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MODELING ADVERTISING MEDIA EFFECTIVENESS

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ABSTRACT

While the media planning literature boasts a long tradition of media simulations, the discussions rarely include practical information regarding the establishment of parameters for the models. This paper discusses the development of media effectiveness evaluations in the context of marketing, advertising, and media simulation games. It outlines a practical set of steps for developing media effectiveness measures, including guidelines for establishing the key parameters.

INTRODUCTION

One of the first applications of the emerging power of computers in the early 1960s was the development of media simulations (see Gensch 1973; Aaker and Myers 1982 for reviews). The most comprehensive simulations address a relatively large and complete set of media and related effects (Gensch 1 969, 1 970; Little and Lodish 1969; Aaker 1975). However, they do not specify either the specific parameters required by the simulation, or the procedures required to develop them.

This is not meant to be a criticism. These models represent an important contribution to the literature. They also have immediate value as planning tools in data rich organizations, or in organizations where media planners have sufficient expertise to estimate the parameters accurately. However, the simulations are typically used in an educational setting, where neither data nor practical knowledge of parameters are likely to be abundant, even among game administrators.

The purpose of this paper will be to outline a set of guidelines for modeling media effectiveness in the context of marketing simulation games. It will not only discuss the various variables and relationships, but it will address the issue of para-meters as well. Indeed, it will provide the principles needed to incorporate a realistic set of television or magazine media selections into a marketing simulation game.

MODELING MEDIA EFFECTIVENESS

As noted earlier, media simulations were among the first applications of modern computer technology in business. Indeed, throughout the intervening years, media planning has been one of the major applications of computer technology in marketing. However, notwithstanding this tradition, the planning tools that have actually been developed for practical use remain relatively crude. For instance, one of the standard computer-based planning concepts is effective reach and frequency (Naples 1979), where planners use simulation models to estimate the proportion of the target audience exposed to the media in which a company advertises 0, 1, 2, 3, times, and so forth -- what is referred to as an exposure frequency distribution. While estimates vary on the overall level of acceptance of the effective reach and frequency concept, surveys suggest that it is practiced by the majority of media planners (Kreshel, Lancaster and Toomey 1985; Leckenby and Kim 1994). Typically, target market members are not considered to be “effectively exposed” until they are reached three or more times.

This, of course, ignores the obvious fact that some people will be effectively exposed after one vehicle exposure, and others may require many more. Furthermore, the effective exposure concept implies an “S-shaped” advertising response curve (Stankey 1989), while the overwhelming weight of evidence suggests that in the real world of advertising, these curves are almost invariably concave in nature (Simon and Arndt 1980; Zielske and Henry 1980; Schultz and Block 1986; Wenzel and Speetzen 1987; Stewart 1989).

There are a number of reasons for the anomaly. One is tradition. For years, advertising theorists and practitioners alike have simply assumed an 5-shaped curve, based on its face validity, without the benefit of empirical support. Only recently that they have been confronted with the inconsistency of their position (Cannon and Goldring 1 986; Cannon and Riordan 1994; Jones 1995; Ephron

1995). However, even if the S-shaped curve were descriptive of customer response to advertising, effective reach and frequency would be a crude and inappropriate response. It would be better to assign a value to each level of advertising exposure founded in the exposure distribution, multiply this by the proportion of the target population exposed at this level, and then sum these products to compute a total value for the advertising schedule.

There are two obvious impediments to this approach. The first is that it requires fair amount of computation. But this is not a problem with the availability of today's powerful and readily available microcomputers. Furthermore, effective reach and frequency requires the estimation of an advertising exposure distribution. To weight these by exposure values is a simple spreadsheet exercise.

This leads us to conclude that the second impediment is the real problem. It is the inability of modelers to develop a practical procedure for estimating the response value of different levels of advertising exposure. In place of the relatively demanding task of estimating the specific exposure values of each exposure level in the advertising frequency distribution, effective reach and frequency requires only a single estimate -- the level of effective frequency. Computation is not the issue, but information. What value should be assigned to each level of exposure? The following summarize a series of steps through which media effectiveness can be estimated in the context of a simulation game.

Step 1: Develop the Media Schedule

Step 1 involves the construction of a media schedule. In a marketing or media simulation game environment, this would be done by the student. This might involve both strategic and tactical decisions, but the output would be a an actual set of media selections for a given period of time.

Step **2: Estimating Vehicle Exposure Values**

There are a number of different ways exposure values might be expressed. For instance, Gensch (1970) suggests that there might be a separate value assigned to each customer, depending on their value as a potential customer. However, this is generally implemented by dividing media vehicle audiences up into demographic groups, and assigning a value to each group, depending on the concentration of product users or other purchase criteria. The target market value of the vehicle audience, then, is a summation of the weighted value of an audience's demographic groups. As plausible as this sounds on the surface, research suggests that it provides a relatively poor representation of the vehicle's target market attractiveness (Cannon 1 988; Cannon and Seamons 1994).

The more common solution is to express exposure value as a target market rating, or the proportion of the target market reached by the vehicle. In practice, targets are generally expressed in terms of demographics. However, the preferred approach is to define targets in terms of product usage (Assael and Cannon 1979). Given the fact that the data are being used in a simulation, they should be reasonable, but the demands for accuracy are not as stringent as they would be for a planning tool designed for practitioners. This leaves considerable leeway for developing systems that approximate the effects of single-source data (Cannon, McGowan and Yoon 1995).

Step 3: Estimating Advertising Exposure Values

Audience research services typically provide media exposure, or opportunity to see (OTS), data. Obviously, any audience response will come from actual ad exposures, not OTS. Therefore, an adjustment must be made to convert the vehicle exposure distribution to advertising exposures. Given the prominence of television and magazine media, we will use these two media as example's.

Television ad avoidance research dates back to the early 1 960s, but recent changes in the viewing environment such as remote controls and the huge increase in television channels (cable and broadcast) make ad avoidance far easier than it was in the past. Audience members can avoid TV commercials by leaving the room or changing channels (zapping).

Recent research which observed television audience members found eyes-on-screen time averaged 32.8% for commercials compared to 62.3% for programs (Krugman, Cameron and White 1995). Several recent studies also found zapping is more common for mates, younger viewers, and household's with remote controls, cable and higher incomes (Abernethy 1991; Ainslie 1989; Kneale

1988; Zufryden, Pedrick, and Sankaralingam 1993).

A recent Times Mirror survey has the lowest estimate of TV ad exposure with only 35% of the audience claiming to watch ads (King 1994). Other studies give far higher estimates of TV ad audiences. Perhaps the best estimate is given by Abernethy's (1990) detailed review of observational and survey studies. He estimates 32% television commercial avoidance, or 68% advertising exposure.

An average figure, such as Abernethy's 68% exposure, might be used as a basis for the model. However, a better approach would be to develop different estimates, based on the nature of the media vehicle. For instance, Bearden, Headen, Klompmaker and Teel (1981) reviewed studies addressing attention levels for daytime television, noting that they varied between 20% and 50% of program ratings. In prime time, attention levels were reported at 76% of program ratings for station break and 84% for in-program commercials. In practice, a planner would adjust the exposure estimates up or down, depending on whether an ad was placed in daytime or primetime television, in a station break or in a program. Again, this is sufficiently realistic to address the requirements of a simulation game, even if an agency were able to gather information that is more precise for a given campaign. At this point, better estimates are not even available to most agency planners.

With respect to magazines, in the 1950s, some general interest magazines including Life, Readers Digest and the Saturday Evening Post conducted a series of studies that put a small amount of weak glue between magazine pages. If the "glue spot" was broken, then the reader had viewed the pages and had an opportunity to see the ad (reported in Lucas and Britt 1963 and Raymond 1976). After adjusting for chance glue breakage due to mailing, average opportunity to see the ad was estimated to be 90%.

However, actual ad noting and readership data are collected for most major consumer magazines and many industrial magazines. Given the wide availability of ad noting and readership data for most major magazines, it makes sense to use these data instead of dated glue spot studies to estimate ad readership. According to Starch Adnorms (Roper Starch 1994), the average noting scores for a full page, four color ad is 46.4% which is used in this paper. Practitioners may wish to use average scores from their product categories or from their past advertising as input to their exposure estimation models. Adnorms is generally available and can be used as a basis for developing exposure values in a simulation game environment as well.

A complete review of the advertising exposure rate literature is beyond the scope of this study. However, television and magazines illustrate two different ways of estimating exposure rates. One is to develop a set of adjustment rules, such as the simple ones we cited for television. A more rigorous approach might involve the development of a rule-based expert system to make a final estimate. The second method is to draw on empirically established norms, such as those contained in Roper Starch's Adnorms. Of course, these too can be used to develop an expert system. One approach to developing an expert system would be to build a model that links media and advertising characteristics to exposure rates, perhaps in the form of a regression model (Cannon 1982).

Whatever the method of developing advertising exposure rates, the requirement for developing exposure estimates for a simulation game environment is that each target market rating have associated with it a probability that a given audience member will actually be exposed to the ad. For instance, if the target market rating were 10% and the effective exposure rate were 50%, the adjusted target market rating would be 5%.

Step 4: Estimate Exposure Distribution

Advertising exposure value represents a simple adjustment to vehicle exposure. Therefore, the same procedures can be used to estimate the advertising exposure frequency distribution as have been developed for estimating vehicle frequency distribution. The literature includes a number of different models. The literature suggests that sequential aggregation methods are particularly useful, since they strike a balance between theoretical grounding, accuracy and speed of computation (Lee 1988; Rice and Leckenby 1986). Such methods are also inherent in some proprietary packages used by media planners (Lancaster 1 993; Liebman and Lee 1974).

A simple, but powerful, approach is called MSAD

(Morgenzstern Sequential Aggregation Distribution) and is based upon a reach formula developed by Morgenzstern (Lee, 1988). It has proved to be a very accurate model when used for magazine and television schedule's (Rice and Leckenby, 1986). In sequential aggregation procedures, the vehicle frequency distribution of the first two vehicles is computed first; these are then viewed as a composite, single vehicle to be combined with the next vehicle in the media schedule. The resulting distribution is viewed as that of the second composite vehicle to be combined with the fourth vehicle. This procedure continues until all vehicle's in the schedule have been integrated into one final vehicle exposure distribution.

Other approaches are readily available to the modular from the literature. Virtually all of them have been described in published journal articles. Furthermore, several good reviews have been published as well. These include Gensch (1973), Chandon (1986) and Rust (1986).

Step 5: Estimate the Response Value

In order to illustrate the process of schedule valuation, consider a simple schedule in which 50% of the population is not exposed to any of the media vehicles, 40% are exposed once, and 1 0% are exposed twice. When adjustments are made to account for actual advertising exposure, the estimated exposure distribution was 67.4% unexposed, 31.6% exposed once, and 1.0% exposed twice.

The question that typically eludes modelers is the appropriate exposure value that should be assigned to each group. We can think of exposure value as a conditional probability. If 31 .6% of the population is exposed to one ad in a campaign, and the probability of a given audience member recognizing the message after a single exposure is 20%, the "message recognition" response value for the one-advertisement exposure group would be (.316 x .2 =) 6.32%. If the probability after two exposures were 30%, the value for the two-exposure group would be (.01 x .3 =) .3%. The total value of the campaign would be (.0632 + .0030=) 6.62%.

The problem is how to estimate the response values for each level of advertising exposure. The value depends on the kind of response a campaign hopes to achieve from target market members. Clearly, message recognition is less demanding than brand awareness; brand awareness is less demanding than purchase behavior. The less demanding the desired response, the higher the response value assigned to different levels of advertising exposure.

Response values represent points on an advertising response curve. As a practical matter, the best way to formulate the curve is to estimate the maximum and minimum response that is likely through exposure to a given campaign. Once this is done, the points in between can be estimated by fitting them to a standard curve. As we have noted, this will typically be concave, but it might also be 5-shaped in cases where the minimum is low, relative to the maximum. One rule of thumb suggests that an S-shaped curve is only a possibility in cases where the minimum is less than 1 5% of the maximum.

TABLE 1:
TYPICAL MAXIMUM AND MINIMUM RESPONSE VALUES FOR DIFFERENT KINDS OF OBJECTIVES

Type of Objective	Typical Maximum Range	Typical Minimum Range
Message recognition	85-95%	5-35%
Brand Awareness	85-95%	3-25%
Message recall	70-80%	2-25%
Brand attitude	30-45%	0-5%
Purchase behavior	10-25%	0-5%

Table 1 provides guidelines derived from agency experience for establishing maxima and minima, depending on the kind of objective a campaign is designed to achieve. For instance, it suggest that undemanding tasks, such as message recognition or brand awareness, can be achieved for 85% to 95% of the population, whereas demanding objectives, such as purchase behavior tend to have maximum from 10-25%. Given a maximum and minimum value, and a curve to plot the values in-between, the mathematical' formula for the curve will provide specific values for each level of exposure.

In order to determine the actual minimum and maximum, a planner can select values on the high or low end of the range, depending on the campaign's relative need for exposure frequency. Ostrow (1982) suggests a number of factors that might be used to help estimate this need (Table 2). In order the use the framework, the planner must weight the various factors according to their relevance, and then rate them according to the degree to which they characterize the advertising situation.

TABLE 2:
FACTORS THAT AFFECT THE NEED FOR MORE (+) OR LESS(-) FREQUENCY

Marketing Factors
Establishing brands (-)
High market share (-)
Dominant brand in market (-)
High brand loyalty (-)
Long purchase cycle (-)
Product use daily (+)
Heavy spending category (+)
Special targets (+)
Copy Factors
Complex copy (+)
Unique copy (+)
New copy (-)
Image type copy (+)
Many kinds of messages (+)
High copy wearout (-)
Small ad units (+)
Media Factors
High clutter (+)
Compatible environment (+)
High attentiveness (-)
Pulsed or flighted (+)
Few media used (-)
Repeated ad exposures (-)

In order to apply Ostrow's approach, one need only determine which characteristics are relevant, and then develop an index of relative importance for each by distributing 100 points among them. The resulting allocation can be taken as the percentage of total importance given to each factor. The advertising situation would then be rated relative to each one, using a + 1 to -1 scale. The situation can be evaluated by developing a weighted average rating for each factor. The situational rating is then reverse scored. A high rating places the maximum response at the low end and the minimum response at the high end of the range.

Now, consider a campaign where message recognition is the objective. The maximum response range would be between 85% and 95%. A weighted average response of zero would call of a maximum response value of 90%. A weighted average of + 1 would mean a maximum response value of 85%, a weighted average of -1 a maximum response of 95%. A weighted average of zero would represent a minimum response of 20%. A weighted average of + 1 would represent a minimum response value of 5%, a weighted average of -1 a value of 35%. If the actual' value adjustment were + .23, based on the factors presented in Table 2, the maximum response would be (90% - .235% =) 88.85% and the minimum would be (20% - .2315% =) 16.55%.

TABLE 3:
AN EXAMPLE OF AN ESTIMATED ADVERTISING RESPONSE CURVE

Advertising Exposure	Message Recognition
1	16.55%
2	61.92%
3	78.82%
4	85.12%
5	87.47%
6	88.34%
7	88.67%
8	88.79%
9	88.83%
10	88.85%

In order to convert this maximum and minimum into an actual advertising response curve, one must estimate the period of time over which frequency will be evaluated, the number of exposures required to achieve the maximum response, and the shape of the response curve. The appropriate period of time depends on the durability of advertising effects and the manner in which they interact, however, a quarter of business (13 weeks) is often used as a common base. Campaigns generally achieve maximum effectiveness by the tenth exposure. And, as we have noted, the typical advertising response function tends to be concave in shape. Given these estimates, the advertising response curve can be described in terms of the values shown in Table 3.

Step 6: Estimating Schedule Value

Once steps 1 through 5 have been completed, calculating the schedule value is a simple matter of multiplying the advertising exposure distribution by the corresponding exposure values (illustrated in Table 3 from step 5). The schedule value can be interpreted as the proportion of the target population that is effectively exposed to the campaign, whatever the exposure criterion established for the campaign. In our example, 31 .6% of the population was exposed once to the ad, and 1 .0% twice. We saw from our discussion of step 5 that this was the result of 40% of the target population being exposed to one vehicle exposure (40 GRPs), and 10% being exposed to two (20 GRPs). This yields a total advertising weight of 60 GRPs. The total value of the schedule would be 31 .6% with an exposure value of 16.55%, and 1.0% with an exposure value of 61.92, or (31.6% x 16.55% plus 1.0% x 61.92% =) 5.86%.

The criterion of advertising effectiveness is message recognition. Obviously, the schedule optimal frequency value can be increased by simply increasing the media weight. But this also costs money. The best criterion for evaluating a schedule is the value per GRP, or better yet, the value per media dollar spent. As In most cases, the increase in value will be subject to diminishing returns, resulting from a concave advertising response curve. However, even if the curve is S-shaped, the criterion will still yield valid results. In our case, the value per GRP is (5.86/60=) 9.75%. That is, on the average, one out of each ten advertising exposures results in message recognition.

In a simulation game environment, the value per GRP and value per media dollar spent represent very useful diagnostic measures. However, the impact of media on game performance is strictly a function of schedule value. The greater the value, the greater the impact on sales. The cost of media will be subtracted, so principles of marginal analysis will automatically apply. That is, students would ideally spend on media until the profit impact of additional expenditure is zero. By making more efficient media selections, students can get more value per dollar, thus increasing the profit impact.

SUMMARY AND CONCLUSIONS

The purpose of this paper has been to outline some practical principles and procedures for modeling media effectiveness in the context of a marketing simulation game. While media models are well established in the marketing, advertising, and advertising media literature, they generally fall short of providing practical guidelines for developing realistic parameters to use in the gaming environment. This paper not only discusses modeling issues, but it also provides the guidelines necessary to put them into practice.

The sine between simulation games and simulations developed as part of a media planning decision support system is a thin one. We would anticipate, then, that the guidelines discussed in this paper would also have implications for commercial decision support simulations as well. The main difference is that the gaming environment is much more forgiving to ‘apses in accuracy, as long as the models are realistic. However, we anticipate that on-going research in the area of decision support simulations will also have value for gamers. Conversely, gaming research might prove valuable to actual’ media planners as well, not only in the form of better training tools, but also in the identification of issues that needs to be addressed to make these toots more effective. Along these lines, the present research suggests a number of issues that need to be addressed in the interest of both gaming and decision support simulations.

General Advertising Exposure Norms

As noted in our review, some research has been done. However, so far, research has yet to fully address even the crudest norms for various kinds of media and media options. At very least, we should have exposure norms for different kinds of media, modified for major options (embedded versus station-break commercials, daytime versus prime-time television, etc.). So far, research in this area has tended to be spotty (addressing only some of the major media options) and limited to major media, such as television and magazines.

Principles And Systems for Estimating Variations in Exposure Norms Resulting from Situational Factors

Situational factors might include dimensions such the message, media context (editorial environment, physical or social setting of media exposure, layout and executional format, etc.), audience member knowledge and experience, interactive media/message effects, and the objectives of the campaign. At this point, we have yet to develop even the most rudimentary model of how research in this area should be organized. What dimensions should it consider? What theoretical bases are relevant to the problem?

Advertising Response Functions

Existing research suggests that they are generally concave, although traditional wisdom and some research suggests that they may also be S-shaped in form. Are there other forms as well? What functions and parameters best describe the response curves. In this paper, we have suggested an approach for modeling the curve, drawing on suggested industry norms, such as the ones portrayed in Table 1. Are these norms accurate? Are the factors and process by which they are modified (Table 2) correct. This calls empirical' research across different kinds of advertising situations to see how accurate and robust the functions are.

Validation Studies

Validation studies would presumably address each part of the media response model as it is developed. For instance, models for estimating the shape and position of an advertising response curve should clearly be tested against actual data, as should models for estimating advertising exposure, given media vehicle exposure.
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