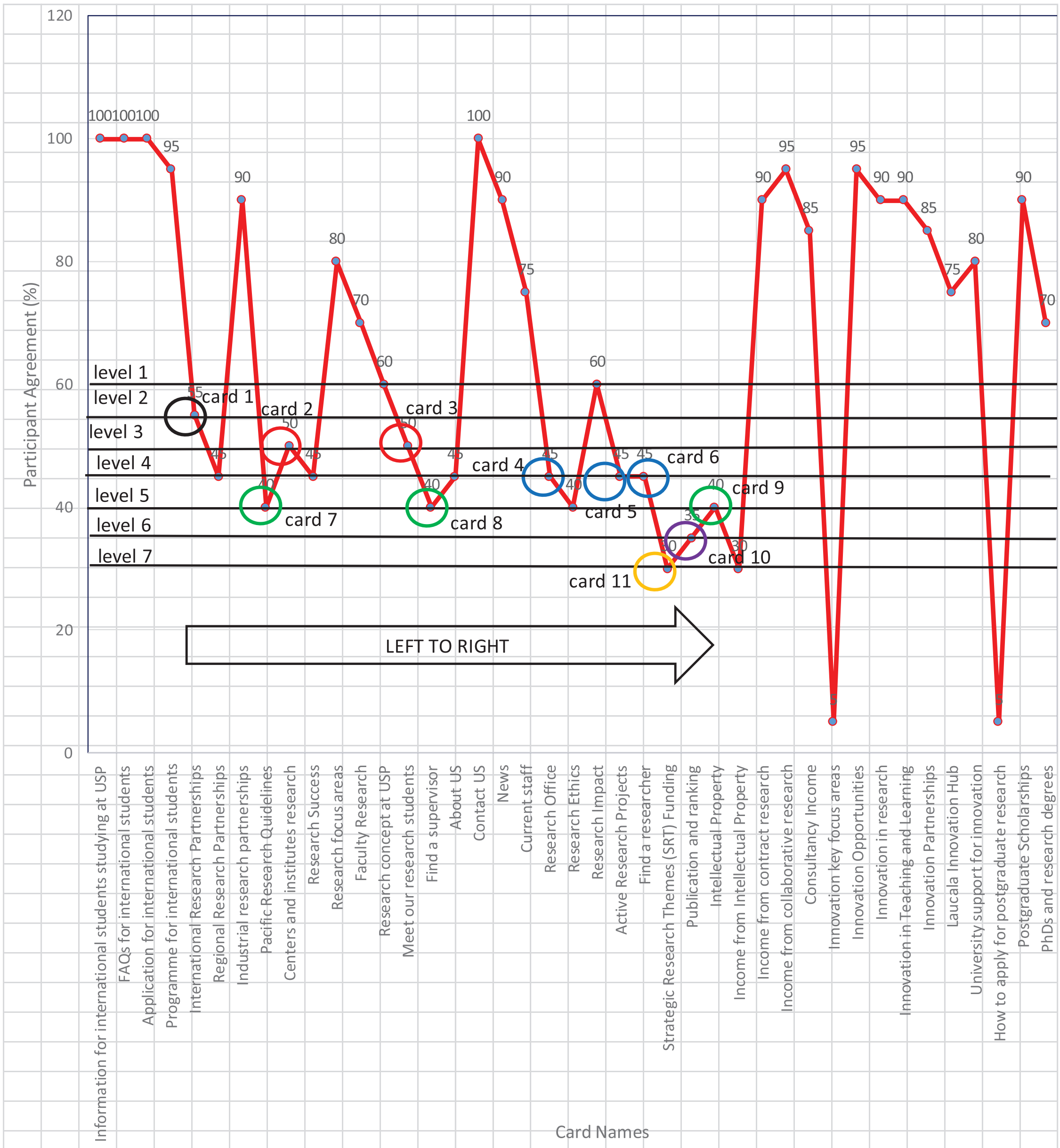

Figure 6. Line graph shows the steps in Part 2 of the proposed algorithm and displays the 11 single clusters for the dataset of this study.

For group 3 (see Table 4)

$$\sum_{i\neq 5}^{I\subset A} C_{5,j} = \beta_5 = C_{5,10} + C_{5,11} + C_{5,12} + C_{5,13} + C_{5,21}$$

$$+C_{5,22} = 0 + 5 + 5 + 0 + 10 + 10 = 30,$$

$$\sum_{i\neq 5}^{I\subset M} C_{5,j} = \alpha_5 = 4C_{5,1} + C_{5,2} + C_{5,3} + C_{5,4} + \ldots\ldots +$$

$$C_{5,41} = 400,$$

and $n = 7$.

Then, $h(5 \subset A) = \dfrac{\beta_5}{\alpha_5} = \dfrac{30}{7(400)} = 0.01.$

The category validity of card 1 in group 3 is therefore 0.01.

The algorithm repeats the same calculation for the rest of the categories to find each category's validity for card 1. Then, it compares the category validity values of all the seven clusters and puts card 1 "International Research Partnerships" in the cluster with the highest category validity value. Therefore, the algorithm places card 1 in group 1. The algorithm repeats the same calculations for all the single clusters indicated in Table 5, Figures 5 and 6. Table 6 shows the final clusters after using the proposed algorithm.

Table 6 demonstrates the combination of Table 4 and 5 findings in five columns, where the first column is focused on the primary level group number. The second column indicates the proposed group labels, based on the highest number of similar group labels chosen by participants. These group labels indicate the most repeated similarities amongst all participants' data, which can be considered as the primary level contents to appear on the chosen website. For instance, Group 4 of Table 6 shows that 83% of participants label primary level "Home," 75% of participants label it "About us," and 67% label it "Essential Information." This result suggests that "Home" can be the proposed label for

Table 6. The proposed clusters for our card sorting dataset after running parts 1 and 2 of the proposed algorithm.

Level 1 group	Proposed group label (%)	Popularity score (%)	Card names	Participant's agreement score
Group 1	**Similar category labels** • International (100) • International student (100) • International partnership (100) • Info for international student (100)	• International (34) • International student (20) • International partnership (10) • Info for international student (5)	5 Cards • Information for international students studying at USP • FAQs for international students • Application for international students • Programme for international students • International research partnerships	805/1000 = 0.805
Group 2	**Similar category labels** • Research partnership (100) • Partnership (75) • Pacific and regional research (75) • Strength (50)	• Research partnership (10) • Partnership (16) • Pacific and regional research (3) • Strength (3)	3 Cards • Regional research partnerships • Industrial research partnerships • Pacific research guidelines	175/300 = 0.583
Group 3	**Similar category labels** • Research at USP (75) • Research strength (67) • Support (64) • Research concept and area (58)	• Research at USP (19) • Research strength (11) • Support (41) • Research concept and area (7)	11 Cards • Research success • Research focus areas • Faculty research • Research concept at USP • Centers and institutes research • Research ethics • Research impact • Research office • Active research projects • Find a researcher • Publication and ranking	1910//5500 = 0.347
Group 4	**Similar category labels** • Home (83) • About us (75) • Essential information (67) • Staff information (56)	• Home (55) • About us (11) • Essential information (4) • Staff information (5)	6 Cards • About us • Contact us • News • Current staff • Find a supervisor • Meet our research students	850/1500 = 0.567
Group 5	**Similar category labels** • Income (83) • Finance (83) • Research and income (83) • Research income and finding (71)	• Income (46) • Finance (10) • Research and income (5) • Research income and finding (5)	6 Cards • Income from intellectual property • Income from contract research • Income from collaborative research • Consultancy income • Intellectual property • Strategic research themes (SRT) funding	750/1500 = 0.500
Group 6	**Similar category labels** • Innovation (100) • Innovation hub (100) • Innovation partnership (100) • Innovation research at USP (88)	• Innovation (86) • Innovation hub (7) • Innovation partnership (7) • Innovation research at USP (7)	7 Cards • Innovation key focus areas • Innovation opportunities • Innovation in research • Innovation in teaching and learning • Innovation partnerships • Laucala innovation hub • University support for innovation	1775/2100 = 0.845
Group 7	**Similar category labels** • Postgraduate (100) • Application (100) • Postgraduate research (75) • Postgraduate student at USP (60)	• Postgraduate (29) • Application (3) • Postgraduate research (3) • Postgraduate student at USP (3)	3 Cards • How to apply for postgraduate research • Postgraduate scholarships • PhDs and research degrees	235/300 = 0.783
	Sum of highest scores in each cluster = 641	Sum of highest scores in each cluster = 307		Total = 6500 = 4.430

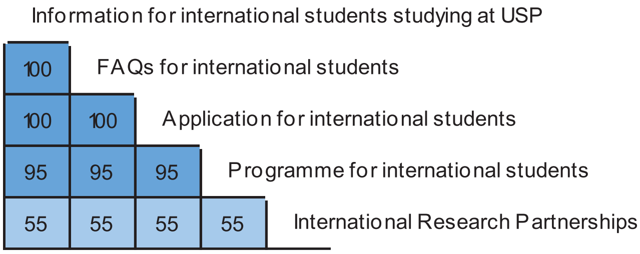

Figure 7. Portion of Figure 5 shows the card names in group 1 of Table 6.

the primary level Group 4 as determined by the list of similar related cards displayed in the fourth column. A similar approach can be repeated for the rest of the proposed group labels in Table 6.

However, the second and third highest similar group labels are also considered to be important representations of participants' card similarities. The third column proposes the popularity score of each category. The total number of cards was counted from the group that each and every participant puts into a category, then divided by multiplying the total number of cards in that category by the total number of participants. The higher the score, the more popular the category is. This is especially useful when resolving ties where two categories may be having the same similar category (group) labels (%). The most popular category could then be adopted as the best category name for that particular group of cards. Column four of Table 6 lists the card names associated with each category. Column five calculates the percentage of participants' agreement in each cluster by summing all the combinations of cards in a category, then dividing by the number of combination cells multiplied by 100.

Given a partition of the elements (calculated, for instance, with the BM-CV-MDS algorithm), we can calculate for each category the participant's agreement using the following formula:

$$\mathrm{PAS}(A) = \frac{\sum_{I=1}^{I\subset A} C_{i,j}}{n \times 100\%},$$

where $\mathrm{PAS}(A)$ is the participant's agreement score of a category A, $I \subset A$ are the elements that belong to the category A and n is the number of the combination cards (cell) in$A$category including the newly added cards. The algorithm, therefore, sums all the cells of the elements which belong to the same category of k, then divides by $n \times 100\%$. The final step is to sum all the category participant's agreements. An example is provided to explain the calculation better. Refer to Group 1 of Table 6 and Figure 7.

The same calculation was applied to the other six categories. Total participant's agreement measures the strength of a method compared to others. The same calculation of PAS is employed in the last column of Tables 7 and 8.

3.1.3. Part 3: Multidimensional scaling (MDS) visualization

The main purpose of Part 3 is to use MDS to visualize the position of the cards in the proposed clusters (Table 6) and, thus, support a human (practitioner, researcher) in making sense of the BM-CV-MDS algorithm results. We made this choice in the context of explainable artificial intelligence, which is particularly important today. MDS and goodness of fit were described in section 2. MDS reduces the difficulty of interpreting a plot containing too much data, long labels, and inconsistent patterns. Figure 8 is designed to represent the relationships between cards in a multidimensional space. Placing the cursor over any color markers will highlight the card name that the markers represent, the group number, and the coordinates. Some of the cards have the same coordinates in Figure 8. Figure 8 shows three markers assigned to Group 1 but there are five cards in Group 1 according to Table 6. This is because the 3 cards have the same coordinates (see Figure 8 Group 1). The current study plots the MDS of the dataset and then uses the result in Table 6, column 4 to cluster the MDS as shown in Figure 8.

4. Existing techniques applied to our dataset: Hierarchical agglomerative clustering and *K*-means

Before the actual comparative analysis between the BM-CV-MDS algorithm and the existing popular techniques, i.e., Hierarchical Agglomerative Clustering (HAC) and *K*-means, we provide a brief description of how we used each one for our dataset.

4.1. Hierarchical agglomerative clustering

To examine the underlying patterns of dataset behaviors, we conducted a hierarchical cluster analysis in *R* using Ward's method. Ward's method is an agglomerative clustering method that merges pairs of clusters based on a given criterion, often the minimum variance between clusters (Murtagh & Legendre, 2011; Ward, 1963). This method is the most straightforward and accepted to compute distances and it is useful to handle raw data (Murtagh & Legendre, 2011).

We plot the dendrogram resulting from the hierarchical cluster analysis of our card sorting dataset. Figure 9 shows seven group solutions from the dataset given in Figure 5,

$$\begin{aligned}\mathrm{PAS}(\text{Group } 1) &= \frac{\sum_{I=1}^{I\subset A} C_{i,j}}{n \times 100\%} = \frac{C_{2,1}+C_{3,1}+C_{3,2}+C_{4,1}+C_{4,2}+C_{4,3}+C_{5,1}+C_{5,2}+C_{5,3}+C_{5,4}}{6(100)}\\ &= \frac{100+100+100+95+95+95+55+55+55+55}{10(100)} = \frac{805}{1000} = 0.805.\end{aligned}$$

Table 7. The findings from the dendrogram resulting from the hierarchical cluster analysis of our card sort data.

Level 1 group	Proposed group label (%)	Popularity score (%)	Card names	Participant's agreement score
Group 1	**Similar category labels** • Home (100) • Essential information (100) • Header/footer (75) • About us (50)	• Home (46) • Essential information (4) • Header/footer (3) • About us (7)	4 Cards • About us • Contact us • Current staff • News	525/600 = 0.875
Group 2	**Similar category labels** • Strength (67) • Research assistant (50) • Research project (38) • Research support (36)	• Strength (28) • Research assistant (5) • Research project (5) • Research support (10)	9 Cards • Active research projects • Centers and institutes research • Intellectual property • Pacific research guidelines • PhDs and research degrees • Publication and ranking • Research ethics • Research impact • Strategic research themes (SRT) funding	880/3600 = 0.244
Group 3	**Similar category labels** • International (100) • International student (100) • International partnership (100) • Info for international student (100)	• International (34) • International student (20) • International partnership (10) • Info for international student (5)	5 Cards • Application for international students • FAQs for international students • Information for international students studying at USP • International research partnerships • Programme for international students	805/1000 = 0.805
Group 4	**Similar category labels** • Income (100) • Research income (100) • Finance (80) • Research and income (80)	• Income (44) • Research income (4) • Finance (8) • Research and income (4)	4 Cards • Consultancy Income • Income from collaborative research • Income from contract research • Income from intellectual property	530/600 = 0.883
Group 5	**Similar category labels** • Research strength (70) • Support (67) • Research (67) • Research concept and area (60)	• Research strength (11) • Support (34) • Research (6) • Research concept and area (6)	8 Cards • Faculty research • Find a researcher • Find a supervisor • Meet our research students • Research concept at USP • Research office • Research success • Research focus areas	1130/2800 = 0.404
Group 6	**Similar category labels** • Postgraduate (50) • Partnership (50) • Postgraduates information (50) • Research partnerships (40)	• Postgraduate (20) • Partnership (12) • Postgraduates information (2) • Research partnerships (8)	4 Cards • How to apply for postgraduate research • Industrial research partnerships • Postgraduate scholarships • Regional research partnerships	195/600 = 0.325
Group 7	**Similar category labels** • Innovation (100) • Innovation hub (100) • Innovation partnerships (100) • Innovation research at USP (88)	• Innovation (86) • Innovation hub (7) • Innovation partnerships (7) • Innovation research at USP (7)	7 Cards • Innovation in research • Innovation in teaching and learning • Innovation key focus areas • Innovation opportunities • Innovation partnerships • Laucala innovation hub • University support for innovation	1775/2100 = 0.845
	Sum of highest scores in each cluster = 587	Sum of highest scores in each cluster = 292		Total = 5840 = 4.381

Table 8. The findings from the *K*-means method for our card sort data.

Level 1 group	Proposed group label (%)	Popularity score (%)	Card name	Participant agreement score
Group 1	**Similar category labels** • Income (100) • Research income (100) • Finance (80) • Research and income (80)	• Income (44) • Research income (4) • Finance (8) • Research and income (4)	**4 Cards** • Consultancy income • Income from collaborative research • Income from contract research • Income from intellectual property	530/600 = 0.883
Group 2	**Similar category labels** • International (100) • International student (100) • International partnership (100) • Info for international student (100)	• International (34) • International student (20) • International partnership (10) • Info for international student (5)	**5 Cards** • Application for international students • FAQs for international students • Information for international students studying at USP • International research partnerships • Programme for international students	805/1000 = 0.805
Group 3	**Similar category labels** • Home (83) • About us (75) • Essential information (67) • Staff information (56)	• Home (55) • About us (11) • Essential information (4) • Staff information (5)	**6 Cards** • About us • Contact us • Current staff • Find a supervisor • Meet our research students • News	850/1500 = 0.567
Group 4	**Similar category labels** • Research strength (73) • Support (70) • Research at USP (67) • Research concept and area (64)	• Research strength (11) • Support (40) • Research at USP (18) • Research concept and area (7)	**10 Cards** • Active research projects • Centers and institutes research • Faculty research • Find a researcher • Research concept at USP • Research ethics • Research focus areas • Research impact • Research office • Research success	1720/4500 = 0.382
Group 5	**Similar category labels** • Strength (75) • Partnership (60) • Research support (43) • Research partnership (40)	• Strength (12) • Partnership (13) • Research support (3) • Research partnership (8)	**4 Cards** • Intellectual property • Industrial research partnerships • Regional research partnerships • Strategic research themes (SRT) funding	165/600 = 0.275
Group 6	**Similar category labels** • Innovation (100) • Innovation hub (100) • Innovation partnership (100) • Innovation research at USP (88)	• Innovation (86) • Innovation hub (7) • Innovation partnership (7) • Innovation research at USP (7)	**7 Cards** • Innovation key focus areas • Innovation opportunities • Innovation in research • Innovation in teaching and learning • Innovation partnerships • Laucala innovation hub • University support for innovation	1775/2100 = 0.845
Group 7	**Similar category labels** • Postgraduate (80) • Application (60) • Postgraduate research (50) • Postgraduate student at USP (43)	• Postgraduate (32) • Application (3) • Postgraduate research (3) • Postgraduate student at USP (3)	**5 Cards** • How to apply for postgraduate research • Pacific research guidelines • PhDs and research degrees • Postgraduate scholarships • Publication and ranking	330/1000 = 0.330
	Sum of highest scores in each cluster = 611	Sum of highest scores in each cluster = 304		Total = 6175 = 4.087

with each cluster shown by a different group number. The dendrogram resulting from the hierarchical cluster analysis suggests the findings presented in Table 7.

4.2. *K*-means

K-means clustering intends to partition n cards into k clusters in which each card belongs to the cluster with the nearest

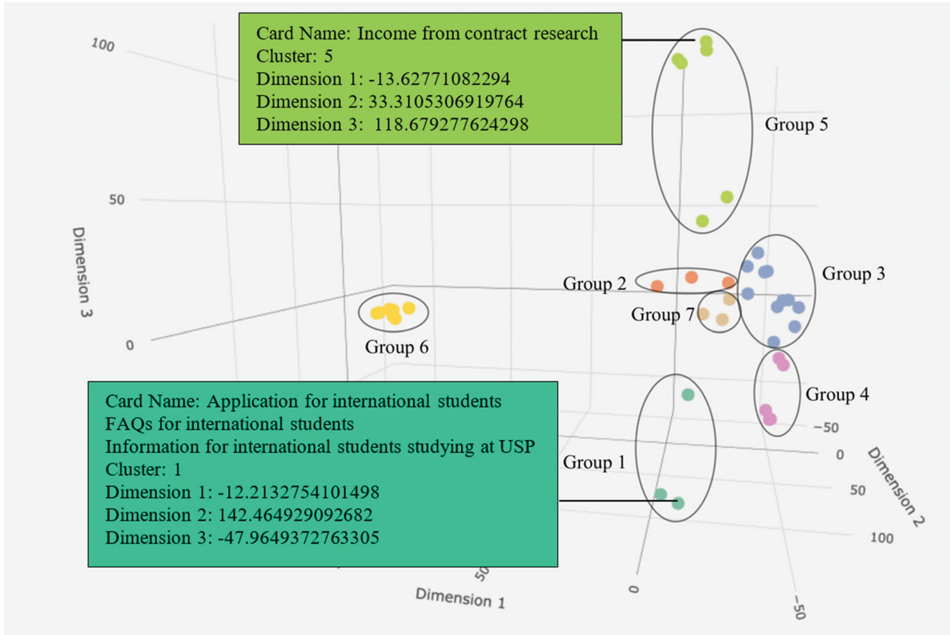

Figure 8. Multidimensional scaling of the clustering results from Table 6. Using parts 1 and 2 of the proposed algorithm produced seven cluster solutions for our dataset, with each cluster shown in different colors.

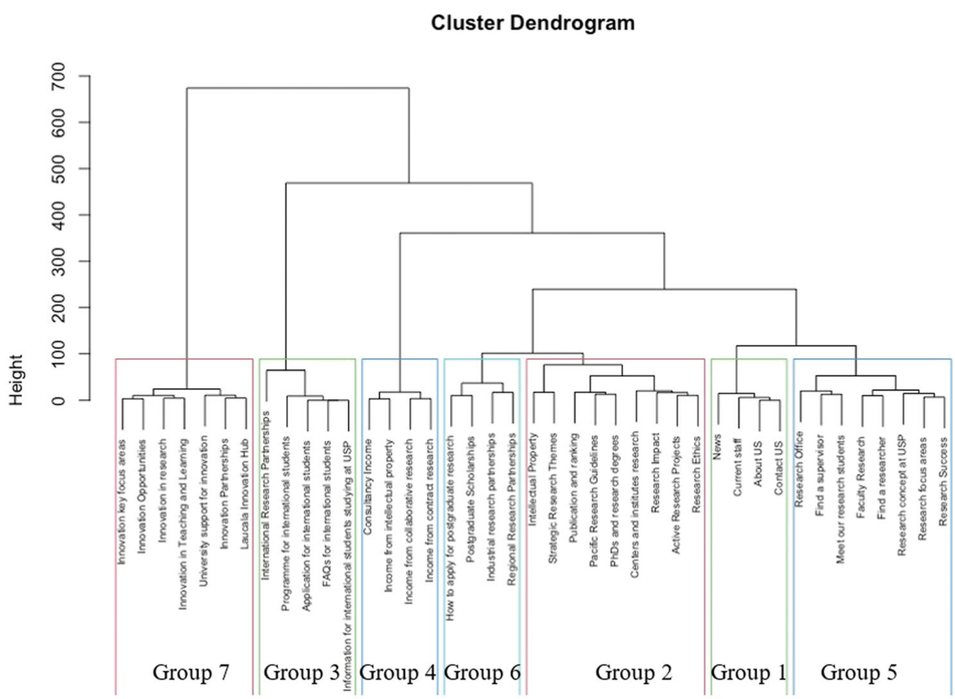

Figure 9. Dendrogram clustering results for our card sort data based on hierarchical cluster analysis in *R* using Ward's method.

centroid/mean (Karaboga & Celal, 2010; MacQueen, 1967). *K*-means algorithm is straightforward to implement, relatively fast and easy to adjust, and therefore first used in Paea and Baird (2018) for card sort datasets. This method produces exactly *k* different clusters of the greatest possible distinction. The best number of clusters *k* leading to the most significant separation (distance) is not priorly known and must be computed from the data set. *K*-means clustering aims to minimize total intra-cluster variance or the squared error function (Somasundaram & Rani, 2011). Each cluster is represented by an adaptively changing centroid (also called cluster center), starting from some initial values named seed points (Fränti & Sieranoja, 2019; Huang, 1998). *K*-means computes the squared distances between the inputs (also called input data points) and centroids and assigns inputs to the nearest centroid.

This article uses the random centroids initialization technique by Fränti and Sieranoja (2019) approach. We first find the number of *k* discussed in section 2 and use it in the *K*-means algorithm. This improvement to the *K*-means algorithm for clustering card sorting datasets is another contribution of the article. We use R to write our program. The K-means analysis suggests the findings presented in Table 8.

5. Discussion

This section compares the proposed algorithm (BM-CV-MDS) with the two existing methods (HAC and K-means) to provide valuable insights into which method obtains better clustering quality.

5.1. Proposed navigation schemes

All three algorithms described in this article for open card sort data analysis (i.e., BM-CV-MDS, HCA, and K-means) claim a statistically optimal solution for website IA design. The proposed approach (BM-CV-MDS) is a technique based on the BMM, CVT, and MDS to visualize the results.

For the proposed algorithm and HAC, Tables 6 and 7 reveal that 73.2% of cards have been arranged precisely in both techniques. HAC applies a hierarchical clustering method to partition the cards into clusters. Clusters are divided in a way to ensure that the most similar cards are grouped together. One group in Table 7 has clustered two cards that were never placed together by a participant. In specific, the HAC group 6 (Table 7) has the following cards: "How to apply for postgraduate research," "Industrial research partnerships," "Postgraduate Scholarships," "Regional Research Partnerships." For this group, Table 9 shows the participant's agreement with each card related to others. It can be seen that "Postgraduate Scholarships" and "Regional Research Partnerships" were never placed together by a participant and had 0%. The HAC method is inconsistent in clustering the cards related to participant's agreement in Figure 5. BM-CV-MDS algorithm overcomes this challenge by grouping similar cards using CVT.

For the proposed algorithm and K-means, Tables 6 and 8 reveal that 90.2% of cards have been arranged precisely in both techniques. K-means is a centroid-based algorithm, or distance-based algorithm, where the distance is calculated by assigning points to a cluster. In Table 8, group 5 has the following cards: "Intellectual Property," "Strategic Research Themes (SRT) Funding," "Industrial research partnerships," "Regional Research Partnerships." Table 10 shows the participant's agreement with each card related to others. It can be seen that "Strategic Research Themes (SRT) Funding" and "Regional research partnerships" were placed together by one participant and had 5%. According to Table 10 "Intellectual Property" and "Strategic Research Themes (SRT) Funding" have very low participant's agreements related to the other cards. These two cards "Intellectual

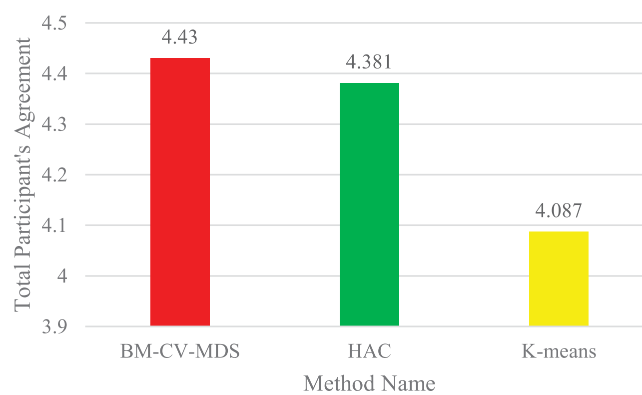

Figure 10. Total values of the participant's agreements in the three methods.

Table 9. The participant's agreement relations of Group 6 in Table 7.

	How to apply for postgraduate research	Postgraduate scholarships	Industrial research partnerships	Regional research partnerships
How to apply for postgraduate research		90	5	5
Postgraduate scholarships	90		5	0
Industrial research partnerships	5	5		90
Regional research partnerships	5	0	90	

Table 10. The participant's agreement relations of Group 5 in Table 8.

	Strategic research themes (SRT) funding	Intellectual property	Industrial research partnerships	Regional research partnerships
Strategic research themes (SRT) funding		35	10	5
Intellectual property	35		10	15
Industrial research partnerships	10	10		90
Regional research partnerships	5	15	90	

Table 11. The participant's agreement relations of Group 5 in Table 6.

	Income from intellectual property	Income from contract research	Income from collaborative research	Consultancy income	Intellectual property	Strategic research themes (SRT) funding
Income from intellectual property		90	85	85	30	20
Income from contract research	90		95	90	20	30
Income from collaborative research	85	95		85	20	30
Consultancy income	85	90	85		15	20
Intellectual property	30	20	20	15		35
Strategic research themes (SRT) funding	20	30	30	20	35	

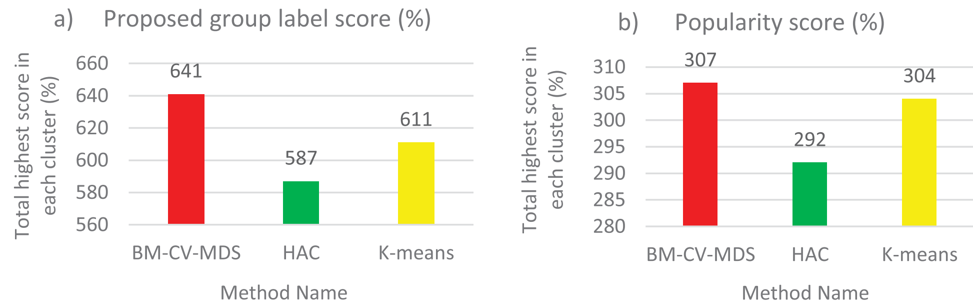

Figure 11. Total percent (a) proposed group label (%) and (b) popularity score (%) in the three methods discussed in this article.

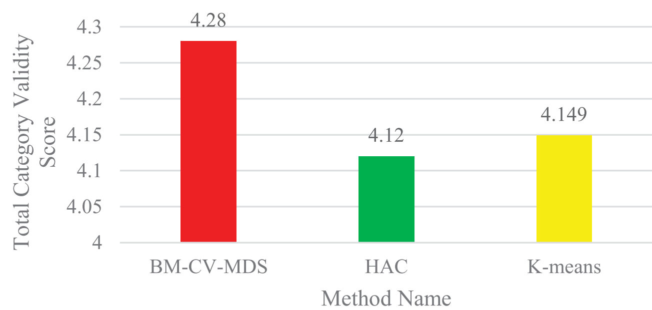

Figure 12. Total category validity scores of the three methods.

Property" and "Strategic Research Themes (SRT) Funding" are grouped together in a different cluster from "Industrial research partnerships" and "Regional Research Partnerships" by the BM-CV-MDS algorithm in Table 11. Table 11 shows that the BM-CV-MDS algorithm did group the two cards, "Intellectual Property" and "Strategic Research Themes (SRT) Funding" with other cards that contain higher participant's agreements compared to the *K*-means method in Table 10.

5.2. Method strength

Figure 10 shows the total value of the participant's agreement in each method. These values are included in column five of Tables 6–8. Measuring each method's strength depends on the total value of the participant's agreement score—the larger the total score, the better the technique. Figure 10 shows that the BM-CV-MDS algorithm has the highest total score (4.43) in red color compared to HAC and *K*-means. The result from Figure 10 displays that BM-CV-MDS algorithm does combine the most similar cards in the seven clusters. The similar cards were selected based on their relationship and closeness depicted by the participant's agreement.

Figure 11 shows the sum of the highest scores in each of the clusters. These values are also shown in the second and third columns of Tables 6–8. These two bar graphs provide insight on how to identify the quality of a clustering method. Figure 11(a) displays the sum of the highest in each cluster proposed group label (%) and Figure 11(b) demonstrates the sum of the highest in each cluster popularity score (%) of the three methods. It can be seen from Figure 11, both (a) and (b), that the proposed algorithm contains the highest scores compared to HAC and *K*-means. This result further supports our claim that the proposed algorithm is better in card sorting clustering.

Figure 12 shows the category validities (see Appendix 2, Tables A6–A8). The proposed algorithm has the highest category validity score. At its best, the proposed algorithm is clustering the 41 cards into the 7 groups more cohesively. In Figure 12, the proposed algorithm appears to be a robust method for analyzing cards meaningfully in relation to how the open card sorting data collection is being carried out.

The proposed algorithm does handle the overlaps and outliers quite well by plotting the final result in three dimensions and listing every card coordination. It allows single cards to be grouped together with their closest core clusters and treats outliers by choosing the stronger similarity cards in the similarity matrix.

5.3. Initial clusters

The quality of initial clusters is extremely important and directly affects the final clustering quality. We calculated the total participant's agreement score (4.43) of the initialization technique (BMM) in Table 6. The result shows that the initialization technique (BMM) has a direct effect on the final clustering quality shown in our BM-CV-MDS algorithm result in Figure 10. It can be seen that the BM-CV-MDS algorithm has the highest total participant's agreement score compared to the existing methods HAC and *K*-means. Our BM-CV-MDS supports Fränti and Sieranoja (2019) finding that the clustering result depends on the goodness of the initialization technique.

6. Conclusion

This article proposed an algorithm to cluster and visualize open card sorting data. The algorithm first creates the initial core clusters using the BMM and then applies the CVT to cluster the rest of the cards. Next, it visualizes the clustering results using MDS. The rationale for the proposed algorithm is that the clustering results heavily depend on the goodness of the initialization technique. Indeed, study results showed that the quality of initial clusters is extremely important and directly affects the final clustering quality.

The proposed algorithm (BM-CV-MDS) provides valuable insights and an improved clustering result compared to the existing techniques, such as HAC and *K*-means. It was also shown that the proposed algorithm compares favorably to other algorithms, obtaining better clustering quality as operationalized by the sum of each method total participant's agreements and the total category validity score. Our analysis shows that the proposed algorithm is closer (90.2% of cards have been arranged precisely in both techniques) to *K*-means than the HAC method.

There is a need for more in-depth future research of components using qualitative data to provide deep and rich insights into card-sorting findings. In addition, we plan to investigate the effect (if any) of various open card sort study parameters (e.g., website domain, number of cards) on the obtained results using the proposed BM-CV-MDS algorithm against existing approaches. One potential limitation of this study is that it concerned the redesign of an existing website, and thus involved participants that were already familiar with the existing structure of the website. Future work involves exploring the performance of the proposed algorithm for the initial design of a website. Future research also includes conducting a user testing study that compares the IA produced by the proposed algorithm against the IA produced by HAC and/or *K*-means in terms of users' interaction effectiveness, efficiency, and satisfaction.

Note by the Editors

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Ethical approval

The University research office has approved the human ethics application for this research project in July 2019.

Consent to participate

The University has approved the human ethics application for this research project in July 2019.

Consent for publication

I (Sione Paea) will be responsible for providing a copy of the authors' final manuscript, including all publishing and peer-review process modifications.

For any other inquiries regarding this article, please do not hesitate to contact me.

Author contributions

The authors of this article agreed to be accountable for all aspects of this study in confirming that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved honestly. We provided substantial contributions to the design of this study, clarifying and interpreting the data, and revised it critically for intellectual content.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Code availability statement

The code availability for this study is available on request to the corresponding author.

ORCID

Sione Paea http://orcid.org/0000-0003-3038-4984
Christos Katsanos http://orcid.org/0000-0001-9031-3083

Data availability statement

The datasets produced for this study are available on request to the corresponding author.

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About the Authors

Sione Paea is a mathematician at the University of the South Pacific (USP) who graduated with a PhD (2011) in Mathematics from Victoria University of Wellington, New Zealand. He teaches undergraduate and postgraduate mathematics courses at USP. He is interested in researching nanocrystal growth, coal pyrolysis, information architecture, and differential equation application.

Christos Katsanos is an Assistant Professor of Human-Computer Interaction in the Department of Informatics, Aristotle University of Thessaloniki, Greece. His research interests include human-computer interaction, human-robot interaction, user experience, information architecture, web accessibility and educational technologies. He has at least 1231 known citations and h-index=18. Contact him at ckatsanos@csd.auth.gr.

Gabiriele Bulivou is a PhD student at the School of Information Technology, Engineering, Mathematics, and Physics (STEMP) from the University of the South Pacific (USP). His research interests include cluster analysis, mathematical programming and optimization, and card sorting analysis. Contact him at Gabiriele.Bulivou@usp.ac.fj.

Appendix 1

An example is provided to help explain the BMM calculations better. The analysis is specific to the example shown below. Let the number of participants equal to 10 and the number of cards to be sorted equal to 5.

Step 1: Card names are a, b, c, d, and e. Table A1 shows five categories with one card each and their participant's agreement scores.

Table A1. Five categories with a card each.

Category number	1	2	3	4	5
Category	[a]	[b]	[c]	[d]	[e]
Participant's agreement score (%)	100	100	100	100	100

Step 2: Combinations of two cards. The based pair with the highest score is locked in as a new construct category. In this stage, each new construct category is independent of the other new construct category. Table A2 shows ten categories with two cards each and their participant's agreement scores. There are two locked in categories in Table A2: category 1 and category 10.

Table A2. Ten categories with two cards each.

Category number	1	2	3	4	5	6	7	8	9	10
Pair	[a, b]	[a, c]	[a, d]	[a, e]	[b, c]	[b, d]	[b, e]	[c, d]	[c, e]	[d, e]
Participant's agreement score (%)	62	43	43	51	58	36	42	36	41	61

Step 3: Combination of three cards. The process in step 2 repeats, and when a pair is locked in intersects with an existing locked category, the former is agglomerated with the latter. Table A3 shows eight categories with three cards each. The algorithm merges category 1 and category 5 of Table A2 and locked in as the new category. In this stage, the relationship of categories does take into consideration. All subsets of this new category are eliminated; for instance, eliminate category 2 in Table A2.

Table A3. Eight categories with three cards each.

Category number	1	2	3	4	5	6	7	8
Pair (category)	[a, b, c]	[a, b, d]	[a, b, e]	[a, c, d]	[a, c, e]	[b, c, d]	[b, c, e]	[c, d, e]
New category	Merge [a, b] and [b,c]							
Participant's agreement score (%)	163	141	155	115	135	130	141	138

Step 4: Combination of four cards. Repeat step 3. Table A4 shows four categories with four cards each. The algorithm merges category 1 of Table A3 and category 4 in Table A2 and locked in as the new category. All subsets of this new category [a, b, c, e] are eliminated.

Table A4. Four categories with four cards each.

Category number	1	2	3	4
Pair (category)	[a, b, c, d]	[a, b, c, e]	[a, c, d, e]	[b, c, d, e]
New category		Merge [a, b, c] and [a, e]		
Participant's agreement score (%)	275	297	214	213

Step 5: Combination of five cards. Repeat step 4. Table A5 shows one category with five cards and the participant's agreement scores. The algorithm merges category 2 of Table A4 and category 10 in Table A2 and locked in as the new category. All cards are merged into a single category.

Table A5. One category with five cards.

Pair (category)	[a, b, c, d, e]
New category	Merge [a, b, c, e] and [d, e]
Participant's agreement score (%)	473

Step 6: The algorithm stops when all 5 cards are grouped in a single category.

Appendix 2

Table A6. BM-CV-MDS algorithm category validity.

Group	Card name	Validity score
1	Application for international students	0.184
	FAQs for international students	0.184
	Information for international students studying at USP	0.184
	International research partnerships	0.11
	Programme for international students	0.17
2	Industrial research partnerships	0.126
	Pacific research guidelines	0.059
	Regional research partnerships	0.136
3	Active research projects	0.049
	Centers and institutes research	0.05
	Faculty research	0.064
	Find a researcher	0.045
	Publication and ranking	0.041
	Research concept at USP	0.057
	Research ethics	0.055
	Research focus areas	0.067
	Research impact	0.062
	Research office	0.047
	Research success	0.072
4	About us	0.123
	Contact us	0.123
	Current staff	0.109
	Find a supervisor	0.063
	Meet our research students	0.047
	News	0.115
5	Consultancy income	0.133
	Income from collaborative research	0.135
	Income from contract research	0.15
	Income from intellectual property	0.14
	Intellectual property	0.048
	Strategic research themes	0.046
6	Innovation in research	0.122
	Innovation in teaching and learning	0.121
	Innovation key focus areas	0.126
	Innovation opportunities	0.129
	Innovation partnerships	0.123
	Laucala innovation hub	0.125
	University support for innovation	0.12
7	How to apply for postgraduate research	0.151
	PhDs and research degrees	0.114
	Postgraduate scholarships	0.155
		Total = 4.28

Table A7. HAC method category validity.

Group	Card name	Validity score
1	About us	0.145
	Contact us	0.145
	Current staff	0.128
	News	0.137
2	Active research projects	0.05
	Centers and institutes research	0.034
	Intellectual property	0.041
	Pacific research guidelines	0.042
	PhDs and research degrees	0.027
	Publication and ranking	0.056
	Research ethics	0.049
	Research impact	0.047
	Strategic research themes	0.053
3	Application for international students	0.184
	FAQs for international students	0.184
	Information for international students studying at USP	0.184
	International research partnerships	0.11
	Programme for international students	0.17
4	Consultancy income	0.176
	Income from collaborative research	0.17
	Income from contract research	0.191
	Income from intellectual property	0.176
5	Faculty research	0.065
	Find a researcher	0.051
	Find a supervisor	0.05
	Meet our research students	0.051
	Research concept at USP	0.07
	Research focus areas	0.07
	Research office	0.051
	Research success	0.068
6	How to apply for postgraduate research	0.068
	Industrial research partnerships	0.072
	Postgraduate scholarships	0.069
	Regional research partnerships	0.072
7	Innovation in research	0.122
	Innovation in teaching and learning	0.121
	Innovation key focus areas	0.126
	Innovation opportunities	0.129
	Innovation partnerships	0.123
	Laucala innovation hub	0.125
	University support for innovation	0.12
		4.121

Table A8. *K*-means method category validity.

Group	Card name	Validity score
1	Consultancy income	0.176
	Income from collaborative research	0.17
	Income from contract research	0.191
	Income from intellectual property	0.176
2	Application for international students	0.184
	FAQs for international students	0.184
	Information for international students studying at USP	0.184
	International research partnerships	0.11
	Programme for international students	0.17
3	About us	0.123
	Contact us	0.123
	Current staff	0.109
	Find a supervisor	0.063
	Meet our research students	0.047
	News	0.115
4	Active research projects	0.05
	Centers and institutes research	0.053
	Faculty research	0.068
	Find a researcher	0.047
	Research concept at USP	0.06
	Research ethics	0.055
	Research focus areas	0.07
	Research impact	0.062
	Research office	0.05
	Research success	0.076
5	Industrial research partnerships	0.08
	Intellectual property	0.036
	Regional research partnerships	0.083
	Strategic research themes	0.026
6	Innovation in research	0.122
	Innovation in teaching and learning	0.121
	Innovation key focus areas	0.126
	Innovation opportunities	0.129
	Innovation partnerships	0.123
	Laucala innovation hub	0.125
	University support for innovation	0.12
7	How to apply for postgraduate research	0.101
	Pacific research guidelines	0.017
	PhDs and research degrees	0.087
	Postgraduate scholarships	0.104
	Publication and ranking	0.033
		4.149