Brand segmentation using implicit brand measures

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Abstract Segmentation can be a difficult analytical project to pull off. Brand segmentation, in particular, has been challenged to the point that some research has aimed to demonstrate it does not exist. Although such studies have covered many different product categories, they have not addressed the issue using recent developments in the measurement of (brand) attitudes; neither have they used optimal analytical techniques. Both of these have the potential to affect segmentation solutions in a significant way. This paper aims to fill this gap in the literature. It investigates whether brand segments can be identified using implicit attitudes and using segmentation models that are best suited for the data at hand. The study finds evidence of meaningful brand segmentation in over 50 per cent of the categories studied.

KEYWORDS: brand segmentation, K-mode analysis, K-means, implicit attitudes, managerial usefulness

INTRODUCTION

Segmentation, especially if its aim is broad and strategic, is one of the most difficult analytical projects to pull off. Indeed, the perceived failure rate is so high that is not unusual for marketing professionals to suggest that firms avoid such studies altogether. It has been reported that 85 per cent of new product launches in the USA fail because of poor market segmentation.[1] Brand segmentation, in particular, has been challenged: the segmentation literature has failed to produce stable and meaningful brand segmentation results and, indeed, its very existence has been questioned.[2–4] Not everybody agrees, however, as both segmentation bases and segmentation analytics can lead to different outcomes.[5,6] Despite the fact that brand segmentation has been challenged, and despite the practical challenges posed by segmentation studies, firms still pursue market segmentation to get deeper insights into their audience or find areas of unlocked value.

The literature refuting brand segmentation is limited in two ways. First, studies have identified that user profiles do not differ much across various brands when demographic and attitudinal variables are compared. This does not, however, mean that segments do not exist:[7] a different segmentation base could produce different results. Many variables can be used to identify segments, such as demographics, lifestyles, category attitudes, brand attitudes, brand usage, needs, share of wallet, outcomes, etc. Any segmentation base that uses perceptions or attitudes may be vulnerable to response scale bias and this may complicate the identification of segments. This may partially explain why the studies found no meaningful segments based on lifestyle attitudes.[8] An alternative attitude measurement approach, referred to as 'implicit attitudes', has been suggested in the consumer psychology literature.[9] A recent study suggests that implicit attitudes may be less vulnerable to response scale bias effects.[10] If implicit attitudes differ in terms of their susceptibility to response style effects, then one can also expect implicit brand attitudes to lead to different segmentation results compared with explicit brand attitudes.[11]

Secondly, segmentation is typically a multivariate analysis, and it is well known that analytics specifics can make a significant difference in terms of the quality of the segmentation solution.[12]

This paper aims to determine the degree to which implicit attitudes in conjunction with a recommended clustering method may affect whether brand segments can be identified. The study draws on an analysis of binary brand attitude data. The appropriate clustering methodology for such data is K-mode analysis. Four types of analysis are evaluated: (1) explicit data analysed using K-means; (2) implicit data analysed using K-means; (3) explicit data analysed using K-modes; and (4) implicit data analysed using K-modes. Replication rate and silhouette scores are used to determine the optimal number of segments and the existence of meaningful brand segments is evaluated by comparing the segments on average brand attitude top-box percentages and two passive segmentation variables, namely brand usage and brand closeness. The data analysed comprise 51 brands across 17 categories. Only if implicit data are combined with an appropriate multivariate clustering approach is it possible to identify meaningful brand segments.

DATA AND METHODOLOGY

Data

The study uses survey data collected by Ipsos in 2013. The Ipsos study covered 17 product categories, with three brands in each category. Table 1 lists the 51 brands analysed.

Respondents evaluated one category and one brand in that category. They were asked if they agreed with a set of 12 brand statements, eg This is a brand that... (1) I would recommend; (2) is for me; (3) is different; (4) is high quality; (5) is highly recommended; (6) is on its way up; (7) is popular; (8) is socially responsible; (9) is trustworthy; (10) sets the lead; (11) stirs my emotions; and (12) meets my needs. Brand statements were evaluated on a five-point

Table 1: Overview of categories and brands

Categories	Brands
Chocolate	Cadbury's Dairy Milk, Maltesers, Galaxy
Social media	Facebook, Twitter, LinkedIn
Department stores	Marks & Spencer, Amazon, John Lewis
Cars	Kia, Toyota, Volkswagen
Airlines	Delta, United, American
Credit cards	Visa, MasterCard, American Express
Smartphones	Apple, Samsung, BlackBerry
Fashion retail	Zara, H&M, Mango
Carbonated soft drinks	Coca-Cola, Pepsi, Sprite
Toothpaste	Colgate, Blend-a-met, Lacalut
Beer	Brahma, Antarctica, Budweiser
TV	Samsung, LG, Sony
Feminine deodorant	Nivea, Dove, Garnier bi-o
Facial tissues	Vinda, Mind act upon mind, Tempo
Sportswear	Nike, Adidas, Li-Ning
Laundry detergent	Tide, Liby, Blue Moon
Banks	First Direct, Lloyds, Natwest

scale (disagree to agree). For each brand association, the variables were recoded into binary variables: top-two box versus bottom-box (the study started by using the original five-point scale but this did not result in useful segments). In addition, for each of these brand associations, a parallel variable was used to record how quickly the response was given; details for this are provided elsewhere.[13] Where the respondent gave the brand association a top-two box rating and they gave it quickly (as indicated by the speed variable), it remained a top-two box score. Where the rating was neutral or a top-two box rating was given slowly, a (1) was recoded into a bottom-box score (0). A bottom-box score remained a bottom-box score regardless of the speed at which it was given. Recoding in this manner gives more weight to the implicit responses.

The study also used two variables for profiling the segments: respondents were asked (1) how close they feel to each brand (a standard question in Ipsos Brand Value Creator approach);[14] and (2) whether they used the brand. These two variables are used as indicators of the overall commercial appeal of a segment along with its size.

Methods

The study compares two methods: *K-means*[15] and *K-modes*.[16,17] The former remains the most commonly used approach in commercial practice and hence is used as a benchmark. For the dataset in the present study, however, where the variables are all binary, the standard K-means approach is not appropriate. Instead an extension of the approach is used: the K-modes approach. This approach uses a simple matching dissimilarity measure (ie Gower's coefficient[18]) and uses mode values instead of mean values.

Evaluation of results

The quality of the empirical segmentation solution was evaluated on reproducibility,[19] Silhouette score[20] and managerial usefulness.

Silhouette score is a popular method to evaluate segmentation solutions in practical (eg commercial) analyses. There are two ways to use a Silhouette analysis. The present study uses only the numerical value: this is a number from −1 to 1, where a 1 means good separation, a 0 means a poor separation and a negative value indicates the possibility of an incorrect classification.

Managerial usefulness is determined in two ways. First, the percentage top-box scores are compared across the various segment solutions. Solutions with an obvious pattern are deemed less interesting. For example, in a two-segment solution, one segment has low top-two box scores on all variables, and one segment has high top-two box scores. Such a solution is suspect as it may have been caused by a response-style halo effect. Secondly, the segments are profiled on overall brand attitude value and on usage. These are used as measures for overall segment appeal. A segmentation solution that includes a clear differentiation on these two measures is considered more actionable.

RESULTS

First, K-means and K-modes for both explicit and implicit data were compared. A two to four-segment solution was run on each brand for each method (K-means versus K-modes) and for each data type (explicit versus implicit). Segmenting into further clusters resulted in very sparse segments and the statistics did not improve. The brand segmentation solution was evaluated on both replicability and Silhouette score. The optimal number of segments was then selected based on these two metrics. Table 2 presents an example pertaining to three brands, using K-modes analysis.

For example, using explicit data for Blue Moon, a two-segment solution would be optimal because both replicability and Silhouette score are highest. However, when using implicit data, the four-segment solution has a higher replicability than the two-segment solution, while the Silhouette score is mostly similar across the segment solutions. Hence a four-segment solution seems to be best.

This type of analysis and optimal segments solution selection was done for all 51 brands. The results are summarised in Tables 3a and 3b. Table 3a shows the K-means results and Table 3b shows the K-modes results.

Table 2: Example of a K-modes analysis: Replicability and Silhouette score

Brand	Replicability explicit	Silhouette score	Replicability implicit	Silhouette score
Liby				
2 clusters	*0.88*	*0.53*	*0.72*	*0.13*
3 clusters	0.78	0.45	0.43	0.11
4 clusters	0.70	0.43	0.39	0.1
Blue Moon				
2 clusters	*0.92*	*0.47*	*0.32*	*0.23*
3 clusters	0.78	0.37	0.34	0.21
4 clusters	0.83	0.36	0.42	0.22
Tide				
2 clusters	*0.92*	*0.46*	*0.65*	*0.17*
3 clusters	0.73	0.38	0.53	0.15
4 clusters	0.72	0.37	0.43	0.14

Table 3a: Optimal K-Means solutions for explicit and implicit data

Brand	Explicit			Implicit		
	Replicability	Silhouette	Optimal solution	Replicability	Silhouette	Optimal solution
1	0.91	0.40	2 segments	1.00	0.26	2 segments
1	0.99	0.37	3 segments			
2	1.00	0.35	2 segments	1.00	0.26	2 segments
3	0.94	0.4	2 segments	1.00	0.33	2 segments
4	1.00	0.39	2 segments	0.97	0.32	2 segments
5	1.00	0.40	2 segments	1.00	0.39	2 segments
6	1.00	0.55	2 segments	1.00	0.59	2 segments
7	0.91	0.37	2 segments	0.96	0.30	2 segments
7	0.98	0.31	3 segments			
8	1.00	0.41	2 segments	0.99	0.22	2 segments
9	1.00	0.44	2 segments	1.00	0.35	2 segments
10	1.00	0.62	2 segments	1.00	0.70	2 segments
11	1.00	0.54	2 segments	0.95	0.65	2 segments
12	1.00	0.52	2 segments	1.00	0.61	2 segments
13	0.90	0.49	2 segments	0.99	0.54	2 segments
13	0.93	0.43	3 segments			
14	1.00	0.45	2 segments	1.00	0.40	2 segments
15	1.00	0.42	2 segments	0.97	0.28	2 segments
16	1.00	0.44	2 segments	1.00	0.35	2 segments
17	1.00	0.47	2 segments	1.00	0.38	2 segments
18	0.99	0.45	2 segments	1.00	0.37	2 segments
19	1.00	0.39	2 segments	0.98	0.20	2 segments
20	0.91	0.37	2 segments	1.00	0.27	2 segments
21	0.99	0.46	2 segments	0.93	0.49	2 segments
22	1.00	0.47	2 segments	1.00	0.26	2 segments
23	0.97	0.44	2 segments	1.00	0.21	2 segments
24	1.00	0.54	2 segments	1.00	0.63	2 segments
25	1.00	0.46	2 segments	0.87	0.23	2 segments
26	1.00	0.52	2 segments	0.99	0.34	2 segments
27	1.00	0.42	2 segments	0.98	0.24	2 segments
28	0.80	0.47	2 segments	1.00	0.27	2 segments
29	1.00	0.49	2 segments	0.98	0.28	2 segments
30	1.00	0.43	2 segments	0.99	0.32	2 segments
31	0.88	0.46	2 segments	0.92	0.19	2 segments
31	0.96	0.40	3 segments			
32	1.00	0.45	2 segments	1.00	0.24	2 segments
33	1.00	0.46	2 segments	1.00	0.34	2 segments

(Continued)

Table 3a: (*Continued*)

Brand	Explicit			Implicit		
	Replicability	**Silhouette**	**Optimal solution**	**Replicability**	**Silhouette**	**Optimal solution**
34	1.00	0.44	2 segments	0.98	0.24	2 segments
35	1.00	0.44	2 segments	0.98	0.35	2 segments
36	1.00	0.46	2 segments	0.98	0.32	2 segments
37	1.00	0.52	2 segments	1.00	0.13	2 segments
38	1.00	0.44	2 segments	1.00	0.17	2 segments
39	1.00	0.49	2 segments	0.89	0.15	2 segments
40	1.00	0.44	2 segments	0.99	0.18	2 segments
41	1.00	0.42	2 segments	0.98	0.38	2 segments
42	0.91	0.48	2 segments	0.90	0.16	2 segments
42	0.95	0.40	3 segments			
43	1.00	0.48	2 segments	0.90	0.14	2 segments
44	1.00	0.52	2 segments	0.99	0.15	2 segments
45	1.00	0.41	2 segments	1.00	0.26	2 segments
46	1.00	0.52	2 segments	0.81	0.10	2 segments
46	1.00	0.41	2 segments			
47	1.00	0.40	2 segments	0.95	0.20	2 segments
48	1.00	0.51	2 segments	0.65	0.09	2 segments
49	1.00	0.52	2 segments	0.98	0.13	2 segments
50	0.98	0.46	2 segments	0.98	0.23	2 segments
51	1.00	0.46	2 segments	0.96	0.16	2 segments

Table 3b: Optimal K-Modes solutions for explicit and implicit data

Brand	Explicit			Implicit		
	Replicability	**Silhouette**	**Optimal solution**	**Replicability**	**Silhouette**	**Optimal solution**
1	1.00	0.40	2 segments	0.78	0.25	2 segments
2	0.87	0.35	2 segments	1.00	0.26	2 segments
3	1.00	0.40	2 segments	0.75	0.33	2 segments
4	1.00	0.39	2 segments	0.79	0.31	2 segments
5	1.00	0.39	2 segments	0.76	0.38	2 segments
6	1.00	0.54	2 segments	0.72	0.57	4 segments
7	1.00	0.37	2 segments	0.71	0.28	2 segments
8	1.00	0.42	2 segments	0.92	0.20	2 segments
9	0.91	0.44	2 segments	0.79	0.34	2 segments
10	0.96	0.62	2 segments	0.67	0.67	3 segments
11	0.9	0.54	2 segments	0.61	0.63	4 segments
12	0.97	0.52	2 segments	0.81	0.61	2 segments
13	0.93	0.49	2 segments	0.70	0.52	4 segments

Table 3b: (*Continued*)

Brand	Explicit			Implicit		
	Replicability	Silhouette	Optimal solution	Replicability	Silhouette	Optimal solution
14	0.96	0.45	2 segments	0.71	0.39	2 segments
15	0.92	0.41	2 segments	0.65	0.27	2 segments
16	0.92	0.44	2 segments	0.37	0.34	3 segments
17	1.00	0.46	2 segments	0.37	0.37	2 segments
18	0.91	0.45	2 segments	0.20	0.37	2 segments
19	0.94	0.39	2 segments	0.27	0.20	2 segments
20	0.95	0.37	2 segments	0.49	0.27	2 segments
21	1.00	0.46	2 segments	0.26	0.49	2 segments
22	1.00	0.47	2 segments	0.20	0.26	2 segments
23	0.90	0.45	2 segments	0.61	0.20	2 segments
24	0.92	0.54	2 segments	0.22	0.61	4 segments
25	1.00	0.46	2 segments	0.31	0.22	2 segments
26	0.93	0.52	2 segments	0.24	0.31	4 segments
27	0.94	0.42	2 segments	0.26	0.24	2 segments
28	1.00	0.51	2 segments	0.29	0.26	2 segments
29	1.00	0.49	2 segments	0.31	0.29	2 segments
30	1.00	0.43	2 segments	0.18	0.31	2 segments
31	1.00	0.46	2 segments	0.22	0.18	2 segments
32	1.00	0.45	2 segments	0.35	0.22	4 segments
33	0.94	0.46	2 segments	0.23	0.35	2 segments
34	1.00	0.44	2 segments	0.35	0.23	2 segments
35	0.91	0.44	2 segments	0.31	0.35	2 segments
36	0.88	0.46	2 segments	0.11	0.31	2 segments
37	0.94	0.54	2 segments	0.16	0.11	3 segments
38	0.89	0.45	2 segments	0.13	0.16	3 segments
39	0.94	0.49	2 segments	0.18	0.13	3 segments
40	0.91	0.44	2 segments	0.38	0.18	2 segments
41	0.90	0.42	2 segments	0.16	0.38	2 segments
42	0.95	0.50	2 segments	0.14	0.16	2 segments
43	0.96	0.48	2 segments	0.15	0.14	2 segments
44	0.92	0.53	2 segments	0.27	0.15	2 segments
45	0.90	0.41	2 segments	0.08	0.27	2 segments
46	0.80	0.53	2 segments	0.21	0.08	2 segments
47	0.88	0.40	2 segments	0.08	0.21	4 segments
48	0.93	0.53	2 segments	0.13	0.08	2 segments
49	0.92	0.53	2 segments	0.22	0.13	2 segments
50	0.93	0.47	2 segments	0.17	0.22	4 segments
51	0.92	0.46	2 segments	0	0.17	2 segments

First, one can observe from Table 3a (K-means) that a two-segment solution seems to be optimal for most brands with explicit data and for all brands using implicit data. Using explicit data, six brands showed some ambiguity. Using implicit data there is no ambiguity. All the two-segment solutions were reviewed in terms of the percentage top box. In each case, one segment scored low on all attributes, while a second segment scored high on all attributes. This seems to confirm the view of the literature refuting the existence of brand segments that there are only small and big brands.

Secondly, one can observe that, overall, both replicability and Silhouette scores are lower under the implicit data. Raw brand data are vulnerable to halo effects: those who like the brand might give it a high score on all attributes; those who do not like the brand give it low scores. This results in a nice clean split, hence the high replicability rates and Silhouette scores. Implicit data have been found to be less vulnerable to such response biases and hence the results may not look as clean. However, even the implicit results from the K-means consistently show a two-segment solution.

Thirdly, reviewing Table 3b (K-modes analysis), the explicit data still consistently recommend two-segment solutions. In all cases, one segment will have all low scores while the other segment will have all high scores. When using the implicit data, however, 13 brands across 11 categories out of a total of 17 categories have either a three or four-segment solution. In almost none of these cases was there any ambiguity. This means there is some brand segmentation in more than half of the categories.

Two brands were selected to review in more detail: Blue Moon (laundry detergent) and Delta (Airlines). Full detailed results are available upon request. The two K-means two-segment solutions were compared for both implicit and explicit data (Tables 4a and 5a) and the explicit two-segment K-modes solution were compared with the implicit four-segment K-modes solution (Tables 4b and 5b).

Table 4a: K-Means: Two-segment explicit and implicit solution (Blue Moon laundry detergent)

Brand attributes	Explicit		Implicit	
	Segment 1 n = **181**	**Segment 2** n = **123**	**Segment 1** n = **149**	**Segment 2** n = **155**
For me	0.84	0.12	0.38	0.08
I would recommend	0.87	0.20	0.36	0.11
Is different	0.88	0.33	0.33	0.11
Is high quality	0.82	0.06	0.47	0.06
Highly recommended	0.82	0.13	0.41	0.09
On its way up	0.88	0.12	0.36	0.06
Popular	0.94	0.24	0.55	0.12
Socially responsible	0.72	0.06	0.32	0.08
Trustworthy	0.90	0.14	0.34	0.05
Sets the lead	0.90	0.19	0.53	0.08
Stirs my emotions	0.90	0.19	0.38	0.12
Understands my needs	0.92	0.20	0.58	0.04
Average	0.87	0.15	0.42	0.08
Usage	0.36	0.32	0.35	0.34
Closeness	0.70	0.49	0.68	0.56

Table 4b: K-Modes: Two-segment explicit and four-segment implicit solution (Blue Moon laundry detergent)

Brand attributes	Explicit		Implicit			
	Segment 1 $n = 124$	Segment 2 $n = 180$	Segment 1 $n = 62$	Segment 2 $n = 39$	Segment 3 $n = 22$	Segment 4 $n = 181$
For me	0.12	0.84	0.23	0.69	0.73	0.06
I would recommend	0.20	0.88	0.32	0.59	0.14	0.13
Is different	0.32	0.89	0.37	0.31	0.18	0.14
Is high quality	0.06	0.82	0.42	0.69	0.14	0.12
Highly recommended	0.13	0.82	0.74	0.21	0.05	0.11
On its way up	0.12	0.88	0.26	0.31	0.77	0.09
Popular	0.25	0.94	0.40	0.85	0.32	0.19
Socially responsible	0.06	0.72	0.29	0.33	0.27	0.12
Trustworthy	0.15	0.89	0.29	0.31	0.27	0.12
Sets the lead	0.19	0.89	0.69	0.41	0.32	0.13
Stirs my emotions	0.19	0.89	0.24	0.72	0.32	0.14
Understands my needs	0.21	0.92	0.74	0.31	0.91	0.07
Average	0.17	0.87	0.40	0.42	0.31	0.11
Usage	0.32	0.36	0.27	0.33	0.41	0.36
Closeness	0.36	0.70	0.58	0.74	0.77	0.58

Table 5a: K-Means: Two-segment explicit and four-segment implicit solution (Delta Airlines)

Brand attributes	Explicit		Implicit	
	Segment 1 $n = 177$	Segment 2 $n = 158$	Segment 1 $n = 202$	Segment 2 $n = 133$
For me	0.14	0.87	0.04	0.46
I would recommend	0.20	0.95	0.08	0.54
Is different	0.06	0.62	0.03	0.31
Is high quality	0.16	0.95	0.07	0.59
Highly recommended	0.11	0.88	0.03	0.50
On its way up	0.07	0.79	0.05	0.33
Popular	0.32	0.88	0.13	0.51
Socially responsible	0.09	0.71	0.04	0.33
Trustworthy	0.19	0.93	0.06	0.69
Sets the lead	0.05	0.72	0.03	0.28
Stirs my emotions	0.07	0.52	0.02	0.23
Understands my needs	0.12	0.81	0.07	0.36
Average	0.13	0.80	0.06	0.43
Usage	0.27	0.50	0.29	0.50
Closeness	0.05	0.41	0.09	0.41

Table 5b: K-Modes: two-segment explicit and four-segment implicit solution (Delta Airlines)

Brand attributes	Explicit		Implicit		
	Segment 1 n = 191	Segment 2 n = 144	Segment 1 n = 249	Segment 2 n = 57	Segment 3 n = 29
For me	0.16	0.90	0.10	0.65	0.21
I would recommend	0.25	0.97	0.16	0.68	0.31
Is different	0.07	0.65	0.09	0.25	0.41
Is high quality	0.21	0.97	0.12	0.72	0.79
Highly recommended	0.15	0.90	0.09	0.58	0.62
On its way up	0.10	0.83	0.09	0.32	0.48
Popular	0.34	0.91	0.18	0.72	0.34
Socially responsible	0.12	0.74	0.06	0.23	0.79
Trustworthy	0.23	0.95	0.16	0.75	0.76
Sets the lead	0.05	0.78	0.05	0.21	0.66
Stirs my emotions	0.08	0.55	0.06	0.25	0.21
Understands my needs	0.15	0.85	0.10	0.67	0.03
Average	0.16	0.83	0.11	0.50	0.47
Usage	0.27	0.52	0.33	0.56	0.45
Closeness	0.06	0.42	0.14	0.53	0.31

Using K-means (Tables 4a and 5a), one finds only two-segment solutions, and these only differentiate between those respondents who seem to like the brand and those who do not. Even the K-modes solutions, when based on explicit data, follow this pattern. Things look different, however, if one reviews the K-modes solutions based on implicit data. The implicit four-segment K-modes solutions look much more differentiated and actionable. For Blue Moon (Table 4b), the segment with the highest closeness score and the highest usage does not have the highest average brand attitude scores. Only on three brand attitudes does this segment get higher scores than the other segments (for me; on its way up; and understands my needs). Segment 2 appears to indicate a potential segment where Blue Moon could grow its usage numbers, most likely by improving perception on 'understands my needs'. On the raw data, Blue Moon scores 63 per cent top box; for implicit, however, that number drops to 30 per cent, so there is clearly a lot of room for improvement. Similar results are observed for Delta (Tables 5a and 5b). In this case, the K-modes implicit three-segment solution shows that the highest usage segments are 'for me' and 'understands my needs'. It is notable that when using K-modes on implicit data, the segment with low scores across all brand attributes is larger than under the explicit results.

Overall, the K-modes implicit results suggest that halo effects are successfully eliminated and the segment results are not merely the result of a halo response.

DISCUSSION

This paper has investigated whether meaningful brand segments can be identified by using better clustering methods (ie K-modes instead of K-means) and by using attitude measurements that are less susceptible to response-style effects (implicit measurement instead of explicit measurement).

Using K-means clustering on binary brand association data yields obvious two-segment solutions only and these two segments are very similar across brands. Secondly, even if one employs the K-means approach using implicit data, in most cases it is still a two-segment solution. For the most part, this seems to confirm the argument of the literature refuting the existence of brand segments. However, using K-modes in combination with implicit data obtains meaningful brand segments in more than 50 per cent of the categories. This finding can be added to other studies that have used creative approaches to identify successful and stable brand segments.[21]

This area should be studied further. First, many commercial brand studies contain numerous brand attribute statements, ranging from around 20 to all the way up to 100. It would be good to see empirical results on such data. Secondly, other types of measurements are now being proposed, eg the use of visual stimuli to assess how people feel about brands or the use of open-ended questions to capture brand associations. The question as to how such alternative brand data can identify meaningful brand segments is also a topic for further research.

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