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Decision Aiding

A tactical model for resource allocation and its application to advertising budgeting

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Abstract

Models for optimal product positioning have received considerable attention by marketing researchers and marketing scientists over the past decade. Typically, optimizing models take the viewpoint that the manager wishes to find a specific vector of product attribute levels that, in the face of competitors' product profiles, maximizes the firm's market share (or, perhaps, return) over some designated planning horizon. This class of models emphasizes long run strategic modeling.

In contrast, the authors introduce a tactical, short-term model, called SALIENCE, whose purpose is to allocate sales efforts in such a way as to increase the relative importance of attributes for which the sponsoring firm's current product has a (possibly temporary) differential advantage. In this case emphasis is on short-run, tactical decision making.

We describe the SALIENCE model, both informally and mathematically. The model is applied, illustratively, to a real (disguised) study of overnight air shipment delivery.

Keywords: Marketing; Decision analysis; Expert systems

1. Introduction

Concomitant with the development of conjoint analysis as a preference measurement technique (Green and Rao, 1971; Johnson, 1974), has been the design and application of buyer choice simulators. Even the earliest applications of conjoint analysis used choice simulators to estimate market

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shares across competing product/service attribute descriptions.

As the conjoint field matured in terms of new measurement methods (particularly choice-based conjoint modeling), so did its simulators. Sawtooth Software, for example, has recently developed a general conjoint simulator, capable of handling either ratings-based, full-profile, or choice-based part-worths, as obtained from its suite of conjoint programs.

The simpler ratings-based simulators, in turn, have now been augmented by models that can include *optimization* of either market share or financial return. Green and Krieger's SIMOPT and SIMACT optimizers (Green and Krieger, 1993) contain a variety of optimization features. Choi et al. (1990) have developed a "dynamic" simulator that considers retaliation, competitive moves, and potential Nash equilibrium solutions. In sum, there are currently a variety of conjoint choice simulators that are available commercially. Consulting firms are beginning to develop their own proprietary simulators and optimizing models, as well.

The conjoint simulators that currently exist have been primarily used to find the firm's specific *attribute-level* profile that maximizes its long-run return (or market share, as the case may be), given competitive suppliers' attribute-level profiles. In this paper, however, our emphasis is on shorter term, *tactical* efforts that exploit the sponsor firm's differential attractiveness across a subset of existing product attribute levels. The motivation here is to emphasize a subset of attributes where the firm's differential advantages can be exploited, over the short run, by making some attributes relatively more important (or salient) to potential buyers.

Of course, the firm would like to choose those attributes (for importance stretching), and the amount of effort to be applied to each of them, so as to increase its *own* product's differential advantage over competitors. Thus, while the chosen attribute importances could become more salient for evaluating *all* competing products, they would be chosen so as to provide the highest benefit to the firm's *own* product profile, vis-à-vis those of its competitors.

The SALIENCE program implements an allocation-of-effort model that examines the consequences to the firm's market share/return as different amounts of some common resource (e.g., dollars, man-hours of effort, TV commercial minutes) are applied to increasing the salience of its selected product/service attributes.

We motivate our discussion by first considering a real (albeit disguised) problem involving the overnight air shipment of small packages and letters. We then describe how SALIENCE is used tactically to increase the market share of Alpha (one of five competitors) over the short run. In so doing, we describe SALIENCE's features, both informally and mathematically.

Companies typically engage in both long-term and short-term strategies. Long-term strategies emphasize product design and product differentiation. In this case the firm designs and implements a *general* marketing plan for achieving longer firm revenues that reflect the unique attributes of its product, pricing, and distribution plans.

Porter (1980), Choffray and Lilien (1980), and Aaker (1991) emphasize the importance of longer-term goals and the role that they play in shaping short-range tactics involving advertising, pricing, and public relations.

Shorter-term tactics tend to be highly responsive to competitive offerings where advertising, distribution, and short-term goals are implemented. Both long-term and short-term goals are important to the firm's success. This paper emphasizes shorter-term tactics.

2. The problem

The data of our illustrative problem are based on a real example involving five competitors, herein called Alpha, Beta, Gamma, Delta, and Epsilon. All five competitors are large companies engaged in the overnight air delivery of packages and letters to domestic and foreign countries. Illustratively, we assume that Alpha is our supplier of interest. All five suppliers offer basically similar delivery services but differ in terms of service details.

Alpha's management is interested in developing and executing a direct mail campaign to small businesses (fewer than 20 employees), located in the three far west states: Washington, Oregon, and California. It is estimated that the campaign will require an advertising budget of $15 million to be spread over three months. Alpha's advertising content will emphasize its recently enhanced tracking system for locating and retrieving lost (or delayed) packages and letters.

Ordinarily, Alpha would commission a traditional conjoint study that obtains part-worths for each competitor and then submits these data (along with respondent background data) to a conjoint simulator. In this typical case, emphasis is on *long-term* strategic interests where its service attribute levels could be improved, if need be.

In contrast, the SALIENCE model focuses on a different problem. Over the short term, what can be done (say, with advertising and promotion) to focus on Alpha's *current* product by emphasizing its relative benefits (and playing down its relative deficiencies)?

2.1. Market survey

Alpha began its marketing research project by commissioning a market survey of small business users of overnight delivery services in Washington, Oregon, and California. (Our analyses are based on actual data collected in this study, but are disguised with respect to attribute-level details.) The sample consisted of 436 small businesses.

Alpha's marketing research team designed a study that collected four kinds of data at the individual respondent level: self-explicated attribute-level desirabilities and attribute importances, followed by full profile ratings and respondent background data. The survey contained a set of 15 overnight-delivery attributes. Table 1 lists the 15 attributes and their levels. (Supplier name was treated like any other attribute.)

2.2. Respondent tasks

Each respondent received three tasks:

- For each level, for each attribute in turn, the respondent was first asked to indicate how desirable that level of service was to her. For example, if the attribute were the tracking (of packages) with levels:
  - Not available.
  - Within 1 hour.
  - On-line automatic (at a 5% premium).

Each of the levels was separately rated on a 0–10 desirability scale, where 0 indicates "highly undesirable" and 10 indicates "highly desirable". All levels of the 15 attributes were similarly rated on the same 0–10 desirability scale, and were later rescaled to vary between 0 and 1.0.

- The second task requested that the respondent carefully examine all 15 attributes and think about their *relative importance* in choosing suppliers.
- Then each respondent was asked to distribute 100 points across the 15 attributes so as to reflect her view of their relative importance in choosing a supplier.
- Following this, each respondent received a set of eight full-product profiles for evaluation. Part-worths were then obtained via a hybrid conjoint model.

After these tasks, each respondent was asked a series of background questions.

In sum, there are 15 attributes in the study, ranging from two through five levels per attribute. Table 2 shows the specific level that each supplier currently delivers on each attribute. Table 3 shows the background variables of respondents, as categorized by company size, industry, etc.

2.3. The data

From the marketing researcher's point of view, there are two sets of data of primary interest:

- the rescaled (0–1.0) desirability ratings of each level of each attribute (where each rating was originally expressed on a 0–10 desirability scale), and
- the attribute importance ratings derived from the part-worths—one importance rating for each attribute. The 15 importance ratings are scaled so as to sum to 1.0.

Table 1
Attributes and levels for sample problem

Overnight for AM delivery	*Tracking*
1. Delivery by noon (10% discount)	1. Not available
2. Delivery by 10:30 AM (no discount)	2. 2. Within 1 hour (base)
	3. On-line automatic (5% premium)
Overnight night for PM delivery	*Carrier*
1. Unavailable	1. Alpha
2. Delivery by 3 PM (20% discount)	2. Beta
3. Delivery by 5 PM (30% discount)	3. Gamma
	4. Delta
	5. Epsilon
Price (base)	*Extra insurance*
1. \$7.50	1. No
2. \$10.00	2. Yes
3. \$12.50	
4. \$15.00	
5. \$17.50	
Second day delivery	*Reimbursement*
1. Delivery by 10:30 AM (15% premium)	1. Written request
2. Delivery by noon (10% premium)	2. Automatic credit
3. Delivery by 5 PM	
Third day delivery	*Dimension/weight pricing*
1. Not available	1. Additional premium
2. Delivery by 5:00 PM (35% discount)	2. No charge
Tracing time	*Weight limits*
1. More than 1 day (5% discount)	1. 1 pound
2. Same day (2% discount)	2. 3 pounds
3. Within 1 hour (base)	3. 5 pounds
4. On-line (5% premium)	
Access	*Billing detail*
1. 5:00 PM pickup	1. Total cost only
2. 6:00 PM pickup	2. Weekly/premiums/discounts
3. 5:00 PM, 7:00 PM drop	3. At package level
4. 5:00 PM, 7:00 PM drop; 8:00 PM on demand	
5. 5:00 PM, 7:00 PM drop; 8:00 PM, 9:00 PM on demand	
	Shipment pricing
	1. Not available
	2. Available

The SALIENCE model takes each respondent's attribute level desirability ratings as "given". That is, except for normalizing to vary between 0 and 1.0, the desirabilities are *not* changed in the model. However, the attribute importance weights are assumed to be malleable and capable of being modified by promotional (or other marketing effects) aimed at changing attribute saliences.

3. What might be done?

At this point, the researcher has a set of attribute desirability scores (scaled to vary between 0 and 1.0) and a set of attribute importances, scaled to sum to 1.0. Clearly, scaled attribute desirabilities that are already high for a given supplier are to be valued by that supplier. In addition, attribute

Table 2
Attribute levels delivered by each of five suppliers (see Table 1 for details)

	Alpha	Beta	Gamma	Delta	Epsilon
1	2	2	1	1	2
2	2	3	1	1	3
3	3	4	1	2	5
4	2	3	3	1	1
5	1	2	2	1	2
6	2	4	3	3	4
7	2	1	5	3	5
8	2	1	1	3	3
9[a]	1	2	3	4	5
10	2	2	1	1	2
11	2	1	1	2	2
12	2	1	1	2	1
13	2	1	2	3	3
14	1	3	1	2	3
15	2	1	1	1	2

[a] Carrier: Alpha, Beta, Gamma, Delta, Epsilon.

Table 3
Background attributes and levels for illustrative problem

Company size	*Package value*
Small	\$25 or less
Medium	\$26–\$100
Large	\$101–\$499
Megalarge	\$500 or more
	Don't know
Industry	*Geographical*
Educational	US only
Manufacturing	US and Canada
Services	US, Canada, and Europe
Package weight	*Weekly volume*
[Lighter than 1 pound	Small
1 pound]	Medium
[2 pounds	Large
5 pounds]	

saliences that are *below* the average importance weight (of 0.066) permit some "growth" in the salience weights for a given supplier. [2]

[2] In this case we use a modification of SALIENCE that uses both self-explicated importances and *derived* importances from a hybrid conjoint model.

Table 4 shows average (scaled) desirabilities and average saliences for each attribute across the total of 436 respondents. Illustratively, we choose Alpha as the supplier of interest. As recalled, Alpha's attribute-level profile (see Table 2) is

2 2 3 2   1 2 2 2   1 2 2 2   2 1 2.

We note that Alpha's average desirability scores are *high* on attributes 1, 2, 10, 11, and 12. In terms of current saliences, these attributes are also below the average of 0.066.

A naïve approach would focus on these five attributes. But are these the five attributes that *should* be exploited in a promotional campaign? The problem is subtle, in that increases in the salience of attribute 1 are not only beneficial for Alpha, but are also beneficial for Beta and Epsilon, the two other suppliers that can deliver overnight by 10:30 AM In addition, if a campaign is designed to focus on only three attributes, which three of the five attributes (1, 2, 10, 11, and 12) should be emphasized?

In order to resolve these issues, a model needs to be proposed that translates the effort in promoting an attribute to an increase in the salience of that attribute, at the individual buyer level.

Any model that proposes to translate the efforts $f_1,\ldots,f_J$ that a firm expends on each of the J attributes to a new set of saliences at the individual level is bound to be arbitrary. We propose one such translation that is intended to be flexible. The main idea is to take the current salience, w_{ij}, that individual i assigns to attribute j and to interpolate between w_{ij} and a user-specified maximum (typically taken to be 1.0), based on an effort, f_j. For example if $f_j = 0.5$, then the new salience that individual i is assumed to give to attribute j is the average of her current value and the maximum allowed value. What complicates the problem further is that after each salience is modified, all saliences for an individual are then normalized to sum to 1.0. (A formal description is presented below.)

The result of this formulation is a functional relationship between the share (or return) for a selected brand/supplier and the assigned efforts, f_j, $j = 1,\ldots,J$, for each of the attributes.

Table 4
Average saliences and desirabilities across the total sample for Alpha's profile

Attribute	Saliences	Desirabilities				
1	0.0509	0.1737	**0.3259**[a]			
2	0.0404	0.2242	**0.3629**	0.3387		
3	0.1367	0.4932	0.4368	**0.3434**	0.1884	0.0819
4	0.0259	0.1996	**0.2569**	0.3017		
5	0.0128	**0.2469**	0.3014			
6	0.0673	0.1558	**0.2120**	0.3842	0.4133	
7	0.0645	0.2764	**0.2453**	0.2982	0.3679	0.3989
8	0.1104	0.1883	**0.3527**	0.4170		
9	0.2754	**0.3513**	0.2771	0.4244	0.4507	0.3143
10	0.0289	0.1999	**0.3218**			
11	0.0282	0.2805	**0.3223**			
12	0.0245	0.1842	**0.3768**			
13	0.0522	0.2695	**0.2986**	0.3758		
14	0.0801	**0.1709**	0.2331	0.4423		
15	0.0017	0.1966	**0.1373**			

[a] Entries in boldface are scaled desirabilities for Alpha.

4. What SALIENCE does

For given settings of the model's parameters, SALIENCE implements the following analyses for a selected brand/supplier:

1. *A sensitivity analysis*. This option is applied at the individual attribute level (and can be repeated for each attribute in tern). If chosen, the program requests the user to supply an *increment to the current effort* to be expended on the attribute in question. Suppose the user selects 0.1. If so, the program computes the new share/return for the selected supplier as the SALIENCE algorithm iterates through selected effort increases of (illustratively) 0.1, 0.2, . . ., 1.0. By using the sensitivity option, the user can find the differential sensitivity of share/return to effort changes in the attributes, taken one attribute at a time.
2. *An optimal allocation of effort*. If this option is chosen, SALIENCE finds the *best* distribution of efforts across all attributes so as to maximize market share/return for the supplier of interest.

Each of the two options can be implemented for either the total market or for a user-designated segment of the market, as composed of some combination of the levels drawn from the background attribute file (see Table 3).

5. Formal properties of the SALIENCE model

We now turn to a more formal description of the SALIENCE model. Following this, we describe the analysis of the empirical data obtained from the survey.

5.1. Preliminaries

We first assume the availability of the following information (e.g., as might be obtained from a conjoint analysis):

1. d_{ijk} = desirability of individual i for level k of attribute j, where $i = 1, \ldots, I$; $k = 1, \ldots, K_j$, and $j = 1, \ldots, J$, where I is the number of respondents and J is the number of attributes.
2. w_{ij} = importance weight (salience) of individual i for attribute j. Note that $w_i = (w_{i1}, \ldots, w_{iJ})$ is the vector of saliences for individual i and W is the I by J matrix of all saliences.
3. v_i = purchase incidence/amount: weight of individual i.
4. a_i = intercept term for individual i.

We are also given:

1. l_{pj} = attribute level characterizing supplier profile p for attribute j; $p = 1,\ldots,P$.
2. m_p = initial market share for supplier p.

We can then compute the market share of profile p for individual i (as well as the overall shares) as follows:

1. $u_{ip}(w_i) = a_i + \sum_{j=1}^{J} w_{ij} d_{ij\ell_{pj}}$. (1)

2. $t_{ip}(w_i) = u_{ip}^{\alpha}(w_i) \Big/ \sum_{p=1}^{P} u_{ip}^{\alpha}(w_i)$, (2)

where t_{ip} denotes individual i's share for supplier p, and α is a decision parameter value for mimicking max utility, logit, or choice probability rules.

3. $T_p(W) = \sum_{i=1}^{I} v_i t_{Ip}(w_i)$ denotes the total market share for supplier p. (3)

5.2. Modeling the concept of salience

We next assume that there exists a set of efforts $f_1, f_2, \ldots, f_J$ that can be applied to attributes 1 through J. The effect of these efforts is to change the current attribute importance weights, w_{ij}.

We also assume that there is a per unit "cost" r_j that restricts the firm's efforts through the constraint

$$\sum_{j=1}^{J} r_j f_j \leqslant C, \tag{4}$$

where C denotes the overall "budget" constraint, e.g., advertising dollars.

An advertising campaign that focuses on a certain attribute (e.g., overnight/AM delivery) will tend to raise the importance of this attribute in the minds of consumers. The effect to the budget constraint is direct as this relates to the cost of the advertising campaign.

What is more difficult to measure is the impact of the advertising campaign on the importance of the attribute as operationalized by f. A direct approach would be to survey consumers before and after the advertising campaign is executed. The relative importances can be used to estimate f. Short of collecting additional data, sensitivity analysis (as described below) could be used to at least measure whether a given attribute is sufficiently salient to be included in an advertising campaign.

We initially model the effect of effort f_j on attribute salience w_{ij}^* in the following simple fashion:

$$w_{ij}^* = w_{ij} + [1 - w_{ij}] f_j g_j, \quad 0 \leqslant w_{ij} \leqslant 1.0, \tag{5}$$

and

$$w_{ij}^{**} = w_{ij}^* \Big/ \sum_{j=1}^{J} w_{ij}^*, \tag{6}$$

where w_{ij} denotes the original salience of attribute j for individual i and g_j denotes the maximum effort allowable for attribute j. Then, from Eqs. (1) and (3), respectively, we obtain $w_{ip}(w_i^{**})$ and $T_p(W^{**})$.

From an optimization viewpoint the problem is to find the $f_1, f_2, \ldots, f_J$ that maximizes $T_p(W^{**})$, subject to the constraint of Eq. (4).

Moreover, we can generalize Eq. (5) to

$$w_{ij}^* = w_{ij} + [1 - w_{ij}] g_j [1 - (1 - f_j)^{\lambda}], \quad 0 < \lambda \leqslant 1.0, \tag{7}$$

and

$$w_{ij}^{**} = w_{ij}^* \Big/ \sum_{j=1}^{J} w_{ij}^*, \tag{8}$$

where λ denotes an exponent for effort. With this consideration in mind, the two options (sensitivity and optimization) in SALIENCE can be summarized as follows.

5.3. Sensitivity analysis

1. Choose an attribute j^*.
2. Decide on an increment in f_{j^*}.
3. Vary f_{j^*} starting from 0 to the maximum allowable, in specified increments, and observe the share/return for supplier p.

5.4. Optimal analysis

The optimization problem, stated earlier, turns out to be highly nonlinear and cannot be solved by standard methods. Since we believe this particular algorithm to be novel, Appendix B describes the procedure in more detail.

6. An empirical application of SALIENCE

For illustration purposes we now return to the empirical application and continue to choose the Alpha company as our supplier of interest. As noted earlier, Table 2 shows the attribute-level profile of Alpha (along with profiles of the other four suppliers) of overnight package and letter delivery.

Respondents who qualified as potential business users of overnight air delivery were contacted via random sampling from specified industrial and commercial lists. A total sample of 436 respondents were interviewed.

A conjoint design was used in the collection of respondent trade-off data. The master orthogonal design consisted of 128 profiles for the full-profile component of the task. Each respondent received eight (balanced) conjoint profiles, drawn from the master design, plus the self-explicated questionnaire sections and some general background questions. Input data to SALIENCE consisted of a matrix of part-worths, a set of profiles describing the product lines of the five competitors, demographic variables, respondent weights, and an optimized value of α for the decision parameter (see Green and Krieger, 1993).

6.1. Research questions

Illustratively, we consider the following research questions:

1. For each of the 15 attributes, how sensitive is Alpha's market share to effort increases in raising the salience of each attribute, considered singly?
2. What is the *optimal* allocation of effort across the full set of 15 attributes?
3. Suppose we considered only a market segment described by either level 1 ("package weight of one pound or less") or level 2 ("package weight of either two or five pounds"). What is the optimal salience for Alpha, given each case?

While clearly not exhaustive, the preceding questions should give the reader some idea of the variety of strategies that can be evaluated by SALIENCE.

7. Running the SALIENCE program

7.1. Sensitivity analysis

Table 5 first illustrates application of the sensitivity analysis option of SALIENCE. Alpha's current market share (obtained from the survey) is 28% of the total market. The first column of Table 5 shows this summary column as a 0.28 share for each attribute, assuming no application of sensitivity analysis.

Column 2, however, shows that uniform application of a sensitivity effort of 0.25 changes Alpha's share, by attribute, to varying degrees. For example, the new Alpha share could be as high as 0.41 for dimension/weight/price or as low as 0.17 for billing detail. Subsequent efforts of 0.50, 0.75, and 1.0 show still different patterns of Alpha's shares. With an effort equal to 1.0, Alpha's share for the attribute dimension/weight/price goes as high as a 0.53 share.

The reason share decreases when the importance in billing detail increases is because Alpha's performance on billing detail is relatively poor compared to the other suppliers. Increasing the importance of an attribute in which a supplier is strong (weak) will increase (decrease) the share to that supplier. The objective for a supplier is to increase the importance of attributes on which that supplier has a competitive advantage.

Different attributes display different patterns related to increases in effort. For example, overnight/PM delivery shows Alpha's share increasing monotonically as effort levels increase. Alpha's share decreases monotonically as effort

Table 5
Applying sensitivity and optimal analysis to Alpha's market share data

Attribute	Effort					
	0	0.25	0.50	0.75	1.0	Optimal
Overnight/AM delivery	0.28	0.3172	0.3309	0.3303	0.3275	0.000
Overnight/PM delivery	0.28	0.3562	0.4139	0.4440	0.4604	0.8945
Price	0.28	0.2753	0.2847	0.2562	0.2500	0.0000
Second day delivery	0.28	0.2765	0.2779	0.2773	0.2765	0.0000
Third day delivery	0.28	0.2729	0.2710	0.2746	0.2786	0.0000
Tracing time	0.28	0.2257	0.2034	0.1916	0.1839	0.0000
Access	0.28	0.2522	0.2416	0.2355	0.2313	0.0000
Tracking	0.28	0.3645	0.4237	0.4598	0.4808	0.2871
Carrier	0.28	0.2715	0.2633	0.2570	0.2524	0.0000
Extra insurance	0.28	0.3293	0.3448	0.3460	0.3445	0.0821
Reimbursement	0.28	0.2772	0.2678	0.2638	0.2645	0.0000
Dimension/weight/price	0.28	0.4073	0.4739	0.5099	0.5325	1.0000
Weight limits	0.28	0.2623	0.2405	0.2263	0.2181	0.0000
Billing detail	0.28	0.1682	0.1045	0.0758	0.0615	0.0000
Shipment pricing	0.28	0.3113	0.3266	0.3333	0.3339	0.7363
Optimal share						0.6360

levels for carrier increase. Second-day delivery shows little change in Alpha's share with increases in effort. Overnight/AM delivery first shows an increase in Alpha's share which is later followed by a slight decrease as effort is further increased. Clearly, different attributes display different patterns for Alpha as effort levels are changed in the sensitivity option.

7.2. Optimal analysis

For the sake of discussion, we assume the constraint imposed by Eq. (4) to be $\sum_{j=1}^{J} f_j \leqslant 3$. This is in the spirit of placing full salience on only three attributes (although this constraint also allows for spreading fractional effort across more than three attributes).

The sensitivity analysis results (see Table 5) suggest that a reasonable solution is to place full effort on the following three attributes: Overnight/PM Delivery, Tracking, and Dimension/Weight/ Price. This would result in a share of 0.62 for Alpha, but is this result optimal?

Although Overnight/PM Delivery and Dimension/Weight/Price remain salient attributes, a fair amount of effort is placed on Shipment Pricing in the *optimal* solution shown in Table 5. It should be noted that this last attribute never appeared as a contender in either the naïve solution or the one suggested by sensitivity analysis. Furthermore, if maximum effort were placed on Overnight/PM Delivery, Dimension/Weight/Pricing and Shipment Pricing, Alpha's share would be 0.63 (as compared to 0.62 using the three attributes suggested by the sensitivity analysis).

7.3. Additional analyses

Other kinds of research questions can be addressed with the SALIENCE model. As an example, suppose we consider Alpha's optimization, based on two background segments:

- Light packages, weighing either 1 pound or lighter.
- Heavy packages, weighing either 2 or 5 pounds.

Table 3 shows the weight limits utilized here.

Table 6 shows the results for the light package delivery segment and Table 7 shows the results for the heavy package delivery segment. Again,

Table 6
Applying sensitivity and optimal analysis to light package delivery segment

Attribute	Effort					
	0	0.25	0.50	0.75	1.0	Optimal
Overnight/AM delivery	0.2732	0.3096	0.3235	0.3236	0.3217	0.000
Overnight/PM delivery	0.2732	0.3489	0.4065	0.4377	0.4550	0.7500
Price	0.2732	0.2702	0.2585	0.2493	0.2426	0.0000
Second day delivery	0.2732	0.2743	0.2777	0.2775	0.2771	0.0000
Third day delivery	0.2732	0.2733	0.2765	0.2818	0.2867	0.0000
Tracing time	0.2732	0.2180	0.1940	0.1822	0.1750	0.0000
Access	0.2732	0.2439	0.2348	0.2292	0.2251	0.0000
Tracking	0.2732	0.3570	0.4150	0.4504	0.4714	0.0625
Carrier	0.2732	0.2654	0.2580	0.2526	0.2487	0.0000
Extra insurance	0.2732	0.3268	0.3432	0.3453	0.3445	0.1876
Reimbursement	0.2732	0.2701	0.2620	0.2618	0.2639	0.0000
Dimension/weight/price	0.2732	0.4160	0.4889	0.5275	0.5615	1.0000
Weight limits	0.2732	0.2558	0.2334	0.2190	0.2107	0.0000
Billing detail	0.2732	0.1623	0.1013	0.0741	0.0604	0.0000
Shipment pricing	0.2732	0.3038	0.3197	0.3276	0.3290	1.0000
Optimal share						0.6580

Table 7
Applying sensitivity and optimal analysis to heavy package delivery segment

Attribute	Effort					
	0	0.25	0.50	0.75	1.0	Optimal
Overnight/AM delivery	0.3018	0.3412	0.3456	0.3514	0.3458	0.0000
Overnight/PM delivery	0.3018	0.3792	0.4370	0.4638	0.4777	1.0000
Price	0.3018	0.2915	0.2840	0.2780	0.2731	0.0000
Second day delivery	0.3018	0.2837	0.2786	0.2766	0.2745	0.0000
Third day delivery	0.3018	0.2714	0.2537	0.2516	0.2529	0.0000
Tracing time	0.3018	0.2502	0.2335	0.2215	0.2123	0.0000
Access	0.3018	0.2780	0.2633	0.2554	0.2510	0.0000
Tracking	0.3018	0.3885	0.4515	0.4896	0.5104	1.0000
Carrier	0.3018	0.2911	0.2803	0.2714	0.2643	0.0000
Extra insurance	0.3018	0.3375	0.3497	0.3482	0.3446	0.0000
Reimbursement	0.3018	0.2996	0.2862	0.2703	0.2664	0.0000
Dimension/weight/price	0.3018	0.3799	0.4264	0.4540	0.4720	1.0000
Weight limits	0.3018	0.2832	0.2632	0.2500	0.2419	0.0000
Billing detail	0.3018	0.1878	0.1150	0.0812	0.0648	0.0000
Shipment pricing	0.3018	0.3348	0.3484	0.3514	0.3497	0.0000
Optimal share						0.5840

we apply the same procedures used earlier to these two segments.

The light package delivery segment (Table 6) shows that:

- Overnight/PM Delivery
- Tracking
- Extra Insurance
- Dimension/Weight/Price
- Shipment Pricing

are the five most important variables on which to focus. Alpha's optimal share is 0.66.

In the case of the heavy package segment (Table 7), we note that:

- Overnight/PM Delivery
- Tracking
- Dimension/Weight/Price

are the three most important variables. In this case, Alpha's optimal share is 0.58.

Table 8
Initial and final importances obtained from the application of SALIENCE

Attribute	Initial importances	Final importances	Optimal allocation
Overnight/AM delivery	0.051	0.013	0.000
Overnight/PM delivery	0.040	0.230	0.895
Price	0.137	0.035	0.000
Second day delivery	0.026	0.007	0.000
Third day delivery	0.013	0.003	0.000
Tracing time	0.067	0.017	0.000
Access	0.065	0.017	0.000
Tracking	0.110	0.094	0.287
Carrier	0.275	0.070	0.000
Extra insurance	0.029	0.028	0.082
Reimbursement	0.028	0.007	0.000
Dimension/weight/price	0.025	0.256	1.000
Weight limits	0.052	0.013	0.000
Billing detail	0.080	0.021	0.000
Shipment pricing	0.002	0.189	0.763
Optimal share for Alpha			0.636

8. Summarizing the empirical results

We can summarize the preceding empirical findings by the following comments:

1. Intuitively, we first noted that Alpha's desirability scores were high on attributes 1, 2, 10, 11, and 12. Also, Alpha's importances were below average on these attributes. Based only on intuition, attributes 1, 2, 10, 11, and 12 looked like good choices.
2. When SALIENCE was applied, however, differences were noted (see Table 5). In this case, attributes 2, 8, 10, 12, and 15 were most important. Alpha's optimal share was 0.64.
3. Table 6 indicated that attributes 2, 8, 10, 12, and 15 were the most important for the light package segment. Alpha's share was 0.66.
4. Table 7 indicated that attributes 2, 8, and 12 were the most important for the heavy package segment. Alpha's share was 0.58.
5. Table 8 shows how the initial importances are changed when the optimization module of SALIENCE is applied.

9. Discussion

The SALIENCE model makes a number of assumptions regarding consumers' reactions to increased attribute importances and their effect on market shares among competitive products. These include the following:

- The sponsor firm's emphasis on selected attribute importances is also assumed to extend to purchasers of competing services. That is, buyers of competitive products will also be responsive to increased importances of the firm's selected attributes.
- Attribute-level desirabilities of all respondents are unaffected by changes in attribute saliences.
- Attribute saliences are compensatory and constant sum. (If one attribute's perceived importance increases, one or more of the remaining attributes' importances decreases.)
- If attribute saliences are modified, a respondent's decision rule is not affected by these changes.
- The SALIENCE model does not incorporate competitive retaliation.

10. Conclusions

As this paper illustrates both formally and empirically, SALIENCE has been designed as a pragmatic decision support system for evaluating short-range marketing strategy involving the allocation of effort aimed at increasing the salience of one or more attributes relative to others. Our objective is to allocate efforts so as to maximize share/return for the supplier(s)' product/services, conditional on all competitive profiles remaining fixed over the short-run.

SALIENCE has the following features:

1. Market share or return optimization.
2. Total market and/or individual segment forecasting.
3. Sensitivity analyses as well as optimal effort allocation.
4. Ability to incorporate auxiliary suppliers.
5. Calibration of results to existing market conditions.
6. A decision parameter (alpha) that can be used to mimic any of the principal choice rules (max utility, logit, BT).

So far we have used SALIENCE in tandem with SIMOPT (Green and Krieger, 1993). We believe that each has a complementary role to play—SALIENCE for shorter-range advertising and promotion and SIMOPT for longer-range product reformulation strategy and new product positioning, via changes in attribute levels.

We view SALIENCE basically as an "if…then" model and computer program for finding the implications for share/return as the user modifies effort allocations across attributes. In real situations it may be difficult to estimate cost functions for individual attribute increases in effort and other parameter values, such as the growth exponent. It is also an empirical matter as to how well Eq. (7) approximates real-world relationships.

Nonetheless, it is not at all unusual in marketing science to assume a set of plausible response functions and model their normative implications. SALIENCE has been designed in this spirit. Clearly, the empirical side of testing the plausibility of its assumed relationships is an important companion undertaking and ultimately necessary for continued use of the SALIENCE model.

11. Uncited references

Green et al. (2001), Krieger et al. (2004), McFadden (1973), Orme (2003), Vavre et al. (1989), Wind et al. (1989) and Wittink et al. (1994).

Appendix A

In the body of the paper we described two parameters that could affect the behavior of SALIENCE: alpha (α) and lambda (λ).

A.1. The α parameter

α denotes a decision parameter in the SIMOPT model (Green and Krieger, 1993). This parameter appears as a decision value for mimicking the max utility, logit, or BTL rules in the conjoint simulator; see Eq. (2).

As reproduced here, the expression of interest is

$$t_{ip}(w_i) = u_{ip}^{\alpha} \Big/ \sum_{p=1}^{P} u_{ip}^{\alpha}, \tag{A.1}$$

where t_{ip} denotes individual i''s share for supplier p, and $w_i = (w_{i1}, \ldots, w_{iJ})$ is a vector of importance weights.

A sensitivity analysis was run on this expression to see how market shares and derived SALIENCE weights are affected by α. Table 9 shows the results of this analysis.

As noted from Table 9, α is set at each of five (increasing) levels. As one might intuitively expect, shares increase with increases in α. However, the saliences are *not* highly affected. For example, attributes 2, 12, and 15 *still* come out as the important attributes to focus on.

A.2. The λ parameter

The λ parameter refers to the equation

$$w_{ij}^{**} = w_{ij} + [1 - w_{ij}]g_j[1 - (1 - f_j)^{\lambda}], \quad 0 < \lambda \leqslant 1.0 \tag{A.2}$$

which is a generalization of the simpler equation

$$w_{ij}^{*} = w_{ij} + [1 - w_{ij}]f_j g_j, \quad 0 \leqslant w_{ij} \leqslant 1.0, \tag{A.3}$$

where w_{ij} denotes the original salience of attribute j for individual i and g_j denotes the maximum effort allowable for attribute j.

Table 9
Results of sensitivity of shares and attribute importance changes, as related to the *alpha* parameter

Attribute	$\alpha = 1$	$\alpha = 3$	$\alpha = 5$	$\alpha = 10$	$\alpha = 20$
1	0	0	0	0.1055	0
2	0.5383	0.8750	0.8945	0.6251	0.1876
3	0	0	0	0	0
4	0	0	0	0	0
5	0	0	0	0	0
6	0	0	0	0	0
7	0	0	0	0	0
8	0	0	0.2870	0.3906	0.3749
9	0	0	0	0	0
10	0	0.1250	0.0821	0.3163	0.7500
11	0	0	0	0	0
12	1.00	1.00	1.00	1.00	1.00
13	0	0	0	0	0
14	0	0	0	0	0
15	1.00	1.00	0.7363	0.5625	0.6875
Share	0.3995	0.5436	0.6360	0.7478	0.8146

Table 10
Results of sensitivity of shares and attribute importance changes, as related to the *lambda* parameter

Attribute	$\lambda = 1/3$	$\lambda = 1/2$	$\lambda = 1$	$\lambda = 2$	$\lambda = 3$
1	0	0	0	0	0
2	0.5000	0.5000	0.8945	0.8750	0.4161
3	0	0	0	0	0
4	0	0	0	0	0
5	0	0	0	0	0
6	0	0	0	0	0
7	0	0	0	0	0
8	0.5000	0.5000	0.2870	0.3750	0.2228
9	0	0	0	0	0
10	1.00	1.00	0.0821	0.1250	0.1094
11	0	0	0	0	0
12	1.00	1.00	1.00	0.99	0.7812
13	0	0	0	0	0
14	0	0	0	0	0
15	0	0	0.7363	0.6251	1.00
Share	0.6086	0.6095	0.6360	0.6362	0.6356

Table 10 shows (across various values of λ) that shares and allocations are *not* sensitive to changes in the lambda parameter; hence, the simpler equation can be used. The shares are in the range of 0.61–0.64. The allocations favor attributes 2, 8, 10, 12, and 15.

Appendix B

Appendix B provides a more formal description of the SALIENCE model. The purpose of Appendix B is to describe how a set of efforts, $f = (f_1, \ldots, f_J)$ can be found that provide a local optimum for the financial share/return to a desired supplier. To this end, we let $\phi(f_1, \ldots, f_J)$ denote the share to a selected supplier; the problem becomes

$$\max_{(f_1,\ldots,f_J)} \quad \phi(f_1, \ldots, f_J)$$

$$\text{subject to} \quad \sum_{j=1}^{J} r_j f_j \leqslant C,$$

where $0 \leqslant f_j \leqslant 1$ for all j. The r_j values denote "difficulty" factors that are estimates of relative implementation costs.

The actual form of ϕ is nonlinear and ϕ may have many local optima. In a given run, we can only expect to find a single local optimum. There are many algorithms (and associated software packages) available for finding a local optimum for a nonlinear function, subject to linear constraints. However, we elected to write our own program in order to tailor the algorithm to our specific problem and to facilitate the optimizer's use in the main program (as illustrated in the body of the paper).

The algorithm uses ϕ and the partial derivatives $\phi'_j = \partial\phi(f_1,\ldots,f_J)/\partial f_j$ evaluated at f. The specific expressions for ϕ and ϕ'_j are complicated and so we refer to ϕ and ϕ'_j rather than to their actual expressions in describing the algorithm. It suffices to know that ϕ is analytic so that the algorithm below results in a local optimum.

The algorithm begins with an initial set of values $f^{(0)} = (f_1^{(0)},\ldots,f_j^{(0)},\ldots,f_J^{(0)})$ and at each iteration replaces $f^{(p-1)}$ the previous set of efforts, with $f^{(p)}$ a new set of efforts, so that $\phi(f^{(p)}) > \phi(f^{(p-1)})$. The initial set of efforts can be user supplied or the set of efforts that are currently the best, based on the sensitivity option.

We replace $f^{(p-l)}$ with $f^{(p)}$ by first considering changing one element in $f^{(p-1)}$ (univariate change) and, if a univariate change does not exist, then considering changing two elements in $f^{(p-1)}$ (bivariate change). This feature is in contrast to steepest ascent algorithms which consider changes of the form $f^{(p)} = f^{(p-1)} - \gamma t$ where the constraint provides a limit on γ and the gradient determines t. In our problem, we found, most importantly, that using a steepest ascent algorithm generally did not find a superior local optimum.

B.1. Univariate case

We divide the following discussion into two parts, depending on whether the constraint is satisfied or not.

$$1. \quad \sum_{j=1}^{J} r_j f_j^{(p-1)} < C. \tag{B.1}$$

Let $S_0 = \{j | f_j^{(p-1)} = 0\}$ and $S_1 = \{j | f_j^{(p-1)} = 1\}$. We change the effort for attribute j^*, where j^* is the index corresponding to the maximum of ϕ'_j for all $j \in S_0$, $-\phi'_j$ for all $j \in S_1$, and $|\phi'_j|$ for all j not in S_0 or S_1. Note that if for all $j \in S_0$, $\phi'_j \leqslant 0$, for all $j \in S_1$, $\phi'_j \geqslant 0$, and for all j not in S_0 or S_1, $\phi'_j = 0$, we then make a bivariate change (see below). Then $f^{(p)}$ is the result of maximizing $\phi(f^{(p)})$ over $f_{j*}^{(p)}$, where $f_j^{(p)} = f_j^{(p-1)}$, if $j \neq j^*$, subject to the constraint.

$$2. \quad \sum_{j=1}^{J} r_j f_j^{(p)} = C. \tag{B.2}$$

Let $T = (j | f_j^{(p-1)} > 0 \text{ and } \phi'_j < 0)$. If T is empty, then we make a bivariate change (see below). If T is nonempty, then we change the effort for attribute j^*, where j^* is the index corresponding to the maximum of $-\phi'_j$ for all $j \in T$. We then proceed as in step 1 to find $f_{j*}^{(p)}$ which maximizes ϕ where $f_j^{(p)} = f_j^{(p-1)}$ if $j \neq j^*$, subject to the constraint.

B.2. Bivariate case

Let $S_0 = \{j | f_j^{(p-1)} = 0 \text{ and } \phi'_j > 0)$, $S_+ = (j | 0 < f_j^{(p-1)} < 1)$, and $S_1 = (j | f_j^{(p-1)} = 1)$. Note that if j is in S_+ or S_1, then $\phi'_j \geqslant 0$; otherwise univariate changes would have been made. Let j_+^* be the index corresponding to the maximum of ϕ'_j for all j in S_0 or S_+. Let j_-^* be the index corresponding to the minimum of ϕ'_j for all j in S_+ or S_1. (Note that j_-^* and j_+^* correspond to the efforts that are decreased and increased, respectively.) If $\phi'_{j_+^*} \leqslant \phi'_{j_-^*}$ then we stop. Otherwise, $f^{(p)}$ is the result of maximizing $\phi(f^{(p)})$ over $f_{j_+^*}^{(p)}$ and $f_{j_-^*}^{(p)}$ along the line $r_{j_+^*} f_{j_+^*}^{(p)} + r_{j_-^*} f_{j_-^*}^{(p)} = r_{j_+^*} f_{j_+^*}^{(p-1)} + r_{j_-^*} f_{j_-^*}^{(p-1)}$ such that $0 \leqslant f_{j_+^*}^{(p)} \leqslant 1$ and $0 \leqslant f_{j_-^*}^{(p)} \leqslant 1$ where $f_j^{(p)} = f_j^{(p-1)}$ if j is not equal to j_+^* or j_-^*.

There are several additional features related to the above discussion. The program allows the user to simulate the above iterative process univariately. To this end, the value $\phi(f)$, the efforts f, and the partial derivatives $\phi'_j(f)$ are all made available. The user can then observe a stream of values, $\phi(f^{(0)}),\ldots,\phi(f^{(p)})$, and be able to measure how flat ϕ is for a set of efforts that perhaps has more zeros than $f^{(p)}$ and/or is not that near to $f^{(p)}$.

It might also be of practical importance to fix a subset of f, most commonly at zero, and maximize over the other dimensions. Finally, the derivative at zero, $\phi'_j(0)$, is a proxy for the importance of that effort. In the random analysis, rather than generating f according to $U(0,1)$ (and then normalizing to satisfy the constraint), we can generate f on $U(0,\phi'_j(0))$ for all j, such that $\phi'_j(0) > 0$.

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