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A COMPARISON OF TWO TAXONOMIC APPROACHES FOR ATTITUDINAL SEGMENTATION IN TRANSPORTATION

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Summary:

In segmenting the market based on attitudinal or psychographic data, there are two diversent schools of thought. The first school of thought believes that *only one principal dimension* reflecting a major benefit sought is relevant, and therefore, market segments should be formed based on homogeneity of people with respect to their dominant need factor. We call this the Dominant Method. The second school of thought believes in *averaging all dimensions* of benefits sought by people in consuming a product or service, and therefore, market segments should be formed based on homogeneity of people with respect to all the need dimensions. We call this the Profile Method.

The two methods were applied on data generated from a survey of 1004 households living in the Orange County of California about their attitudes toward public transportation (bus system). Based on the criterion of maximizing between to within group variances with respect to the attitudinal profile, both methods did exceedingly well, and, therefore, we cannot say conclusively that one method is superior over the other.

Introduction

Market segmentation is one of several marketing strategies used to achieve specific objectives related to patronage or sales levels. (Sheth 1971) It essentially divides the market into homogeneous subsets of customers (called segments) where any subset may conceivably be selected as a market target to be reached with a distinct combination of product characteristics, price levels, and distribution and promotional expenses. Its primary concern is to help develop and position successfully products and services in the market place in an attempt to meet customer desires.

In identifying homogeneous market segments, different sets of segmentation bases may be considered. For example, segments may be formed on the basis of the demographic and socioeconomic characteristics of potential customers, on their geographic location, on consumption patterns and buying situations or on their perceptions towards some set of situational and product attributes. All these sets of characteristics have been used with varying levels of success (Frank, Massy and Wind, 1972; Arndt, 1972). Wilkie (1971) compared various segmentation bases as they relate to realistic marketing strategies and concluded that attitude or benefit segmentation which identifies target segments by defining the "salient product characteristics" of each segment is superior. He is in agreement with Haley (1968) and Yankelovich (1964) who argue that attitude segmentation is not only conceptionally meaningful but has shown proven market successes.

However, there is disagreement as to whether segments should be formed on the basis of a single dominant or salient benefit or whether segments should be formed on the basis of a profile benefits. This study describes both approaches and provides a basis for comparison since both approaches are applied to the same data source.

However, there is disagreement as to how segments should be derived based on product-specific attitudes. One school of thought reflected in Haley and Yankelovich suggests that attitude segments be based on the dominant or principal benefit (barrier) sought by the customer. In other words, the dominant segmentation strategy utilizes a single predominant benefit (barrier) sought by the customer as a basis for grouping customers with similar predominance. On the other hand, a school of thought emphasizes the concept of a bundle of benefits (barriers) in which some benefits compensate for other benefits or barriers. The disjunctive model underlying the dominant benefit segmentation analysis and the compensatory model underlying the profile benefit segmentation clearly have different implications for market planning.

The objective of this study was to compare the dominant and profile benefit segmentation analysis in the public transportation area. How to motivate people in making greater usage of public transportation such as buses, subways and trains has been a major marketing problem, and recently scholars working in the area have shifted their attention to utilizing attitudinal segmentation as a basis for transportation planning (Sheth 1975; Nicolaidis and Sheth, 1976).

Data and Method

In an attempt to improve the public transportation ridership in Orange County, California, an understanding of the travel needs, desires and patterns of the residents of the county was sought through a market research program administered by the County's Transit District (OCTD). Towards this purpose, a home-interview survey was administered during June and July of 1974. A stratified random sample of households was selected to be included in the survey, resulting in 1804 personal records.

The data base was graciously supplied to the authors for the purposes of developing and testing a market segmentation methodology. The survey included a set of attitudes towards various characteristics of the transportation environment, (measured on a seven-point scale,) as well as socioeconomic, demographic, and other characteristics describing the personal and travel profiles of the residents of the County. The attitudes describing the transportation environment were selected as a segmentation base. Figure 1 lists the 20 attitudes included and their abbreviated forms used in subsequent sections of this study.

In order to establish homogeneous groups of respondents on the basis of these attitudes, we have utilized the two techniques of profile segmentation and dominant segmentation as described earlier. The first technique essentially combines a factor analysis with a clustering algorithm which essentially assigns individuals to the same group if their interpoint distances in the factor space is small. The second much simpler method, assigns an individual to one of as many groups as the number of factors retained from the factor analysis. The individual is assigned to that group for which its corresponding factor score is the largest. The first technique will be subsequently referred to as the "Profile Method", corresponding to a benefit profile segmentation while the second as the "Dominant Method" corresponding to a dominant benefit segmentation.

ATTITUDE AS WORDED ON ATTITUDINAL QUESTIONNAIRE	ABBREVIATION
It is impossible to get a car serviced properly today.	POOR CAR SERVICE
I like to try new and different things.	LIKE TO TRY NEW
I have a lot of confidence in the decisions local government agencies make.	TRUST LOCAL GOVT.
The trouble with riding a bus is the kind of people you have to ride with.	KIND OF PEOPLE/BUS
Public transportation is an effective way of reducing traffic congestion.	PT REDUCES TRAFFIC
I would rather not sit close to someone I don't know.	BAD TO SIT BY STRANGER
Federal funds should be used to subsidize public transportation.	FAVOR FED SUBSIDY PT
If I had more time, I'd be happy to use public transportation.	MORE TIME, RIDE PT
People like me don't have any say about what local governments do.	NO SAY IN LOCAL GOVT.
It would be a big adjustment for me to use public transportation.	BIG ADJUSTMENT TO USE PT
Some form of mass transportation other than buses should be used in our county.	PT OTHER THAN BUSES
It hardly seems proper for someone in a top job to commute by bus.	BUS IMPROPER FOR EXEC.
Traffic today is almost unbearable.	TRAFFIC UNBEARABLE
To keep our environment clean, more people will have to use the bus.	USE BUS FOR ECOLOGY
It's fun to be able to drive my own car.	FUN TO USE OWN CAR
If gasoline were one dollar per gallon, I would rather take public transportation to work.	IF GAS $1, USE PT
The people who use public transportation should pay most of its cost.	TRNS USERS PAY COST
In the future, freeways and autos will continue to be our main method of travel in Orange County.	CAR FUTURE MAIN MODE
I often try new things before my friends and neighbors do.	TRY NEW BEFORE FRIENDS
Sometimes county government seems so complicated that I can't understand what's going on.	CANT UNDERSTAND GOVT.

Figure 1. Twenty General Transportation Attitudes and their Abbreviated Forms

Profile Method

This method combines factor analysis with a clustering routine. First, the correlation matrix for the individuals' attitudes towards the general transportation attributes was factored using principal components analysis. A Varimax orthogonal rotation was then performed to facilitate interpretation (Harman, 1967).

Not all twenty initial general transportation attitudes were included in the factor analysis. A selection process was developed by which only the attitudes with a wide range of ratings were retained in order to ensure sufficient interrespondent variability related to transportation attitudes. Furthermore, attitudes were regressed against the demographic and socioeconomic characteristics of the respondents and eliminated if the relationship was poor. This was done in order to obtain psychological segments which can be easily identified and communicated through mass promotion. As Frank, Massy and Wind (1972) so aptly suggest, there is a serious problem of identification and communication to different market segments which must be properly undertaken in order to ensure implementation of market strategies based on segmentation.

Of the attitudes included in the factor analysis, some were eliminated during an iterative process. The attitudes having low communality and not having a dominant loading on one of the factors were therefore eliminated. Thirteen attitudes were included in the final factor analysis.

The number of factors retained was based on four distinct but complementary criteria: as suggested by Rummel (1971) and Wells and Sheth (1974). (1) comparison of the eigenvalues obtained through the factor analysis of the attributes correlation matrix and the eigenvalues obtained through a factor analysis of a random correlation matrix of the same size; (2) retention of the eigenvalues greater than one; (3) if (1) and (2) are inconclusive include percent of trace explained by each additional factor (elbow of cummulative percent of trace curve); and (4) ease of interpretation provided by the factor loadings.

Figure 2 shows the eigenvalue plot resulting from the factor analysis of the 13 attitudes. Five eigenvalues have values greater than one and are at the same time greater than the corresponding eigenvalues of the random data matrices. Therefore, five factors were retained to describe the latent structure of the 13 attitudes. Figure 3 shows the factor composition and percent variance accounted for by each factor.

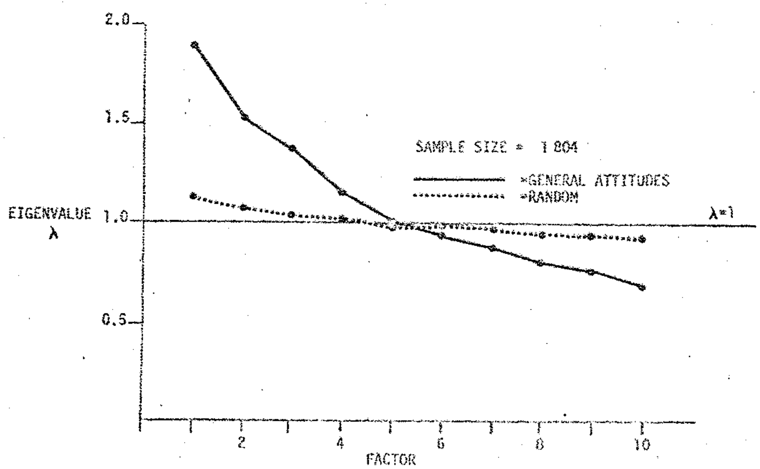

Figure 2. Eigenvalue Plot; 13 General Attitudes

FACTOR DESCRIPTION (% VARIANCE EXPLAINED)	ATTITUDES INCLUDED IN FACTORS			
		PERCENT VARIANCE		
	ATTITUDE	FACTOR LOADING	IN FACTOR	IN ALL OTHER FACTORS
FACTOR 1 DISCONTENT (13%)	CANT UNDERSTAND GOVT. NO SAY IN LOCAL GOVT. TRAFFIC UNBEARABLE POOR CAR SERVICE	.73 .61 .59 .55	53 37 35 31	3 7 7 3
FACTOR 2 PRIVACY (12%)	KIND OF PEOPLE/BUS BAD TO SIT BY STRANGER	-.82 -.80	67 64	1 2
FACTOR 3 SOCIABILITY-INNOVATION (11%)	TRY NEW BEFORE FRIENDS LIKE TO TRY NEW	.83 .82	69 66	0 2
FACTOR 4 SELF SUFFICIENT BUSES (9%)	FAVOR FED SUBSIDY PT TRNS USERS PAY COST PT OTHER THAN BUSES	-.72 .69 -.50	51 48 25	6 6 4
FACTOR 5 TRANSIT PREFERENCE (8%)	FUN TO USE OWN CAR BIG ADJUSTMENT TO USE PT	-.79 -.67	63 45	1 3

Figure 3. Factor Loadings and Percent Variances Accounted For 13 General Attitudes

factor composition and percent variance accounted for by each factor. It also shows the factor loadings and percent variance accounted for by each attitude in its factor and for all other factors. Finally, a brief description of each factor is given.

Each individuals' factor scores, after a Varimax rotation, were subsequently inputted to a clustering algorithm to determine homogeneous groups. Individuals were assigned to the same cluster if their interpoint distances in the factor score space was small. Several clustering routines that can accomplish this grouping are available (Sneath, 1969; Cormack, 1971). An algorithm developed by Ball and Hall (1967) was selected on the basis of its balanced sophistication, ease of use and reasonable computer expense.

For a given number of clusters k in an n-dimensional space, the algorithm assigns each point to one cluster with the property that the distance between that point and its clusters' centroid is smaller than the distance between the point and the centroid of any other clusters' centroid. Let $X = \{X_1, \ldots, X_p\}$ be a collection of cluster centers. The algorithm iterates between the following two steps:

1. Assign point i to cluster j if $||x_i - y_j|| = \min_{h=1,\ldots,k} \{||x_i - y_k||\}$

   where $||x_i - y_j||$ denotes Euclidean distance between points i and j.
2. Once all points have been assigned to the k clusters compute new centroids for each cluster

   $$y_j = \frac{1}{q} \sum_{h=1}^{q} x_{j_h}$$

   where $x_{i_1}, \ldots, x_{i_q}$ is the set of points assigned to cluster j.

Since the number of clusters k has to be a priori specified, an iterative procedure was developed to determine the final number of clusters to be retained. Initially, a large number of clusters were specified which were subsequently reduced by combining adjacent (similar) clusters. Thus, at the first iteration twice as many clusters were defined as the number of factors retained in the factor analysis. The centroids of these clusters were positioned at the most positive and most negative factor score values of each factor. Through the first iteration all points were assigned to one of the initial k clusters. The smallest distance between a pair of resulting centroids was identified and corresponding clusters were replaced by a new cluster whose centroid was at the mid-distance point of the pairs' centroids. The k-1 clusters were thus defined and a new membership allocation process was attempted.

The process is terminated on the basis of two criteria (a) a pseudo F-ratio of the total between-group variance divided by its degrees of freedom (N-1 for N clusters) to the pooled within-group variance divided by its degrees of freedom (P-N, for P points) and (b) the stability in cluster memberships.

The factor scores were submitted to the clustering algorithm to define, through an iterative procedure, the number of clusters to be retained and the clusters' membership composition. Figure 4 shows the frequencies for each combination of number of clusters retained. A pseudo F-ratio is also shown for each case. Figure 5 shows a plot of the pseudo F-ratio versus the number of clusters retained. Although from this figure it would appear that six clusters should be retained, only five were finally retained due to the greater stability of the 5-clusters. The centroids of the first two clusters in the six cluster case were adjacently located and were combined to one cluster. The coordinates of the centroids of the five clusters in the factor space are shown in Figure 6. On the basis of the relative positon of these centroids in the factor space a description for each cluster (segment) is given in Figure 7. Thus, respondents in cluster 1 (segment 1) are identified as having a negative attitude toward buses while respondents of cluster 2 (segment 2) as having a positive attitude toward buses. Respondents in cluster 3 (segment 3) are private, in cluster 4 (segment 4) not sociable-innovative and in cluster 5 (segment 5) they favor public transportation in general given that public transportation is self financed with no governmental subsidies.

	NUMBER OF CLUSTERS						
	10	9	8	7	6	5	4
FREQUENCIES WITHIN CLUSTERS	223*	303	294	365*	358*	505*	661
	154	174	201*	298	311*		
	139	131	156	167	327	389	473
	251	262	260	272	299	318	351
	227*						
	156	158	162	162	216	229	319
	140	158	215	255	293	363*	
	141	170*	247	285*			
	169	212*					
	204	236	269				
	PSEUDO "F" RATIO						
	247.3	265.6	278.6	294.9	317.8	312.4	304.8

*Indicates that cluster was combined with other cluster

Figure 4. Results from Cluster Algorithms

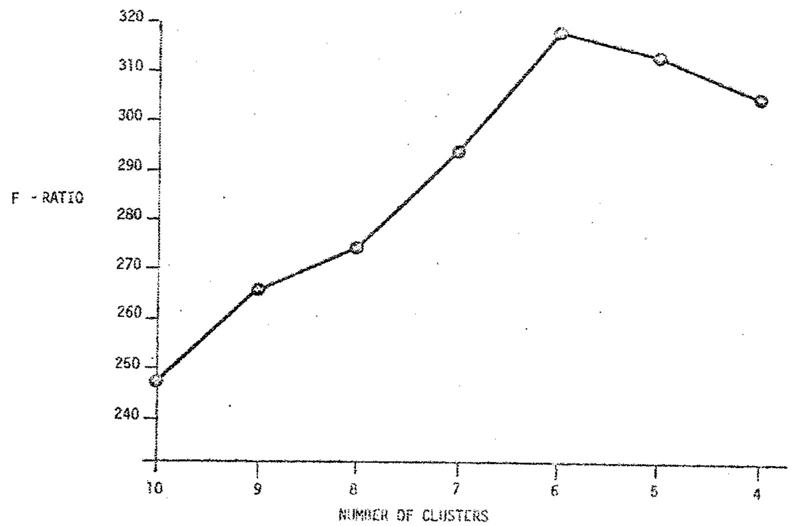

Figure 5. F - Ratio Plot for Profile Method

SEGMENT	COORDINATES OF CENTROIDS ON FACTORS				
	FACTOR 1	FACTOR 2	FACTOR 3	FACTOR 4	FACTOR 5
1	.03	- .45	- .31	.65	.71
2	- .23	- .30	- .35	.29	-1.26
3	- .12	1.65	- .14	.05	.19
4	.04	- .15	1.86	- .05	- .03
5	.28	- .40	- .24	-1.23	.22

Figure 6. Coordinates of Cluster (Segment) Centroids in Latent Factor Space

SEGMENTS	IMPORTANT FACTORS	SIGN	IDENTIFICATION OF CLUSTERS
1	SELF SUFFICIENT BUSES TRANSIT PREFERENCE	- -	NEGATIVE ATTITUDE TO BUSES
2	TRANSIT PREFERENCE	+	POSITIVE ATTITUDE TO BUSES
3	PRIVACY	+	PRIVATE
4	SOCIABILITY-INNOVATIVE	-	NOT SOCIABLE-INNOVATIVE
5	SELF SUFFICIENT BUSES	+	FAVOR PUBLIC TRANSPORTATION

Figure 7. Segment Identification for Profile Method

Dominance Method

The Profile Method was contrasted to a much simpler one by which an individual was assigned to that cluster for which its corresponding factor score was the largest. Members of the same cluster (segment) are similar only with respect to their most dominant latent factor. Based on the factor identification shown in Figure 3, the segments were identified as follows: respondents of Segment 1 as showing discontent with transportation services, of Segment 2 as private, of Segment 3 as sociable-innovative, of Segment 4 as supporting buses that can be financially self-sufficent and finally respondents of Segment 5 as showing a preference for transit.

The two methods resulted in segments with a large number of common respondents. Figure 8 shows that the diagonal entries of a contingency table of segment membership are of significant maghitude. From a total of 1804 respondents, 1014 or 56% are members of common segments. In order to test this ascertion and estimate the degree of association between segment classifications a contingency table of segment membership was formed and a chi-square statistic computed. These results are shown in Figure 8. The chi-square statistic is significant at the 99% level indicating strong association between the two segmentation methods. Also note that Segments 3 and 4 for the Profile Method and Segments 2 and 3 for the Dominant Method contain approximately the same individuals while discrepancies can be observed in the other three segments. These differences occur because of the position of the clusters' centroids in the latent factor spaces of each method. While in the Dominant Method, the centroids are close to the axes of the factor space (on the positive side) in the Profile Method, and particularly for segments 1, 2, and 5, the centroids are located well in the interior of the orthants of the five dimensional factor space. This means that respondents in segments 1, 2, and 5 do not have a factor score dominating but rather have two or more factor scores with similar values.

Comparison of Two Methods

The essential difference between the two methods is that while the Dominant Method results in segments which have only one factor (or benefit)

CHI-SQUARE STATISTIC FOR CONTINGENCY TABLE							
		DOMINANT METHOD					
		SEG 5	SEG 4	SEG 2	SEG 3	SEG 1	
PROFILE METHOD	SEG 1	211	178	3	16	97	505
	SEG 2	1	186	61	55	86	389
	SEG 3	13	15	267	4	19	318
	SEG 4	3	6	0	202	18	229
	SEG 5	135	0	26	54	148	363
		363	385	357	331	368	

$x^2_{16} = 2345.09$ $x^{2*}_{.99,16} = 32.00$

Figure 8. Contingency Table of Segment Memberships

important to the respondents of the segment, the Profile Method does not. The emerging segments from the second method contains respondents who attach similar degrees of importance to various factors (or benefits). Thus, the second method recognizes that while individual benefits may become the focal point for marketing efforts to particular segments, they may, at the same time, appeal to more than one segment.

Past experience from the marketing field suggests that indeed respondent segments prefer more than one benefit at a time. If this multidimensional structure were not to be considered in actual marketing plans, would the resulting segments lead to erroneous marketing implications and plans? While it is difficult to generalize the answer to other case studies it is possible to compare the two sets on (1) number of clusters or segments formed by each method, (2) invariance of segment composition under various rotational schemes of the factor space and (3) the within homogeneity of the resulting segments under each method. While the first two criteria are related to statistical implications associated with each method, the third is related to wider market segmentation strategy implications.

Number of Clusters formed by each Method

The Dominant Method is restricted to form as many clusters as the number of factors recovered from the factor analysis. This number of clusters may be under-specified for small factor space dimensionalities and over-specified for large dimensionalities.

On the other hand the Profile Method has more flexibility in defining an appropriate number of clusters. Although the iterative procedure employed in this study to define this number was based on subjective evaluations, it is still regarded more flexible and realistic.

The fact that both methods resulted in five clusters is to a degree accidental.

Invariance of Cluster Composition to Rotation Schemes

It has been previously mentioned that the factor space of the transportation attitudes was Varimax rotated before the factor scores were inputted to the clustering algorithm or considered in the Dominant Method. Obviously any other rotation scheme (Quartimax, Oblique, etc) or lack of rotation would have left the relative proximity of all points (respondents) invariant. This means that the same clusters would be recovered under different rotational schemes.

The same is not true for the cluster membership under the Dominant Method. Different rotational schemes, would result in factor scores of different relative magnitude and thus of different cluster memberships. The appropriate rotational scheme is selected on the basis of ease of interpretation of the recovered factors.

Homogeneity of Resulting Segments

An objective of market segmentation is to increase the within versus between homogeneity of the resulting segments. Homogeneity can be tested by observing the attitudinal profile of each segment under the two segmentation methods. This can be accomplished through discriminant analysis which identifies a subset of attitudes for which maximum discrimination between groups can be attained (Tatsuoka 1970 and 1971).

The original set of 13 attitudes included in the final factor analysis were used to discriminate the five segments under each segmentation method. The results of the discriminant analysis for each segmentation method are shown in Figure G.

Listed are the Wilks Lambda and its associated F with its degrees of freedom. In both cases the discriminant analysis results are significant at the .01 level of significance. Also shown in Figure G is a classification table of actual versus predicted segment membership for each segmentation method. The vertical axes represent actual segment membership while the horizontal axes represent predicted membership. The percent of correct classification is an indication of how well the discriminant function is able to correctly discriminate respondents and allocate them to their segments.

CLASSIFICATION TABLE

PROFILE METHOD

	SEG 1	SEG 2	SEG 3	SEG 4	SEG 5
SEG 1	486	5	7	6	1
SEG 2	6	364	7	7	5
SEG 3	4	4	302	6	2
SEG 4	10	11	6	188	14
SEG 5	2	2	4	12	343

CORRECT CLASSIFICATION : 93 %

WILKS LAMBDA = 0.044
APPROXIMATE F = 179.55
DEGREES OF FREEDOM = 52 6923

DOMINANT METHOD

	SEG 1	SEG 2	SEG 3	SEG 4	SEG 5
SEG 1	332	8	6	14	8
SEG 2	9	313	5	18	12
SEG 3	7	11	273	15	25
SEG 4	7	11	9	330	28
SEG 5	16	12	8	12	315

CORRECT CLASSIFICATION : 87 %

WILKS LAMBDA = 0.075
APPROXIMATE F = 126.93
DEGREES OF FREEDOM = 52 6923

Figure G. Discriminant Analysis Results

In the Profile Method case, 93% of the respondents were correctly allocated to their original case, while in the Dominant Method 87% of the respondents were allocated to their original segments. In both cases the results indicate a high homogeneity in attitude profile (within each segment) with a slight edge for the Profile Method.

Homogeneity of the resluting segments was also tested on the basis of the socioeconomic and demographic characteristics of the respondents. Discriminant analyses were performed on the segments as created by each segmentation method to test how homogeneous were the segments with respect to their socioeconomic profiles. The results of this effort are not reported because they were inconclusive with respect to any comparative evaluation between the two segmentation methods. The results were statistically significant indicating homogeneity of segments on the socioeconomic variables but results were very similar between the two discrimination efforts associated with each segmentation method.

Conclusions

From the analyses presented above, it seems that the two segmentation methods create segments which are very similar in membership composition and degree of homogeneity in either their attitudinal or socioeconomic profiles. Although the Profile Method seems to have advantages (discussed earlier) over the Dominant Method, these advantages should be weighted against the additional analytical effort associated with the clustering algorithm. Furthermore, the arbitrariness of selection of the particular algorithm used in this study suggests that some other clustering algorithm may have resulted in different segments.

No recommendation can be formulated as to whether the simple Dominant Method can replace the more complicated Profile Method at all times. In this case sutdy, it appears that the Dominant Method performed well. Practical marketing implications of a market segmentation study may eventually dictate the choice of a taxonomic method.

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