Comparison of the Predictive Ability of Four Multiattribute Approaches to Attitudinal Measurement

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In the past decade, attitudinal measurement techniques have been developed that measure the relative attractiveness of specific levels of transportation characteristics. These partial measures are then combined to form overall measures of attractiveness, which makes it possible to simulate market responses under varying conditions. Four techniques that have emerged as leaders in this area are functional analysis, conjoint measurement, trade-off analysis, and unidimensional scaling. Each of these techniques assumes a compensatory utility function; the techniques vary with respect to the assumed integrity of the data (interval or ordinal) and with respect to subject tasks. To test each approach, 300 subjects in Charlotte, North Carolina, were interviewed, then reinterviewed one year later. Each subject was asked four different sets of questions concerning preferences for different transportation alternatives, characterized by various levels of mode and waiting time, cost, and travel time, as well as the subject's background and current mode of travel. Each attitudinal question set was analyzed by the appropriate scaling technique. The analysis showed that relative measures of attractiveness derived from each technique differ somewhat and that these measurement differences have an impact on market simulation. It was also found that techniques that provide the highest predictive ability are those that use a conjoint data set consisting of modes described by all factors simultaneously. It was also found that modal choice is most closely a function of previous choice of mode and that attitudes toward mode and waiting time have the greatest influence on modal split.

Many studies have applied attitudinal measures to transportation. Most of these have used unidimensional analysis or multidimensional analysis of unidimensional responses to choice of mode, i.e., transit versus automobile. As early as 1968, the National Survey of Transportation Attributes and Behavior (1) analyzed feelings in that context. Studies have focused on revealed preferences (2,3), stated preferences (4,5), or simulated choices (6-8). This paper compares four techniques that analyze stated preferences and simulated choices: functional analysis, trade-off analysis, conjoint measurement (monotonic), and unidimensional scaling.

Each of these techniques analyzes decisions as a function of a set of evaluations of the attributes that make up an object. In an early study, Fishbein (9) proposed an additive decision model that relied on univariate scales. Multivariate decomposition techniques were suggested by Kruskal (10) (conjoint measurement), Johnson (11) (trade-off analysis), and Anderson (12) (functional analysis). These techniques are described more fully below.

Functional analysis analyzes attitudes and preferences of individuals toward specific items. Each item is created by combining different levels of a number of factors (in this case, transit characteristics such as cost and travel time). These items, when presented to subjects, are rated on an interval scale and part-utilities are derived from these ratings (7).

The conjoint measurement approach analyzes responses to the same items. However, preference rankings are obtained from individuals instead of preference ratings. Two assumptions are usually made in the approach: (a) that utility is a linear additive function of part-utilities and (b) that stated preferences are monotonically related to the part-utilities (13).

Trade-off analysis is a simplification of the above approach with all factors presented in paired combinations. Levels of each pair of matrices are ranked one at a time. The assumption that the models are additive still holds. The main advantage of this approach is that the data collection tasks are reduced (6,8).

A few studies have made some comparisons between these techniques. Anderson (14) discusses the differences between conjoint measurement and functional analysis in a case study. Green and Wind (13) compare unidimensional and conjoint scales applied in different research settings. Curry, Levin, and Gray (15) compared the analysis of the same conjoint data sets by monotonic (nonmetric) and functional (metric) techniques. Jain and others (16), in a consumer services context, compared different monotonic approaches. The study that is the subject of this paper differs from these studies in the techniques under comparison, the consistency between question format and data analysis, the use of a rigorous before-and-after study design, and the sample size.

This study was designed around stated and revealed preferences in a before-and-after design in conjunction with a transit service change in Charlotte, North Carolina. A population of 300 subjects was interviewed before the service change and again one year later. To test the four techniques, the same information was acquired in forms appropriate to each technique.

DEVELOPMENT OF QUESTIONNAIRES

Early work such as that by Quandt and Baumol (2) and Warner (3) has shown that a transportation mode can be thought of abstractly in terms of its components or elements. The elements that have been shown to be most important are those that affect cost and overall travel time. Attitudinal studies have, for the most part, confirmed these results. Therefore, items for each part of the study questionnaire were formulated from four levels of three factors: (a) mode and (for buses) waiting time between vehicles, (b) travel time, and (c) weekly travel cost.

Separate questionnaire sections were made for each technique, as summarized in Table 1. Questionnaire sections were ordered in each of the 24 possible permutations randomly assigned to subjects. Within each section, questions were also ordered randomly.

STUDY AND SAMPLE DESIGN

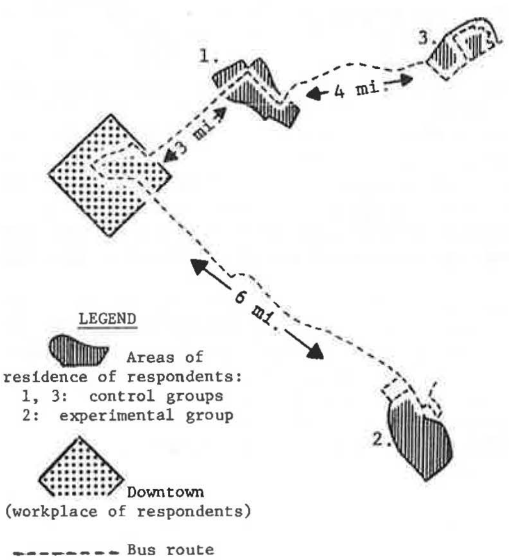
The major objective of this study was to test the four techniques against the impact of transit service changes on the attitudes and preferences of individuals. Another objective was to assess the kind and degree of reactions to increases in the cost of gasoline. A cluster sampling design was deemed most appropriate, and the data collection was designed for three clusters: an experimental group from a middle-income residential neighborhood (designated group 2) and two control groups, one from a low-income neighborhood (group 1) and the other from a middle-income neighborhood and similar in characteristics to the experimental group (group 3). All respondents worked in the downtown area. The major difference between the two middle-income groups was that the control group had transit service whereas the experimental group was scheduled to have services introduced during the period of the study.

The relative locations of the three clusters are

Table 1. Presentation of four measurement techniques in questionnaire.

Technique	Presentation	Response
Functional analysis	Presented as 16 combinations in each of the 4 components of a Latin Square design	Rated from 0 to 100 to indicate degree of preference
Conjoint measures (monotonic)	Presented as 16 combinations in each of the 4 components of a Latin Square design	Ranked from highest (1) to lowest (16)
Trade-off analysis	Presented as 16 combinations of 2 factors (4 levels) at a time (3 sets in all)	Ranked from highest (1) to lowest (16)
Unidimensional analysis	Each level of each factor presented, one at a time (12 elements in all)	Rated from 0 to 100 to indicate degree of preference

Figure 1. Workplace and areas of residence of study respondents in Charlotte, North Carolina.



shown in Figure 1. The round-trip distances to the downtown area from clusters 2 and 3 are about 13 miles, and the distance from cluster 1 is about 6 miles.

During the initial data collection, approximately 100 subjects in each cluster who worked in the downtown area were interviewed. Approximately one year later, the second-phase data were collected. The same respondents were contacted and, if they still lived at the same address and worked downtown, they were asked to complete at least part of a similar questionnaire. Because of the number of respondents who no longer qualified or refused to complete the second questionnaire, an additional random sample was selected to supplement the original sample. The numbers of original and supplementary respondents who were contacted in the second data collection are summarized below:

Group	No. of Original Qualifying Subjects	No. of Supplementary Subjects
1	68	32
2	61	39
3	53	47

PRELIMINARY ANALYSIS OF DATA

Background Descriptors of Subjects

For the initial respondents, the distribution by sex was as expected: Group 2 had fewer working women, which reflected the nature of the families residing in the neighborhood. Minority families were primarily represented in group 1 and to a lesser degree in group 3. Group 2 was in a slightly newer neighborhood and was less representative in its racial composition. Classification of respondent as head or nonhead of household reinforced the pattern of the sex of respondents. In all three groups, households of three or more appeared to predominate. The typically larger households in group 1 may consist more of multiple-family or non-nuclear-family units. The age distribution was as expected, with a bimodal distribution among groups 2 and 3. Data on education of respondents showed better-educated, younger respondents in group 2.

Perhaps the least expected results were found in the data on income distribution and present mode of travel to work. Group 2, the experimental group, appeared to have a lower average income than group 3. In addition, a substantial minority of group 2 used the bus, although no service was available in that neighborhood when the data were collected.

Modal-Choice Behavior

Modal choices of the complete samples for each group are summarized in Table 2. A shift toward bus travel is observed in each group. The experimental group (group 2) demonstrates a slightly smaller change than the control group (group 3), but this is easily explained by the unexpectedly high use of the bus before route modification. As expected, the highest overall use of the bus is by the low-income group (group 1), but the shift toward bus travel is smaller there.

These shifts are not apparent, however, from the data for the original sample summarized in Table 3. The shifts there are smaller, but the apparent stability in choice is misleading. The data given below demonstrate that the stable modal split in group 2 is the result of a complex set of changes:

Phase 1 Modal Choice	Phase 2 Modal Choice: Bus	Car	Other	Total
Bus	5	2	3	10
Car	4	43	0	47
Other	2	2	0	4
Total	11	47	3	61

It is the extent to which these changes can be forecast, as well as overall modal split, that is a true test of the ability of these techniques.

COMPARISON OF PART-UTILITIES ESTIMATED BY EACH TECHNIQUE

To enable comparison of the approaches, part-utilities were estimated for each level of each factor by using appropriate linear compensatory models.

A different analytic technique was used for each approach. Univariate scales were assumed to be interval scaled, and raw data were used in that case. For functional analysis, values for each factor level were found by averaging subjective evaluation scores of modes containing that factor level. For trade-off analysis the New York State

Algorithm (17) was used, and for monotonic conjoint measurement MONANOVA (10) was used.

The results presented here are for the initial respondents. This resulted in a separate estimate of part-utility for each level of each factor, for each technique, and for each subject. The estimates were averaged across subjects in each group, and these averages for the middle-income groups (groups 2 and 3) are presented in Table 4.

Each technique measures utility on a different scale. However, it is the intervals between values that are most important. These scales answer questions such as, Will a 10-cent decrease in fare compensate for a 10-min increase in waiting time? It should also be noted that conjoint measurement, or the monotonic approach, yields estimates that show "higher" utility when the values are more negative.

The range of part-utilities, then, indicates which factor is most salient. Cost has the widest range in virtually all cases. Travel time has the smallest range. However, results for the first factor (mode and waiting time) are bimodal, depending on transport modal preference. For average part-utilities calculated within modal preference groups, the largest range is for the first factor.

Table 2. Modal choice by group and time period: complete sample.

Modal Choice	No. of Respondents					
	Group 1		Group 2		Group 3	
	Phase 1	Phase 2	Phase 1	Phase 2	Phase 1	Phase 2
Car	65	74	86	73	76	77
Bus	21	28	11	18	8	20
Other	14	2	4	8	15	1
Total	100	104	101	99	99	98

Table 3. Modal choice by group and time period: original sample.

Modal Choice	No. of Respondents					
	Group 1		Group 2		Group 3	
	Phase 1	Phase 2	Phase 1	Phase 2	Phase 1	Phase 2
Car	44	48	47	47	45	44
Bus	14	17	10	11	1	4
Other	10	3	4	3	7	5
Total	68	68	61	61	53	53

Sensitivity of Techniques to Changes in Factors

Despite the consistency between techniques in the rank order of the average part-utilities, the intervals between part-utilities vary significantly. For example, in the experimental group (group 2) for functional analysis, a change in weekly cost from \$10 to \$4 had a value of 27, and this more than compensated for a change in mode from car to bus (with 10-min waiting time), which had a value of 9.2. On the other hand, for the same group, with trade-off analysis, a similar change in cost had a value of 0.20, which did not compensate for a similar mode change that had a value of 0.23. Similar differences were observable for all techniques, and these were consistently observed for each cluster.

Correlation of Part-Utilities Between Techniques

For the initial data, Benjamin and Sen (18) reported that the part-utilities derived from each of the four techniques do not correlate highly. Furthermore, those subjects whose decision processes were best described by a linear model did not respond more consistently than the other subjects. It was also found that familiarity with the factors and levels that described a mode led to more consistent results, although correlations between part-utility estimates were still somewhat low.

SIMULATED RESPONSES TO MARKET CONDITIONS

A further demonstration of the impact of the differences between techniques is a comparison of the forecasts of responses to various market conditions. To accomplish this, a simple simulation model was formulated. First, the overall utility was formulated by combining appropriate part-utilities for each mode under consideration. Then the overall utilities were compared and the mode with the highest utility was considered to be the selection of that respondent. The process was completed separately for each respondent and the results were tabulated.

The model was a linear compensatory model (chosen because it was consistent with the disaggregate data): Overall utility = (part-utility of mode and waiting time) + (part-utility of cost) + (part-utility of travel time).

For each simulation it was necessary to create a scenario in which the modes, waiting time, weekly cost, and travel time for each means of travel were described. The simulations forecast responses to the market conditions described by the scenario.

Table 4. Average part utilities for four measurement techniques: middle-income groups.

Factor	Level	Functional		Monotonic		Trade-Off		Unidimensional	
		Group 3	Group 2	Group 3	Group 2	Group 3	Group 2	Group 3	Group 2
Mode and waiting time	Car, 0 min	66.6	70.4	−0.80	−1.01	0.44	0.44	92.2	81.7
	Bus, 10 min	62.1	61.2	−0.18	−0.27	0.21	0.21	64.1	60.5
	Bus, 20 min	55.2	53.6	0.13	0.203	0.16	0.17	59.1	49.0
	Bus, 40 min	40.6	39.7	0.85	1.08	0.19	0.19	23.2	26.2
Weekly cost	\$4.00	71.8	68.2	−1.15	−0.94	0.42	0.39	93.4	84.5
	\$5.00	66.6	63.4	−0.63	−0.56	0.24	0.25	85.7	79.6
	\$8.00	50.2	52.2	0.41	0.38	0.16	0.17	59.7	61.7
	\$10.00	35.5	41.2	1.35	1.13	0.19	0.19	51.2	46.4
Travel time	22 min	59.5	58.3	−0.26	−0.19	0.34	0.32	80.7	78.0
	25 min	58.5	57.8	−0.12	−0.06	0.26	0.27	70.1	69.5
	30 min	54.6	56.1	0.13	0.02	0.22	0.22	58.3	61.6
	37 min	51.9	52.8	0.25	0.23	0.18	0.19	45.5	50.9

Note: Group 3 = control group; group 2 = experimental group.

Table 5. Comparison of simulated and observed modal splits for all data sets.

	Modal Split[a]									
	Simulated									
	Univariate Analysis		Monotonic Approach		Functional Analysis		Trade-Off Analysis		Observed	
Group	Bus	Car	Bus	Car	Bus	Car	Bus	Car	Bus	Car
1	0.17	0.83	0.14	0.86	0.20	0.80[b]	0.03	0.97	0.27	0.73
2	0.13	0.87	0.30	0.70	0.26	0.74[b]	0.13	0.87	0.20	0.80
3	0.04	0.96	0.28	0.72[b]	0.32	0.68	0.07	0.93	0.21	0.79
All (pooled data)	0.11	0.89	0.24	0.76[b]	0.26	0.74[b]	0.08	0.92	0.23	0.77

[a]Proportion of subjects who chose car or bus.
[b]No significant difference at $\alpha = 0.10$ significance level.

Table 6. Discriminant analysis of modal choice by panel: standardized discriminant function coefficients.

Variable	Definition	Univariate Analysis	Monotonic Approach	Functional Analysis	Trade-Off Analysis
ΔU_1	Mode and waiting time	-0.39	0.22	-0.24	-0.22
ΔU_2	Weekly cost	0.16	-0.17	0.10	0.04
ΔU_3	Travel time	0.29	-0.06	-0.02	-0.07
M′	Prior modal choice	0.96	0.95	0.94	0.96
Z_1	Residence zone 1[a]	0.19	0.09	0.07	0.04
Z_2	Residence zone 2[a]	0.05	0.00	-[b]	0.01

[a] Z_1 and Z_2 are 0-1 (dummy) variables representing residence in respective zones; $Z_1 = 0$ and $Z_2 = 0$ indicated residence in zone 3.
[b]Variable not included in analysis to permit convergence.

Results of Simulations of Responses to Existing Conditions for Initial Data Set

Benjamin and Sen (18) reported results of simulations under several scenarios, including a scenario corresponding to the current cost of gasoline and the existing transit service levels and costs. They found that the various techniques did correctly classify the majority of respondents but that each technique demonstrated a bias toward one of the modes.

Results of Simulations of Responses to Second-Year Conditions

By using the same simple simulation model but different part-utilities that correspond to second-year conditions (linear interpolations were used for values between estimated levels), responses to new services and prices were forecast from the original data set. Essentially, three changes had occurred: (a) The new service was introduced in zone 2, (b) bus fares increased from $0.40 to $0.50/trip, and (c) the average price of gasoline rose from $1.25 to $1.30/gal. For the middle-income groups (groups 2 and 3), transportation characteristics are as follows:

Mode	Waiting Time (min)	Cost ($) Weekly	Cost ($) Unit	Travel Time (min)
Car	0	5.20	1.30/gal	22
Bus	10	5.00	0.50/trip	37

The transportation characteristics of the low-income group (group 1) differed from these figures because zone 1 is a shorter distance from the central business district (CBD). For group 1, travel time by car was 10 min and by bus was 16 min. The cost of weekly trips by car was $2.60.

Modal splits forecast by each technique for each group are presented in Table 5 along with corresponding observed modal splits. Modal splits for the data pooled from all groups are also presented in Table 5.

Several trends emerge from that table. First, all techniques overestimate car use by group 1. This is an indication of intervening factors not represented in this simple simulation, such as an income constraint and car availability.

Another trend is that the techniques seem to perform equally well in both middle-income groups (groups 2 and 3). The initial lack of availability of transit service to group 2 did not adversely affect the ability of those subjects to perform the various survey tasks. Finally, the modal-split forecast for the pooled data reveals that two techniques were highly accurate. Monotonic conjoint analysis and functional analysis both predict a modal split that corresponds closely to the observed modal split. In fact, the difference between observed and predicted proportions is not significant at the 0.10 significance level. These techniques also performed well within each zone. At the 0.01 significance level, no significant difference was observed for functional analysis for any group, and for monotonic analysis only for group 1 (which, as mentioned earlier, can be explained by intervening variables). Although monotonic analysis performs a bit better overall, the functional approach seems to predict the modal split for each group more consistently.

The other techniques consistently underestimate the shift toward transit. The primary difference between the techniques that performed well and those that did not is that the former rely on representations of modes described by all key factors at once and the latter represent modes by only one or two factors at a time. Clearly, there is an advantage in representing the most complete picture possible.

ANALYSIS OF MODAL CHOICE FOR PANEL RESPONDENTS

Comparisons of Simulated and Actual Choices

Findings from a comparison of simulated and observed modal split for the panel respondents (those subjects who were interviewed in both the first and second years) were similar to findings for the total sample, which are summarized in a previous section of this paper. More precise than the estimation of modal split is the case-by-case prediction of modal choice. To investigate this, choices were simulated for the panel respondents. When cross-tabulated with the actual modal choice, for each group for each technique, results ranged from 63 to 84 percent correct prediction. Trade-off analysis and univariate analysis performed slightly better than the other techniques because of their tendency to classify the vast majority of cases as automobile drivers, which corresponded to the choice of most respondents. However, when the proportion of correctly classified bus and car users was used as a criterion, functional analysis and monotonic analysis performed best.

Discriminant Analysis of Modal Choice

A more complex simulation model was formulated by using discriminant analysis. In this model, it is assumed that decisions are a result of preference for a mode along with other situational variables (a linear function was assumed):

$$M = f(\Sigma a_j \cdot \Delta U_j + b \cdot M' + cZ) \quad (1)$$

where

M = mode chosen in the second year,
ΔU_j = difference in part-utility between modes for factor j,
M' = mode chosen during the previous year,
Z = variable (or set of dummy variables) representing zone of residence, and
a_j, b, and c = coefficients to be estimated by the discriminant analysis.

Coefficients a_j, b, and c represent the relative importance of each independent variable in predicting choice. The differences in part-utility for each characteristic (ΔU_j) were calculated by subtracting first-year part-utility estimates for car and bus. Model coefficients were estimated separately for part-utilities derived from each technique.

Prior choice of mode (M') was included as a surrogate for familiarity with and accessibility to either car or bus. It is well known to market researchers that people tend to continue to use the same products and brands of products for a variety of reasons. This is confirmed in Table 3 by the majority of panel modal choices over time.

Zone of residence (Z) was included to reveal any overall difference in responses from residents in each zone. Since income and proximity to the CBD were the primary distinguishing factors between zones, this is a surrogate for those factors.

The results of the discriminant analysis are summarized in Table 6. The standardized coefficients listed there reveal that prior modal choice was the dominating factor in this decision. However, other variables also contributed. Of the remaining variables, mode and waiting time affected choice most. Furthermore, coefficients of variables representing zone of residence were small, which indicated that responses of residents in the experimental zone (group 2) were virtually indistinguishable from responses of residents in the control zone (group 3).

The classifications of known cases for each technique were identical; 92 percent of known cases were correctly classified, and the predicted modal split was not significantly different from the actual modal split.

The dominant influence of prior choice is a useful guide where all alternatives are available to the subjects beforehand and only small system changes are planned. In that situation, a change in system attributes must lead to a corresponding change in preference that is large enough to overcome the influence of prior modal choice. For this panel, which included 161 subjects who chose either car or bus both years, 13 subjects reported a change in mode. The discriminant function was unable to correctly classify the majority of these cases.

Because of the small number of those who changed mode, the importance of modal preference in the choice process represented by the discriminant function is understated; a disaggregate simulation based on utility values is needed to discover those who changed mode in this case.

A simple simulation of these 13 subjects resulted in correct classification of approximately half. Once again, functional analysis and monotonic analysis performed best, accurately predicting modal split for this group.

CONCLUSIONS

An empirical study of this type is limited in several ways. Results reflect the sampling frame and procedure, both the content and the form of the questionnaire, and the system characteristics under study. Results are also affected by unexpected events, such as a large number of bus users in the experimental group (which had no bus service) and the large number of people who changed place of employment or who moved during this one-year interval.

Within these limitations, several conclusions can be drawn from these study results. First and foremost, results of attitudinal research are believable. Overall, observed behavior closely reflects attitudes toward these decisions.

Methodological implications also emerge. For example, the best results occur when alternatives are presented in the most complete and realistic manner possible. In other words, techniques that represent all factors simultaneously produce better results. This is particularly relevant when new and different service changes are anticipated and prior choice cannot be a guide.

On the other hand, simpler techniques are most economically administered. When prior choice is applicable, attitudinal measurement does not play as big a role in decision analysis and does not need to be as precise. In this case, univariate measurement performed just as well and is therefore most cost effective.

The development of an attitudinal research project has three critical elements: design of the questionnaire, administration, and analysis. Univariate analysis is simplest and most economical in all respects. The questionnaires for trade-off analysis are more easily developed and administered than those for conjoint analysis, but the results require analysis by special computer programs.

The most difficult questionnaires to develop are those for conjoint analysis (either monotonic conjoint measurement or functional analysis). In the monotonic approach, subjects are asked to rank modes, which is to say that one mode is judged to be better than another on the basis of some criterion. On the other hand, functional analysis requires subjects to rate modes, which implies two tasks: judging one object to be better than another and stating by how much.

We hypothesized that rating is more difficult and time consuming than ranking, since ranking is simpler. However, throughout the research it was observed that the rating task is in fact easier because modes can be rated one at a time and then, when necessary, comparative ratings can be adjusted by the subject. Alternatively, ranking requires an initial overview of all modes before the best mode can be chosen and subsequently all can be ranked. Thus, it was actually easier to administer the functional questionnaire than the monotonic questionnaire. (The use of rankings is appropriate when the subjects are totally unfamiliar with objects and the validity of precise ratings is uncertain. In that case, monotonic conjoint measurement should be used.)

We therefore conclude that, when a conjoint data set is required, functional analysis should be considered, since in this study it was the most cost effective overall. (This statement assumes the validity of the use of rankings; this is a reflection of the modes being compared, as mentioned previously.) However, when precise estimates are not required, the univariate approach seems adequate.

Finally, it should be noted that the study was designed to allow analysis of interactions at the aggregate level. The analysis reported here was at the totally disaggregate level and was limited to linear functions. This is frequently the case with totally disaggregate data and, in this case, it did not seem to impair the predictive capabilities of these techniques.

The results reported here can only be verified by a continuing body of research to document the range of subjects and settings in which these techniques are applicable. Within the limitations of the study, the results confirm that careful attitudinal research provides valuable information for those who plan and design transportation systems.

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