Analysis of means-end chain data in marketing research

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Abstract Means-End Chain Theory has been developed in order to understand how consumers link attributes (A) of products with particular consequences (C), and how these consequences satisfy their personal values (V). The associations in the mind of the consumer between A 's, C 's and V 's are labelled means-end chains (MEC). These chains are often seen as a representation of the basic drive that motivates consumer behaviour. Numerous studies have shown that techniques using MEC are suitable for a wide range of marketing applications. But there is no agreement among researchers as to the way MEC observations should be analysed. In this paper, we review methods of analysis of such observations and suggest the most appropriate procedures. Data from a study of smokers' perceptions of cigarettes in a European city are used for illustration purposes.

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INTRODUCTION

Means-End Chain Theory^{1–6} has been developed in order to understand how consumers link attributes (A) of products with particular consequences (C), and how these consequences satisfy their personal values (V). The associations in the mind of the consumer between A 's, C 's and V 's are labelled means-end chains (MEC). These chains are often seen as a representation of the basic drive that motivates consumer behaviour. A comprehensive history of the MEC approach is presented by Olson and Reynolds.⁷

Numerous studies have shown that techniques using MEC are suitable for a wide range of marketing applications. But there is no agreement among researchers as to the way MEC observations should be analysed. In this paper, we will review methods of analysis of such observations and suggest the most appropriate procedures.

COLLECTING MEC DATA

Let us assume that content analysis of n questionnaires has generated a_i attributes A_i , c_j consequences C_j and v_k values V_k , where $a_i + c_j + v_k = q$. Let p be a number of A – C – V connections (called ladders) provided by n respondents, and let us assume, for the sake of

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simplicity, that each of these ladders has three levels (the procedures that follow are easily adaptable to other numbers of levels as well).

Ladder matrix

Let $L = [l_{rs}]$ be a $p \times q$ matrix with l_{rs} defined as follows: $l_{rs} = 1$, if the s th category was present in the r th ladder among all the ladders that have been elicited from the n respondents, otherwise $l_{rs} = 0$ ($r = 1, 2, \dots, p$; $s = 1, 2, \dots, q$).

Summary implication matrix (SIM)

The individual ladders in L can be aggregated across all the respondents and presented in the form of a summary implication matrix or SIM .⁸ The elements of a SIM represent the number of times each category (the attribute, consequence or value) leads (directly or indirectly) to another category. The following procedure may be used to convert matrix L into a SIM :

Step 1: Partition matrix L into three sub-matrices, A , C and V , whose columns correspond to the attribute, consequence and value categories, respectively. Matrix A is a $p \times a_i$ matrix, C is a $p \times c_j$ matrix and V is a $p \times v_k$ matrix. Thus, $L = [A \ C \ V]$. A typical row of L will contain all 0's except three 1's. A respondent may contribute more than one row to L .

Step 2: Calculate $L'L$, which is a (symmetric) summary implication matrix or SIM of size $q = a_i + c_j + v_k$, and can be represented as follows:

$$SIM = L'L = \begin{matrix} & A'A & A'C & A'V \\ \begin{matrix} C'A \\ C'C \\ C'V \\ V'A \\ V'C \\ V'V \end{matrix} & & & \end{matrix}$$

The elements of an $a_i \times c_j$ matrix $A'C$ represent the number of direct connections in the ladders between each pair of attribute and benefit categories. The elements of a $c_j \times v_k$ matrix $C'V$ describe the number of direct connections between each pair of consequence and value categories. The elements of an $a_i \times v_k$ matrix $A'V$ correspond to the number of indirect connections between each pair of attribute and value categories. The matrices $A'A$, $C'C$ and $V'V$ show on their main diagonals the number of times their corresponding categories are present in the p ladders.

The matrices $A'C$, $A'V$ and $C'V$ may also form an asymmetric summary implication matrix or SIM_{asymm} , if arranged as follows:

$$SIM_{asymm} = \begin{matrix} & A'C & A'V \\ \begin{matrix} 0 & C'V \end{matrix} & & \end{matrix}$$

where 0 is a $c_j \times c_j$ matrix containing all zeros. The SIM_{asymm} is a $(a_i + c_j) \times (c_j + v_k)$ matrix whose size is smaller than that of the (symmetric) SIM and, thus, it is a preferred choice for data presentation.

Illustration

We illustrate all procedures with data from a study of smokers' perceptions of cigarettes that we conducted in 1998 in a European city based on a quota sample of $n = 421$. In a self-administered questionnaire, each respondent provided up to three the most important attributes of cigarettes. Then, he/she defined up to three perceived consequences resulting from each attribute. Finally, he/she identified up to three reasons why each of these consequences was important to him/her. The laddering part of the questionnaire, based on the format introduced, for the first time (to the best of our knowledge), by Mount and Kaciak,⁸ is presented in Figure 1.

Two independent judges classified these categories into seven attribute, eight benefit and seven value categories. Following the content analysis, all associations elicited from the questionnaires were structurally analysed in order to identify the linkages among the attributes ($a_i = 7$), the associated consequences ($c_j = 8$) and the underlying values ($v_k = 7$; hence, $q = a_i + c_j + v_k = 22$). We found $P = 1,828$ ladders that formed a $1,828 \times 22$ ladder matrix L , which was, subsequently, converted into a 22×22 SIM .

ANALYSING MEC DATA

MEC data have been analysed in the literature in a variety of ways. In this paper, we divide them into deterministic and probabilistic methods.

Deterministic methods

Most laddering studies have used deterministic methods. We classify them into two groups: methods applied to a SIM and methods applied to a ladder matrix (L).

Figure 1: The laddering part of the questionnaire. *The same format will be repeated for the second and the third attributes, on pages 2 and 3 of the questionnaire, respectively

Methods applied to a *SIM*

- *Hierarchical value map (HVM)*: Based on a *SIM*, one can draw a hierarchical value map (*HVM*), which constitutes the most popular approach to analysis of laddering data.⁹ The *HVM* is a graphical representation of the most meaningful (ie, exceeding a certain cut-off level, typically 4–5 per cent of *n*) relationships among the categories in the *SIM*. For illustrative purposes, we present in Figure 2 the *HVM* obtained in our study of smokers' perceptions of cigarettes.
- *Cluster analysis of a SIM*: Identifying the dominant clusters of *A*, *C* and *V* categories has been proposed as an alternative to the *HVM*.¹⁰

Data-reduction methods applied directly to a ladder matrix *L*

- *Correspondence analysis (CA) and multiple correspondence analysis (MCA)*: CA and MCA are a natural choice for the laddering data

because of their binary nature.^{11,12,13} Both methods produce coordinates of the laddering categories in a multidimensional space.

- *Nonlinear canonical correlation analysis — NCCA*: Valette-Florence¹⁴ applied this method to a ladder matrix *L* expanded by observations representing the respondent's country. The method produces coordinates of the variables' centroids in a multidimensional space.

Probabilistic methods

Probabilistic methods have been applied, to the best of our knowledge, in only two laddering studies.

Multidimensional scaling of the matrix of probabilities of inter-item similarity

Aurifeille and Valette-Florence¹⁵ have proposed an alternative to the *HVM* method for uncovering dominant MEC from laddering data. Their procedure involves three steps: (i) calculate hypergeometrical probabilities of links between pairs of laddering items; (ii) perform nonmetric MDS on the resulting matrix of probabilities and (iii) apply a clustering procedure to the

coordinates of the laddering categories in the MDS space.

Probabilistic segmentation model

ter Hofstede *et al.*¹⁶ have proposed another approach alternative to the *HVM* — a method of constructing probabilistic means-end map segments. They have calculated the probabilities of a respondent choosing a link between an attribute and a consequence or between a consequence and a value, and then have used the strengths of these links as the basis for segmentation.

The diversity of the above listed methods suggests that there is no clear agreement among researchers as to which approach is more appropriate. The probabilistic methods, although very promising, have not been used by many researchers, probably due to lack of easily accessible software. In this paper, we will therefore focus on the deterministic methods only.

RESEARCH ISSUES AND METHODOLOGY

Hierarchical value map (*HVM*)

The most popular method of analysis of laddering data, beyond question, is the hierarchical value map.⁹ The *HVM* graphically displays the data contained in the *SIM* in their least distorted form (the degree of distortion will only depend on the choice of the cut-off level). Other methods introduce certain transformations to the data, for example, dimensionality reduction. On the other hand, these methods, unlike the *HVM*, can accommodate the respondent/product characteristics necessary for segmentation purposes. In this paper, we will determine which method produces the least distorted picture of the structure in the *HVM*. The quality of a laddering structure emerging from the analysis will be evaluated from two perspectives: (i) its ability to preserve associations within all possible pairs of laddering categories observed in the input data and (ii) its ability to preserve associations within all possible triads of laddering categories. These two measures are comparable to the structure measure of the MEC network used by ter Hofstede *et al.*¹⁷

Data-reduction methods

We will consider the following three data-reduction methods (to the best of our knowledge, *MDS_SIM* and *CCA_L* have never been reported in the literature).

Multidimensional scaling of *SIM* (*MDS_SIM*)

The only method, other than the *HVM*, that has been applied to a *SIM* is cluster analysis.¹⁰ Because the elements of *SIM* can be treated as proximities (similarities) between different laddering categories (the larger the element in a *SIM*, the closer the two corresponding categories), the use of the MDS is also a natural choice for this type of data.

Multiple correspondence analysis of *L* (*MCA_L*)

Valette_Florence¹⁴ has applied nonlinear canonical correlation analysis (NCCA) to a ladder matrix *L*, expanded by observations representing the respondent's country. Such expanded matrix *L* is a natural choice for the NCCA if at least one of the sets contains more than one variable. When each of the sets has only one variable, the NCCA and MCA produce identical results. Since the ladders in our matrix *L* have only three levels, the two methods are equivalent.

Canonical correlation analyses of *L* (*CCA_L*)

When only two sets are involved, and at least one of them has more than one variable, NCCA becomes canonical correlation analysis. We assigned the three variables (*A*, *C* and *V*) in *L*, into two sets so that one set included one variable, and the other — two variables, and analysed each pair of the two sets with the CCA.

Comparing the *HVM* and the data-reduction methods

In order to compare the *HVM* and the data-reduction methods, we propose two similarity measures: the strength of connections within pairs (A_i, C_j), (A_i, V_k) and (C_j, V_k), and the strength of connections within triads (A_i, C_j, V_k).

The strength of connections within pairs (A_i, C_j) , (A_i, V_k) and (C_j, V_k)

For each of the three methods, we measured the similarity of any two laddering categories as the Euclidean distance between the corresponding two vectors of coordinates produced by this method in a six-dimensional space (we chose six dimensions based on the scree plot in factor analysis of the correlation matrix of the 22 laddering categories in L).

The smaller the distance between two categories, the more similar they are across all the ladders. These distances were subsequently compared to the occurrences of all possible bilateral linkages among A 's, C 's and V 's. Such occurrences can be found in the SIM , where each element represents the number of times a category (attribute, consequence or value) leads to another category. Ideally, large elements in the SIM should match small distances in the space.

We evaluated the degree of match between the distances and the (converted to dissimilarities) elements of SIM by calculating the corresponding Pearson correlation coefficients (Table 1). The correlations indicate that the bilateral associations between the categories are best represented by the MDS of the SIM . The results of both the MCA and the CCA of L match these bilateral associations with a slightly lesser precision.

The strength of connections within triads (A_i, C_j, V_k) of laddering items

For each of the three methods, we measured the similarity of any three categories as the (Euclidean) perimeter of a triangle created by the corresponding three vectors of coordinates

produced by the method in a six-dimensional space. The smaller the perimeter of a triangle formed by three categories, the more similar they are across all ladders. We then compared these perimeters to the occurrences of all possible trilateral linkages among A 's, C 's and V 's. Such trilateral linkages are not present in the SIM , for it shows only bilateral connections between the categories. In this paper, we propose a method for determining a matrix that displays occurrences of all the trilateral linkages. We term this matrix a summary ladder matrix or SLM . To the best of our knowledge, this matrix has never been reported in the literature.

Constructing a summary ladder matrix (SLM)

A SLM can be obtained as follows:

Step 1: Sort the rows of L by any of the category concepts, that is, either by attributes, consequences or values. Let us assume that the consequence categories have been chosen as a sorting criterion. (A choice of attributes or values will generate the same outcome.) As a result, one obtains a sorted L with the first group of rows representing all the ladders that include the first consequence category, followed by all the ladders with the second consequence category, etc. Let us assume that there are p_j ladders containing the consequence category C_j ($j = 1, 2, \dots, c_j$), so that $p_1 + p_2 + \dots + p_{c_j} = p$. The sorted L can therefore be represented as follows (for the sake of space, we represent L in the transposed form): $L' = [L_1' \ L_2' \ \dots \ L_{c_j}']$, where $L_j = [A_j \ C_j \ V_j]$, and where A_j , C_j and V_j are sub-matrices of L_j with dimensions $(p_j \times a_i)$, $(p_j \times c_j)$ and $(p_j \times v_k)$, respectively.

Table 1: Pearson correlation coefficients between the distances and the elements of SIM

	SIM_{dissim}	MDS_{SIM}	MCA_L	$CCA_{A/CV}$	$CCA_{C/AV}$	$CCA_{V/AC}$	MDS_L
SIM_{dissim}	1	0.895	0.818	0.760	0.797	0.736	0.534
MDS_{SIM}	0.895	1	0.833	0.758	0.793	0.719	0.653
MCA_L	0.818	0.833	1	0.786	0.952	0.890	0.574
$CCA_{A/CV}$	0.760	0.758	0.786	1	0.736	0.633	0.496
$CCA_{C/AV}$	0.797	0.793	0.952	0.736	1	0.859	0.520
$CCA_{V/AC}$	0.736	0.719	0.890	0.633	0.859	1	0.456
MDS_L	0.534	0.653	0.574	0.496	0.520	0.456	1

Note: All the correlations are significant at the 0.01 level (two-tailed).

Table 2: Pearson correlation coefficients between the triangles' perimeters and the elements of SLM

	SLM _{dissim}	MDS_ <i>SIM</i>	MCA_ <i>L</i>	CCA_ <i>A/CV</i>	CCA_ <i>C/AV</i>	CCA_ <i>V/AC</i>	MDS_ <i>L</i>
SLM _{dissim}	1	0.714	0.591	0.558	0.573	0.525	0.472
MDS_ <i>SIM</i>	0.714	1	0.816	0.753	0.778	0.716	0.681
MCA_ <i>L</i>	0.591	0.816	1	0.766	0.955	0.917	0.579
CCA_ <i>A/CV</i>	0.558	0.753	0.766	1	0.725	0.707	0.538
CCA_ <i>C/AV</i>	0.573	0.778	0.955	0.725	1	0.865	0.530
CCA_ <i>V/AC</i>	0.525	0.716	0.917	0.707	0.865	1	0.476
MDS_ <i>L</i>	0.472	0.681	0.579	0.538	0.530	0.476	1

Note: All the correlations are significant at the 0.01 level (two-tailed).

Step 2: Multiply V_j' by A_j , $j=1, 2, \dots, c_j$. Each $v_k \times a_i$ matrix $V_j' A_j$ represents a number of ladders between all attribute and value categories that pass through the consequence category C_j .

Step 3: Stacking the matrices $V_j' A_j$ ($j=1, 2, \dots, c_j$) on top of each other creates a *SLM*:

$$SLM = \begin{matrix} V_1' A_1 \\ \dots \\ V_{c_j}' A_{c_j} \end{matrix}$$

Since each matrix $V_j' A_j$ is a $v_k \times a_i$ matrix, and there are c_j such matrices, the dimensions of a *SLM* are $(c_j \times v_k) \times a_i$. Elements of a summary ladder matrix represent numbers of times each three categories (A_i, C_j, V_k), $i=1, 2, \dots, a_i$; $j=1, 2, \dots, c_j$; $k=1, 2, \dots, v_k$, have been linked together by respondents across all laddering interviews. Matrices *SLM* and *SIM* are related. One can obtain the *SIM* from the *SLM* but the reverse procedure is impossible.

We evaluated the degree of match between the perimeters of the triangles and the (converted to dissimilarities) elements of the *SLM* by calculating the corresponding correlations, presented in Table 2. The correlations indicate that the trilateral connections between the categories are, again, best represented by the MDS of the *SIM*.

SUMMARY OF THE RESULTS

Based on the above analyses of bilateral and trilateral associations between the laddering categories, we conclude that the MDS of the *SIM* produces results that best match the structure of the underlying *HVM*.

This result is important because supplementing the *HVM* with MDS of the *SIM* permits market

segmentation. For this purpose, we expanded the ladder matrix *L* by consumer/product characteristics (*S*) to $L_E = [A \ C \ V \ S]$, then converted it to the $SIM_E = L_E' L_E$ and applied the MDS procedure. We then repeated the analyses of the bilateral and trilateral associations between the laddering categories extracted from this new MDS solution. We obtained the correlation coefficients similar to the ones found previously for the (unexpanded) *SIM*. This result indicates that the MDS of the SIM_E preserves the relationships among the laddering categories found by the MDS of the *SIM* and thus matches well the structure of the underlying *HVM*. The variables' MDS coordinates can then be analysed with a clustering method in order to identify market segments — the dominant associations between the MEC and the consumer/product characteristics. For example, the *HVM* presented in Figure 2, in combination with MDS followed by a clustering method, provides an easily accessible summary of the complex network of attributes, consequences and values related to the consumers' perceptions of cigarettes. Identifying and understanding the relationships among the nodes in this *HVM* may help to better understand the behavioural underpinnings of tobacco consumption. Such a summary, enhanced by knowledge of the consumer/product characteristics, could, for example, be valuable for those responsible for public health issues. An examination of the chains linking attributes of cigarettes, through the consequences, to the values that underlie the choice of cigarette could provide an opportunity for more precisely targeting public health initiatives. The objective would be to create persuasive communications

Figure 2: Hierarchical value map of smokers' perceptions of cigarettes ($n=421$)

that might discourage smoking by tapping, for example, directly into the consumers' values rather than focusing trivially on the product's attributes.

DISCUSSION, CONCLUSIONS AND LIMITATIONS

In this paper, we have evaluated the results of three data-reduction methods of analysis of laddering data, comparing them to the *HVM*, the most popular technique in the laddering research. To the best of our knowledge, two of these methods (the MDS of the *SIM* and the CCA of *L*), have not been used for analysis of laddering data before. The *HVM*, although very popular, has one significant limitation. It does not enable the inclusion of the respondent/product measures and, therefore, does not allow for market segmentation. On the other hand, it represents the data in their least distorted form, which depends only on the choice of the cut-off level. The data-reduction techniques have exactly the opposite features. They can accommodate the respondent/product characteristics, necessary for segmentation purposes; however, they introduce certain transformations to the data. Therefore, it makes sense to seek a data-reduction technique that would minimise the distortions of the original data, that is, would match the laddering structure

in the *HVM* in the best possible way. This was the objective of this paper.

In order to evaluate these methods, we introduced two similarity measures, comparable to the structure measure of the MEC network used by ter Hofstede *et al.*¹⁷ The first similarity measure involved *pairs* of the laddering categories, and was based on the summary implication matrix (*SIM*). The second measure focused on *triads* of the laddering categories, and was based on the summary ladder matrix (*SLM*), that we have presented, for the first time, in this paper.

We have found that although the best results can be obtained with the MDS of the *SIM*, other data-reduction techniques such as MCA or CCA, applied directly to the ladder matrix *L*, produce comparable results. Our finding has practical implications for those who might hesitate as to which method they should use for analysis of what form of laddering data. Ideally, one could try all the approaches mentioned above and interpret only patterns present across all the solutions.

Our findings suggest that for market segmentation purposes, the *HVM* can be used in tandem with MDS of the summary implication matrix (*SIM_E*) expanded by consumer/product characteristics. Other data-reduction techniques (eg, MCA, NCCA or CCA), applied directly to

the expanded ladder matrix $L_E = [A \ C \ V \ S]$, although (based on our results) somewhat inferior to the MDS of SIM_E , may also shed some additional light on the relationships among the laddering categories and the consumer/product characteristics. We also suggest that one should always perform data-reduction procedures, such as MCA, NCCA and/or CCA, on the consumer/product characteristics (S) alone. The patterns emerging from such analyses should be matched against the patterns found in the previous (aggregated) analyses. Only the patterns that are present in all outcomes may be considered for segmentation purposes.

The summary ladder matrix (SLM) that we have introduced in this paper contains more information than the traditional summary implication matrix (SIM). It provides information not only about which *pairs* of the laddering categories were elicited from the respondents but also which *triads* of categories were formed. We point to an interesting additional benefit stemming from the knowledge of the SLM . Based on this matrix, we can calculate a ratio of the number of $A-C-V$ ladders represented in the HVM to the total number of ladders. This ratio, which we introduce for the first time in this paper, and name the SLM ratio, may be used together with the traditional SIM ratio⁹ to evaluate the quality of the hierarchical value map. In many laddering studies, the reported SIM ratio was rather low (eg, 44–54 per cent,¹⁸ 44–51 per cent,¹⁹ 47 per cent²⁰), which might create a rather pessimistic impression of the quality of the resulting HVM s. This pessimistic impression may be somewhat softened if the quality of the HVM is measured with the SLM ratio. For example, in the study described in this paper, the traditional SIM ratio was 50.8 per cent, whereas the SLM ratio was found to be 79.3 per cent! The SLM ratio is a measure of the quality of the HVM that focuses on the original ladders in the SLM rather than on the associations in the SIM , and as such provides additional information about the accuracy of the map.

Our study has some limitations. First, we have based our conclusions on the results from the analyses of only one data set (in future

research, these methods should be applied to a number of synthetic ladder matrices L generated in a Monte Carlo study). Secondly, we have focused only on deterministic methods for analysing laddering data (future research is required that will also involve probabilistic methods in the comparative analysis).

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