Mixed-media modeling may help optimize campaign recognition and brand interest

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HEADLINE
Mixed-Media Modeling May Help
Optimize Campaign Recognition and Brand Interest

SUBHEADLINE
How to Apply "Mixture-Amount Modeling"
To Cross-Platform Effectiveness Measurement

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ABSTRACT
The current study applied a "mixture-amount modeling" statistical model—used most often in biology, agriculture, and food science—to measuring the impact of advertising effort and allocation across different media. The authors of the current paper believe advertisers can use the mixture-amount model to detect optimal advertising-mix allocation changes as a function of their total advertising effort. The researchers demonstrated the utility of the model by analyzing Belgian magazine and television data on 34 advertising campaigns for beauty-care brands. The goal: to help advertisers maximize desirable outcomes for campaign recognition and brand interest.

MANAGEMENT SLANT

- The authors found different optimal media-mix allocations for campaign recognition and brand interest,
- Based on the mixture-amount model, advertisers can explore scenarios with different campaign weights and media allocations in a dynamic way, using the prediction profiler in JMP software.
- Future research can apply the model to other media, such as online and mobile channels, radio, and newspapers.

INTRODUCTION
Advertisers repeatedly must decide on the total amounts of advertising effort to invest, and on how to allocate this effort across different media. In 2013, advertising expenditure worldwide amounted to $516.5 billion is expected to grow to $667.65 billion by 2018 (Statista, 2015).

According to the authors' knowledge—and despite its relevance to advertisers and media planners—research on the optimal allocation of advertising budgets across different media is lacking (Schultz, Block and Raman, 2012).

The current study's objective is to partly fill this void by investigating how advertisers can maximize campaign recognition and brand interest by optimizing their advertising effort across different media, for different levels of total advertising efforts.

To this end, the researchers adapted what is known in food science and agriculture as a "mixture-amount regression" model to their study. The novelty of this model is that it explicitly allows advertisers to simulate how the optimal media-mix allocation changes for varying amounts of advertising investment (See "Mixture-Amount Models," below).

Existing studies on media-mix and synergy effects can be classified into two broad categories:

- studies involving real-life data
- experimental studies.

Most published advertising studies on media-mix synergy effects are experimental, exposing people to advertising stimuli in different media and measuring their responses in terms of attitudes and behavioral intentions (*e.g.*, Danaher and Rossiter, 2011; Voorveld, Neijens and Smit, 2011). These studies often suffer from a lack of practical validity, as they

- include only a single advertising campaign with a limited number of possible allocations to different media;
- are conducted under forced exposure conditions;
- measure responses immediately after exposure to the advertisement.

The current study used real-life data from 34 advertising campaigns for skin and hair-care products brands with a large spread in advertising effort (gross rating points) across Belgian magazines and television channels.

Television and magazines are still the two major media employed for beauty care advertising in the country under study. Most of the beauty care advertising campaigns in the current study did not use online advertising

Most prior real-life data studies have modeled an aggregated relation between cross-media ad spends, on the one hand, and product sales or other measures of return on investment (such as shop visits) on the other (*e.g.*, Färe *et al.*, 2004). The outcomes of these studies usually involve a single optimal media-mix allocation for a given budget level.

Importantly, neither of the latter streams of research (experimental or modeling) have investigated how shifting advertising-effort allocations (gross rating points) between media in a campaign affects campaign effectiveness, and how this impact can be different for campaigns differing in size. The current study addressed these gaps (See Table 1).

Mixture-Amount Models

The type of regression model used in this study was inspired by research in food science and agriculture, where fertilizers and pesticides commonly are used to enhance the yield of a crop, as the fertilizers and pesticides are mixtures of various ingredients. Statistical models for studying the yield of the crop do not only use the amount of fertilizer as an independent variable but also the proportions of the different ingredients.

These models commonly are referred to as “mixture-amount” models, and allow the optimal proportion of the ingredients to depend on the dose of fertilizer or pesticide (Cornell, 2002). Choosing the right amount of fertilizer and the right proportion of the different ingredients given the amount of fertilizer may lead to an improved plant growth (Niedz and Evens, 2011).

Just like farmers and food scientists have to decide on how much fertilizer to use and what its composition should be for an optimal crop yield, advertisers must decide on how much to spend on an advertising campaign and on how to allocate the budget to different media. The authors believe that the effect of a campaign is influenced by the total amount spent on advertising as well as by the allocation of this investment to the different media. So, conceptually in their view, the decision problem of advertisers, on the one hand, and farmers and food scientists, on the other hand, is exactly the same.

The authors of the current paper believe, therefore, that mixture-amount models serve as an useful tool for studying the impact of the advertising budget and its allocation to different media on advertising effectiveness (See “How Mixture Amount Modeling Works,” page tk).

Based on the results of the mixture-amount model, the authors further proposed a measure for synergy effects between different media. An overview of 50 years of media-mix research, argued that, after 1994, the concept of synergy became increasingly important (Assael, 2011):

- Synergy is the interaction of multiple elements in a system (different media) to produce an effect different from the sum of their individual effects.
- Positive synergy is created when investments in multiple media produce an effect greater than the sum of their individual effects.

A large number of studies indicate that marketers can create positive synergy effects by spreading their effort across different media (Chang and Thorson, 2004; Havlena, Cardarelli and De Montigny, 2007; Naik and Raman, 2003; Reynar, Phillips and Heumann, 2010; Vakratsas and Ma, 2005; Voorveld, Neijens and Smit, 2011). At the same time, other studies detect poor (or no) synergistic effects (Frison *et al.*, 2014; Pfeiffer and Zinnbauer, 2010; Wakolbinger, Denk and Oberecker, 2009), or even negative effects (Dijkstra, Buijtels and van Raaij, 2005; Godfrey, Seiders and Voss, 2011; Tsao and Sibley, 2004).

These inconsistencies may be explained by the fact that these various studies only considered potential synergistic effects for very specific combinations of media (which are not necessarily optimal) at a specific level of advertising investment.

By contrast, the largest void in the literature on advertising is research on budgetary-allocation guidelines that can optimize synergistic cross-media effects (Assael, 2011). The current paper contributes to the debate by measuring synergy in the optimal, best possible media mix and by investigating how synergistic effects change for a range of advertising investment levels.

In sum, the proposed mixture-amount model provides additional insights into cross-media effects in a dynamic way. It explicitly allows the optimal media mix to depend on the total advertising effort. Compared to more traditional regression models, mixture-amount models do not only

allow for optimization, but also for simulations to predict responses for different combinations of advertising effort and cross-media allocation.

Further, the estimated mixture-amount models can be interpreted and used for prediction and optimization by means of dynamic prediction profilers available in the software JMP. To the current authors' knowledge, JMP is the only software that is capable of dynamical mixture-amount model visualization. JMP prediction profiler allows to maximize a mixture-amount model response for each change of individual factors.

As such, the current article contributes to the literature on synergistic effects of advertising media, and provides a tool to advertisers to help optimize their advertising investments. Mixture-amount models have been widely used in biology, chemistry, food science, and agriculture. To the authors' knowledge, this paper represents the first application of the mixture-amount modeling approach in marketing.

To illustrate the applicability of the model for advertising planning purposes, the article includes an application involving:

- real-life advertising investment and cross-media allocation data for 34 beauty-care campaigns:
- data on individual consumer responses—campaign recognition and brand interest—to these campaigns.

Using mixture-amount modeling, the authors asked following research questions:

RQ1: How does the allocation of advertising efforts to different media in a campaign affect campaign recognition, and how is this impact different for campaigns differing in size?

RQ2: How does the allocation of advertising efforts to different media in a campaign affect brand interest, and how is this impact different for campaigns differing in size?

RQ3: How does media-mix synergy change for different advertising investment levels?

LITERATURE REVIEW

The advertising literature documents a long tradition of sales-response modeling to quantify the effect of advertising budgets on sales or market shares (Arndt and Simon, 1983; Dekimpe and Hanssens, 1995; Dukes and Liu, 2010; Gatignon and Hanssens, 1987; Longman, 1971; Porter, 1976; Wright, 2009). Establishing this relationship, however, is not easy: "There is no more difficult, complex, or controversial problem in marketing than measuring the influence of advertising on sales" (Bass, 1969).

The problem becomes even more difficult when modeling not only the effect of the total advertising effort, but also including the effect of the allocation of this effort to different media (*e.g.*, Danaher and Dagger, 2013; Dekimpe and Hanssens, 1995).

A few studies have tried to include allocation considerations by:

- analyzing the optimal resource allocation to advertising and sales force (Gatignon and Hanssens, 1987; Gopalakrishna and Chatterjee, 1992);
- creating an empirically validated model of how national and regional advertising generate sales over time for a cosmetics brand (Aravindakshan, Peters and Naik, 2012) in which profit was derived by maximizing total budget, its optimal split between national and regional spends, and its optimal allocation across multiple regions;
- developing a model to optimize advertising and promotion efforts, which explicitly includes interactions between advertising and promotion, and interactions between actions of competitive brands (Naik, Raman and Winer, 2005)

These studies do not, however, consider allocations to different media. One study did develop an advertising response model to determine the optimal budget allocation across 10 different media, based on clients' self-reported media exposure in an online questionnaire (Danaher and Dagger, 2013). Another examined the relative effectiveness of 11 media in terms of respondents' purchase intention after being exposed to a hypothetical advertising scenario in a survey (Danaher and Rossiter, 2011). Neither of these two studies, however, addressed potential interactions or synergy effects between the different media.

Quite recently, a large number of studies have been devoted to studying interactions or synergy between different media. This research has yielded inconsistent results: The majority of the studies indicated that advertising campaigns involving multiple media produce better results than campaigns using a single medium—*i.e.* they find a positive synergistic effect (Chang and Thorson, 2004; Havlena, Cardarelli and De Montigny, 2007; Naik and Raman, 2003; Naik, Raman and Winer, 2005; Reynar, Phillips and Heumann, 2010; Vakratsas and Ma, 2005; Voorveld, Neijens and Smit, 2011).

One experiment found that showing an advertisement on both television and the Internet was superior to repeating that advertisement in either of the media in terms of attention, perceived message credibility, and number of total and positive thoughts (Chang and Thorson 2004). In another experimental study, exposure to cross-media advertising (television and the Internet) resulted in a more positive attitude toward the brand; the attitude toward the television commercial; and purchase intention than repetitive single-medium exposure (television or the Internet) (Voorveld, Neijens and Smit 2011).

Still another study optimized media spending and allocations of the advertising budget for consumer packaged goods across a variety of media to maximize revenues and profits. The results supported the existence of positive synergy effects, through the indirect effect one medium has on another (Reynar, Phillips and Heumann 2010) And, another piece of research demonstrated that sales for Dockers clothing benefited from positive synergy between magazine and television advertising (Naik and Raman 2003).

These studies derived optimal levels for advertising spending in both magazines and television advertising, and offered a number of propositions concerning the synergy between media. And the authors of the current paper believe that their proposed model is generalizable to more media.

At the same time, other studies have detected poor or no multimedia synergistic effects (Pfeiffer and Zinnbauer, 2010; Wakolbinger, Denk and Oberecker, 2009) or even negative effects—*e.g.*, cannibalization (Dijkstra, Buijtels and van Raaij, 2005; Godfrey, Seiders and Voss, 2011; Tsao and Sibley, 2004).

One such investigation reported positive synergy between television and print advertising measuring on traditional brand metrics and positive perceptions of the brand for a consumer packaged good, but found few or no synergy effects when online banner advertising was added to the media mix (Havlena, Cardarelli and De Montigny 2007). And an experimental study demonstrated the superiority of television-only campaigns over multiple-media campaigns in evoking cognitive responses, adding that print-only campaigns are as effective as multiple-media campaigns for most responses (Dijkstra, Buijtels and van Raaij 2005).

The conflicting evidence between these different studies may be due to the fact that most only considered potential synergistic effects for very specific combinations of media (which are not necessarily optimal) at a specific level of advertising investment. For example, the experimental studies that included two media confronted respondents with one advertisement in each medium, resulting in a 50/50 allocation.

In reality, however, brand managers can choose any possible allocation between the media. The optimal media-mix and synergistic effects also are likely different for smaller and larger campaigns. Although some media-mix modeling papers have included a discussion on the total budget (Naik and Raman, 2003), the authors believe that their mixture-amount regression model in this paper is the only model that explicitly includes the interaction between the total advertising effort and its allocation across media, thereby allowing to derive multiple optimal allocations in function of the total advertising effort.

As a result, the method also allows for investigating how synergistic effects change for a range of advertising investment levels.

TABLE 1
Main Differences among Related Studies

Features	Gopalakrishna and Chatterjee (1992)	Naik and Raman (2003)	Bruce, Foutz and Kolsarici (2012)	Danaher and Dagger (2013)	Current study
Interactions	Sales force by advertising	Print by television advertising	WOM by advertising	Sales force by advertising	Print by television advertising
Estimation method	Nonlinear least squares regression	Kalman filter estimation	Bayesian dynamic linear model	Type II Tobit model	Mixture-Amount Model
Investigates effects of interaction on	No	Yes	Yes	Yes	Yes

optimal decisions					
Cross-validation	No	Yes	Yes	No	Yes
N-media generalization	No	Yes	No	Yes	Yes
Number of brands in dataset	1	1	360	1	13
Synergy changes for a range of advertising efforts	No	No	No	No	Yes

METHODOLOGY

How Mixture-Amount Modeling Works

Various types of mixture-amount models have been proposed to model the impact of mixture composition and mixture amount on a dependent variable (Cornell, 2002). Suppose a mixture has q ingredients, and denote the proportion of the ith ingredient by x_i and the total amount of the mixture by A. To model linear and nonlinear blending among the q mixture ingredients, a suitable mixture-amount model is…

$$\eta = \sum_{i=1}^{q} \beta_i x_i + \sum_{i=1}^{q-1} \sum_{j=i+1}^{q} \beta_{ij} x_i x_j + A(\sum_{i=1}^{q} \gamma_i x_i + \sum_{i=1}^{q-1} \sum_{j=i+1}^{q} \gamma_{ij} x_i x_j),$$

Equation (1)

… where η represents an outcome, the regression coefficients β_i and β_{ij} can be viewed as the base effects of the mixture composition, and γ_i and γ_{ij} represent the interaction effects of the amount A with the mixture's composition (*i.e.*, how the amount affects the effects of the mixture composition).

The mixture-amount model in Equation (1) is a special type of regression model, involving several terms that capture interaction effects between different ingredients and interaction effects between the total amount and the ingredient proportions. This allows the optimal values of the proportions to depend on the total amount. Regression models for mixture data, such as the model in Equation (1), do not explicitly include an intercept because the sum of all ingredient proportions equals 1. This fact is well documented in literature concerning regression models tailored to data involving mixtures, (Scheffé, 1958).

Mixture-amount models mainly are used for prediction and optimization of the optimal proportions of the ingredients for any given total amount (Cornell, 2002). The focus on prediction is, to a large extent, due to the high degree of multicollinearity in data sets involving mixtures. As a matter of fact, the different proportions cannot be changed independently: When one proportion goes up, at least one other proportion has to go down, since all proportions always sum to 1. This

makes the usual significance tests for individual coefficients, which implicitly assume that all the regression coefficients can be interpreted independently, essentially meaningless.

In the context of advertising, q corresponds to the number of media types used and x_i corresponds to the proportion of advertising in the ith medium, for example:

- x_1 = proportion of advertising spent on television,
- x_2 = proportion of advertising spent in magazines,
- x_3 = proportion of advertising spent on the Internet.

The amount is a measure of the total amount of advertising (*i.e.*, the advertising budget for the campaign). The mixture-amount modeling approach, the current authors believe, is generic and can be used for any number of media and any range of budgets.

The Data

The authors collected advertising-investment data and consumer responses for 34 skin and hair-care (shampoo, facial cream, soap) campaigns that ran in magazines and/or on television in Belgium between June and December 2011 (thus, in this dataset, there are two media, television and magazines, so that $q = 2$) (See Table 2). Eighteen campaigns ran in Flanders (the northern, Dutch-speaking part of Belgium); the remaining 16 ran in Wallonia (the southern, French-speaking part of Belgium). The campaigns involved 13 brands from four mother brands (*e.g.*, the brands Youth Code and Revitalift from the mother brand L'Oréal Paris). Some brands had multiple campaigns in the tested period, and were included several times.

To quantify the advertising effort in each campaign, the authors used Gross Rating Point (GRP) indicators. A GRP is the number of contacts of a campaign expressed as a percentage of the target audience (De Pelsmacker, Geuens and Van den Bergh, 2010). GRPs are more suitable to measure advertising effort than campaign budgets, because the latter are biased by the discounts offered by media companies that typically vary across campaigns, brands, and media. GRPs were calculated for magazine and television campaigns in the six weeks preceding the data collection (this represents the "amount" A). For each campaign, data were available on the number of GRPs invested in television advertising and in magazine advertising. The GRP values for the campaigns under study ranged from 9.2 to 624.4.

As dependent variables, the authors used two consumer responses, namely campaign recognition and brand interest. These responses were collected from individual respondents through a survey conducted by GfK, a market research agency.

As the selected campaigns involved skin and hair products for women, the respondents in the study were women randomly selected between the ages of 20 to 50 years (the target group for these products), a group that was representative of the Belgian population in terms of education and social class. The data were collected at five different time points, which the authors referred to as "waves". The measurements were spread over time to obtain a larger selection of campaigns. In each wave, about 500 different respondents were recruited for both Flanders and Wallonia to evaluate between two and four campaigns. In total, the analyzed dataset contains 177,93 responses from 4,399 respondents, 2,135 of which were Flemish.

TABLE 2
Snapshot of the Available Data

Campaign	Brand	Mother Brand	Region	Wave	GRPs invested	x_{mag}	x_{TV}	Respondent ID	Campaign Recognition	Brand Interest
1	1	1	Flanders	1	95.6	.21	.79	1	1	4
1	1	1	Flanders	1	95.6	.21	.79	2	0	1.1
…	…	…	…	…	…	…	…	…	…	…
2	2	1	Flanders	1	409.0	.12	.88	1	0	4
3	3	2	Flanders	1	227.4	0	1	1	1	4
4	4	2	Flanders	2	497.8	.40	.60	505	1	5
5	5	3	Flanders	2	385.4	.20	.80	512	0	3.8
8	1	1	Flanders	3	374.5	.21	.79	1,023	1	4.9
18	12	3	Flanders	5	48.8	1	0	2,356	0	6.5
…	…	…	…	…	…	…	…	…	…	…
19	1	1	Wallonia	1	9.2	1	0	2,588	0	4.4
20	2	1	Wallonia	1	255.6	.13	.87	2,588	0	4.5
22	11	4	Wallonia	4	190.6	.28	.72	4,005	1	3.3
34	13	1	Wallonia	5	624.4	0	1	4,690	1	5.6

Campaign recognition is a binary variable indicating whether or not a campaign was recognized by the respondent (as self-reported during the survey). The binary response variable takes the value 1 if a respondent reported she recognized the campaign and 0 otherwise (See Table 2). Brand interest was measured using a 10-item, 7-point Likert scale, including, for example,

- "This campaign has led me to pay more attention to the brand in the store";
- "This campaign has encouraged me to try the brand.".

To obtain a single score for brand interest, respondents' scores were averaged across the 10 items. This is justified by a factor analysis that showed that 95 percent of the total variance was captured by a single factor ($\alpha = 0.97$). As a result, the study includes one binary response variable (campaign recognition) and one metric response variable (brand interest).

The Method

The specification of the mixture-amount model utilized in this study:

- recognized that advertising in magazines and on television might have a different impact;
- allowed for a possible interaction effect between magazine and television advertising (*i.e.*, allowed for a (positive or negative) synergistic effect);
- allowed for a possible interaction effect between the amount of advertising and the proportion of magazine or television advertising.

Therefore, addressing RQs 1 and 2, the model can be used to determine an optimal media-mix allocation for each advertising amount, including interpolation to advertising amounts not present in this dataset.

The model also included a fixed effect to allow for different intercepts between the northern and southern parts of Belgium. To capture all the dependencies between responses in the data, the authors included a number of random effects in the mixture-amount model.

- Random effects were included to control for the fact that the data include measurements at different points in time (*e.g.*, to capture seasonal effects).
- Similarly, random effects were included to model the dependency between answers from the same respondent and to capture the dependency between all answers for the same campaign and for the same brand. Hence, the authors adopted a multilevel generalized linear model (GLM) approach when estimating the mixture-amount model for campaign recognition and brand interest.

Multilevel GLMs have linear predictors that consist of two parts: a systematic part and a random part (Hardin and Hilbe, 2012):

$$\eta = \eta_{sys} + \eta_{random}.$$

Equation (2)

In order to answer RQ1, for the campaign-recognition response model, the authors used the logit-link function and assume a binomial distribution for the response. In order to answer RQ3, for the brand-interest response, the authors used the identity link function and assume a normal distribution (Hardin and Hilbe, 2012). The systematic part of the linear predictor in the authors' GLM models for campaign recognition and brand interest is given by…

$$\eta_{sys} = \beta_{mag} x_{mag} + \beta_{TV} x_{TV} + \gamma_{mag} x_{mag} A + \gamma_{TV} x_{TV} A + \beta_{\text{int}} x_{mag} x_{TV} + \gamma_{\text{int}} x_{mag} x_{TV} A + \theta d_{region},$$

Equation (3)

… where x_{mag} and x_{TV} represent the proportions of magazine and television advertising (note that the sum of these proportions is always 1), A is the natural logarithm of the GRP value, and d_{region} is a dummy variable that indicates the region (See Table 2).

A feature of the linear predictor used in this paper is that the authors did not consider interaction effects with the region dummy variable. This is due to the limited number of campaigns in the data set, which did not allow the estimation of different regression coefficients for each region. Therefore, in this study, the optimal media mix allocations the authors determined were identical for both regions.

In order to answer RQ3, a synergy coefficient (ς_m) was developed that indicates the synergistic effects of optimally combining the two advertising media in campaign differing in size, explained further in Results.

RESULTS

Using mixture-amount modeling, the authors tested how the allocation of advertising efforts to different media in a campaign affects campaign recognition and brand interest, and how this impact is different for campaigns differing in size. Additionally, they explored how media mix synergy changes for different advertising investment levels.

To assess the goodness-of-fit of the campaign-recognition model based on Equation (3), the authors used a 5-fold cross-validation. Cross-validation has become a standard method in predictive modeling to avoid overfitting and to acquire a nearly unbiased estimate of the future error rate (Efron and Tibshirani, 1997). Five-fold cross validation procedures use five training samples and five holdout samples.

The resulting receiver-operating characteristic (ROC) area under the curve (AUC) is 0.74, which indicates a fair model performance (Pepe, 2000; Vitacco *et al.*, 2009). To measure the performance of the brand-interest model, the authors used a concordance-correlation coefficient (ρ_c), which is employed in mixed models as a substitute of R^2. The ρ_c value for the brand interest response equals 0.74, which indicates a good fit (Vonesh, Chinchilli and Pu, 1996).

The authors interpreted the estimated regression models for campaign recognition and brand interest in a graphical fashion using the prediction profiler embedded in the software package JMP. The prediction profiler visualizes the change in the predicted responses as a function of the GRP amount and the media-mix allocation, and allows the exploration of the interaction (synergy) effects for various scenarios.

It is an interactive tool that can be used to optimize the dependent variable for a given GRP amount, and to investigate to what extent the response value deteriorates if one deviates from the optimal media-mix allocation.

The authors created graphs (See Figures 1-4) in which the vertical axis represented either the probability of campaign recognition (expressed as a percentage), or the level of brand interest (on a 7-point scale).

Below, the authors describe the two mixture-amount models (Campaign Recognition and Brand Interest), for different GRP levels, obtained from the SAS procedures GLIMMIX and MIXED (See Figures 1-4)

Campaign Recognition
Addressing the first research question:

> **RQ1: How does the allocation of advertising efforts to different media in a campaign affect campaign recognition, and how is this impact different for campaigns differing in size?**

For a campaign in Wallonia (Region = 0) with a campaign weight of 200 GRPs, an allocation of 40 percent (80 GRPs) to magazine advertising and 60 percent (120 GRPs) to television advertising led to the highest possible campaign recognition probability, in this example 57 percent (See Figure 1). Any other allocation of magazine and television advertising led to a smaller recognition probability and, as a result, demonstrated a presence of positive synergistic effect. For Flanders, the predicted campaign recognition using the same GRP value and media-mix allocation would be 48 percent.

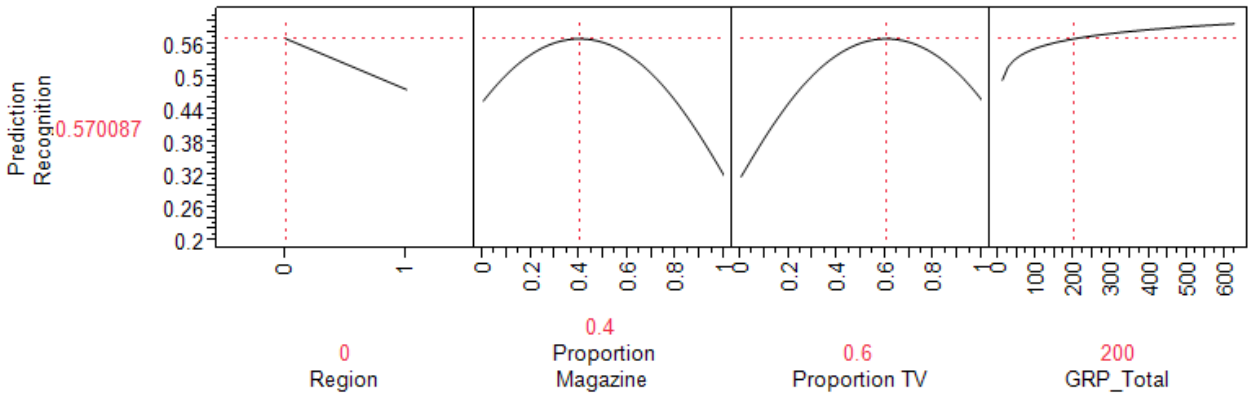

FIGURE 1
Optimal media-mix allocation for campaign recognition in Wallonia when the advertising budget is 200 GRPs.

In Figure 1, the horizontal axis shows the levels of the four explanatory variables in the mixture-amount model:

- The left panel shows the effect of the region dummy variable (where "0" referred to Wallonia and "1" referred to Flanders).
- The second panel from the left shows the impact of the proportion of magazine advertising.
- The third panel shows the effect of the proportion of television advertising (recall that together, these three proportions sum up to 100 percent).
- The final (right) panel visualizes the effect of the total advertising investment expressed in GRPs.

In each of the above panels, dashed vertical lines indicate the selected levels of the explanatory variables (which can be dragged dynamically when using the software package). The solid convex lines in the middle two panels show how the value of the dependent variable changes as a function of the allocation of campaign spends to television and magazines.

The researchers found that when the advertising budget increased from 200 GRPs to 620 GRPs, the optimal investment proportions to magazines and television changed. Indeed, the proportions 20 percent and 80 percent turned out to be optimal for magazine and television advertising, respectively (See Figure 2). For Wallonia, this resulted in a predicted campaign recognition probability of 61 percent.

Comparing the results for a GRP value of 200 and for a GRP value of 620, a larger proportion of the campaign budget should be allocated to television advertising for a larger GRP value. For Flanders, the predicted probability of campaign recognition was 52 percent for a GRP value of 620, assuming the same optimal media-mix allocation is used.

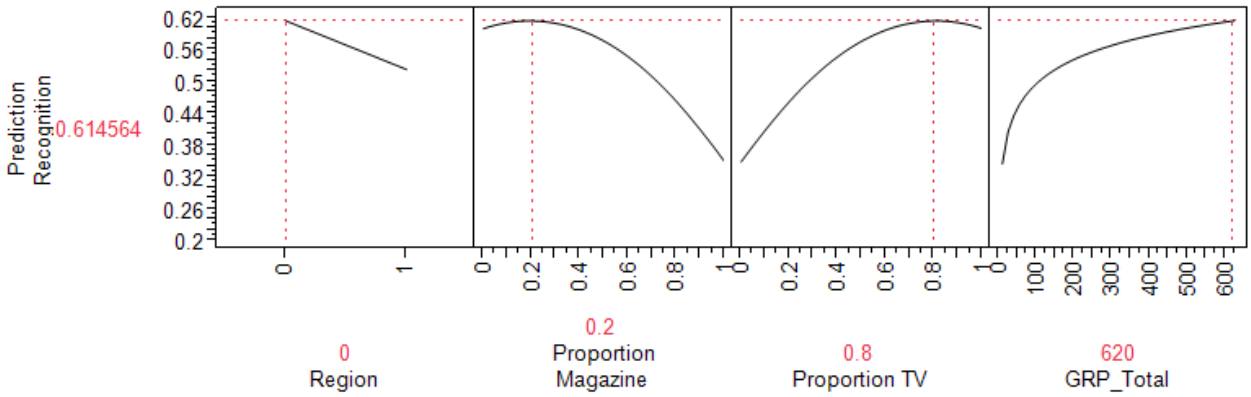

FIGURE 2
Optimal media-mix allocation for campaign recognition in Wallonia when the advertising budget is 620 GRPs

Brand Interest

Addressing the second research question:

> **RQ2: How does the allocation of advertising efforts to different media in a campaign affect brand interest, and how is this impact different for campaigns differing in size?**

For a campaign in Wallonia with a weight of 200 GRPs, a proportion of 34 percent for magazine advertising and 66 percent for television led to the highest level of brand interest, with a score of 3.91 (See Figure 3). For Flanders, the predicted brand interest in this scenario was 3.65 (out of 7).

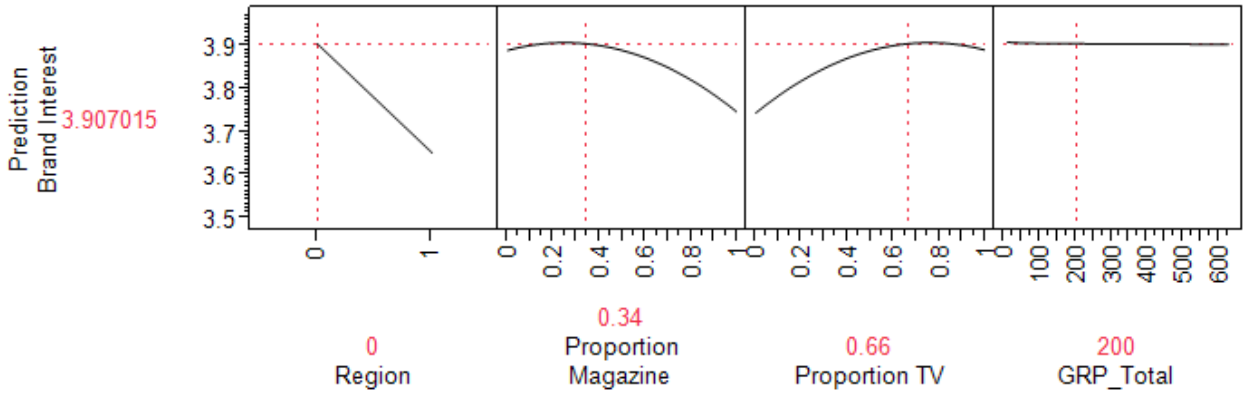

FIGURE 3
Optimal media-mix allocation for brand interest in Wallonia when the advertising budget is 200 GRPs

Given an allocation of 34 percent for magazines and 66 percent for television, there was no point in increasing the total budget (See Figure 3). All possible GRP levels resulted in a score of 3.9 for brand interest under the 34/66 allocation. When the advertising budget increased from 200 GRPs to 620 GRPs, for a campaign in Wallonia, the optimal media-mix allocation changed to 50

percent for magazine and 50 percent for television advertising. For Wallonia, this resulted in a predicted brand interest of 3.92 (See Figure 4). Under the new allocation scheme, it was useful to invest more. For Flanders, the predicted brand interest level was 3.67 when 620 GRPs were used, along with 50/50 allocation to television and magazines.

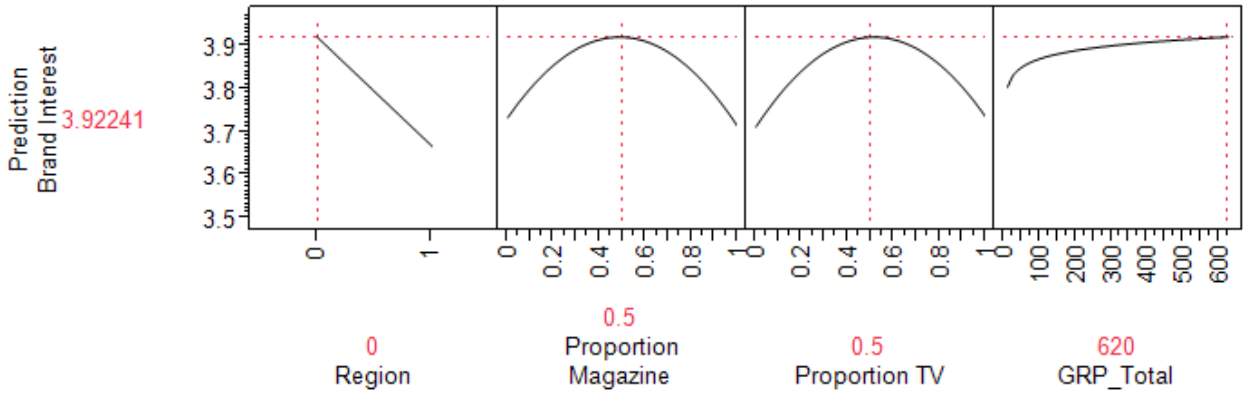

FIGURE 4
Optimal media-mix allocation for brand interest in Wallonia when the advertising budget is 620 GRPs

A Measure for the Synergistic Effect

Addressing third research question:

RQ3: How does the media mix synergy change for different advertising investment levels?

The study's results showed that, when the goal was to maximize campaign-recognition probability and the level of brand interest, it is generally best to use both magazine advertising and television advertising.

To measure the synergistic effect between these two types of advertising, the authors proposed a synergy coefficient (ς_m), defined as the difference between the value of the dependent variable for the optimal media mix and the average of all scenarios involving single medium investments.

The mathematical expression for the synergy coefficient, which can be calculated for any given GRP value, is…

$$\varsigma_m = \tau_{opt} - \frac{\sum_{i=1}^{q} \kappa_i}{q},$$

Equation (4)

… where τ_{opt} represents the value of the dependent variable for the optimal media-mix allocation, and κ_i represents the value of the dependent variable if the entire campaign budget is invested in medium i.

As an illustration, the authors calculated the synergy coefficient for campaign recognition, based on the mixture-amount model estimates. Recall the optimal media mix (40 percent of magazine advertising, 60 percent of television advertising) resulted in a predicted campaign recognition probability of 57 percent (See Figure 1). Thus it is clear that, if an advertiser were to fully allocate the 200 GRPs to magazine advertising, the predicted recognition probability would be merely 32 percent. If the 200 GRPs were fully invested in television advertising, the predicted recognition probability would be 46 percent.

Therefore, the synergy coefficient for campaign recognition under this scenario is equal to

$$\varsigma_m = 0.57 - \frac{0.32 + 0.46}{2} = 0.18..$$

Equation (5)

The synergy coefficient for the same scenario is equal to 0.09 for the brand interest measure.

This means that, in the given scenario, by spreading their efforts across magazine and television advertising according to the optimal media mix derived by the mixture-amount model, advertisers can increase the probability of campaign recognition by 18 percent and brand interest by 0.09 points, compared to when they would invest all of their GRPs either on television or in magazines. When the advertising budget is 620 GRPs, the media-mix synergy coefficient is 14 percent for campaign recognition probability and 0.20 points for the brand interest score.

To show how the synergistic effect changes as a function of the total advertising investment, the authors calculated the synergy coefficient for the entire range of GRP values in the dataset, using the results from the prediction profiler outputs. The synergy for campaign recognition dropped from about 33 percent to 14 percent as the invested GRPs increased (See Figure 5). And the curve for 200 GRPs is indeed more convex than the one for 620 GRPs (See Figures 1 and 2).

For 620 GRPs (the maximum in the current dataset), the difference in campaign-recognition probability between 100 percent of television advertising and the optimal media-mix allocation is small. For 200 GRPs, this difference is noticeably larger. This difference is numerically captured in the synergy coefficient.

For brand interest, the authors observed a positive relationship between the synergy coefficient and the GRP value (See Figure 6). As mentioned above, for 200 GRPs, the synergy coefficient is 0.09, and it increases to 0.20 for campaigns of 620 GRPs.

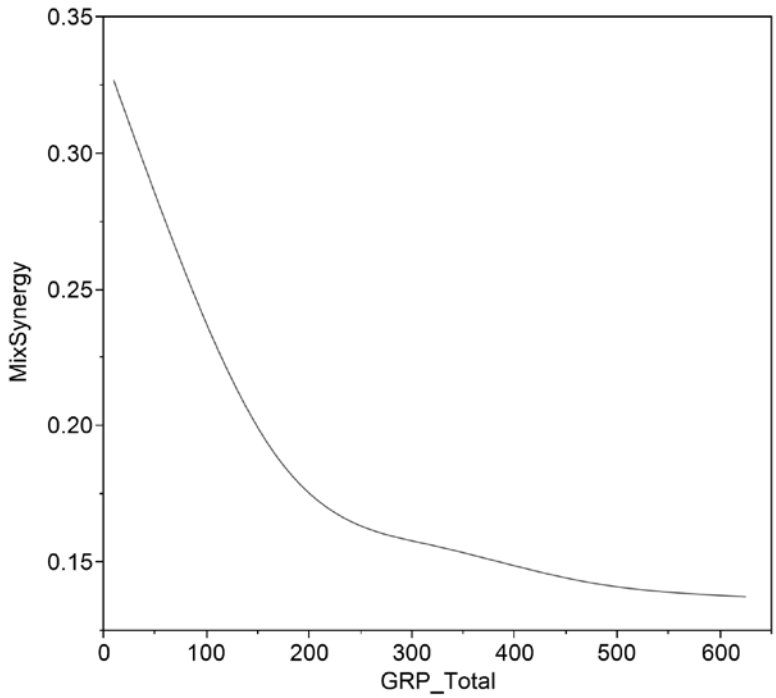

FIGURE 5
Synergy coefficient for campaign recognition as a function of the GRP value

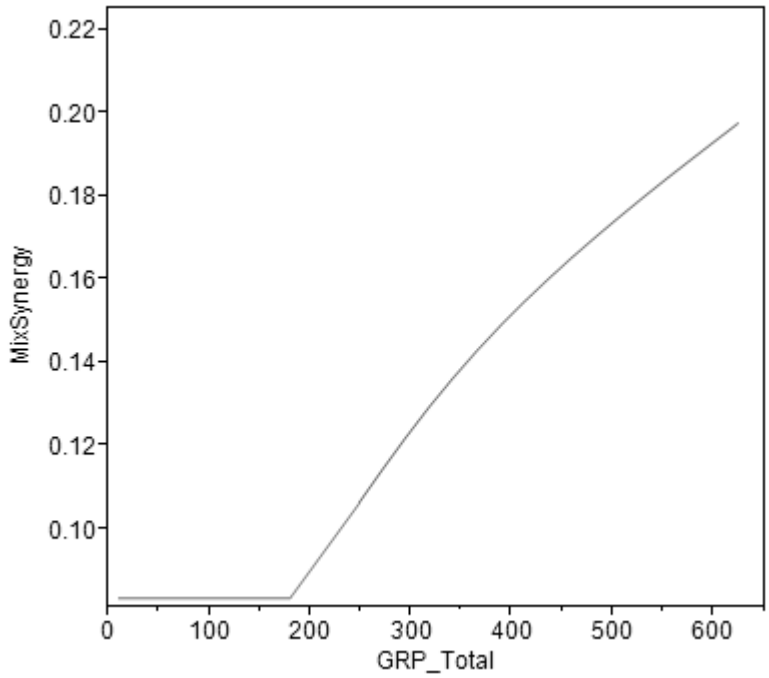

FIGURE 6
Synergy coefficient for brand interest as a function of the GRP value

DISCUSSION AND CONCLUSIONS

The current article proposes a mixture-amount modeling approach for advertisement investment optimization. The researchers applied the approach to determine optimal cross-media investments to maximize campaign recognition and brand interest based on beauty care data.

The results for the given dataset demonstrated that both brand interest and the probability of campaign recognition increase with the number of GRPs used. The positive effect of adding additional GRPs, however, is greater for campaign recognition than for brand interest. This could be due to the fact that the brands used in the current study were all well-known global brands. Attitudes toward established brands are stable and hard to affect through advertising (Machleit, Allen and Madden, 1993; Mazodier and Merunka, 2012) because consumers already are familiar with the brand and have formed expectations regarding its advertising (Alden, Mukherjee and Hoyer, 2000; Dahlén and Lange, 2005). Therefore, adding additional GRPs to a campaign unlikely would affect brand interest.

The optimal media mix also is different for brand interest and campaign recognition. With increasing budgets, campaign recognition benefits from a greater focus on television advertising, while brand interest benefits from a relatively larger share of magazine advertising.

Several possible explanations exist for this difference:

- Television is believed to lead to a more intense visual stimulation, which benefits memory (Leigh, 1991).
- At the same time, television advertising may be negatively perceived and has the highest score on irritation (Bronner and Neijens 2006). This may reflect negatively on brand interest.
- Compared to television, magazine advertisements are more self-paced, providing readers with an opportunity to more thoroughly process specific information in advertising (Speck and Elliott, 1997).
- Although magazine advertisements, in general, may not be so vivid as to be remembered, they may do a better job at stimulating brand interest. This may be the reason why the optimal media mix involves a larger proportion of magazine advertising for brand interest than for campaign recognition.

The results of the study suggest that increasing the proportion spent on television advertising raises campaign recognition, but at the same time lowers brand interest. Conversely, a relatively larger proportion of advertising effort in magazines has a negative impact on campaign recognition, but enhances positive impact on brand interest.

Additionally, the results also show that the optimal media mix changes as a function of the total number of GRPs invested. This result is new to the literature.

Consistent with the majority of previous studies (*e.g.*, Havlena, Cardarelli and De Montigny, 2007; Reynar, Phillips and Heumann, 2010; Vakratsas and Ma, 2005), the results of the current study support the existence of a positive synergistic effect between television and magazine advertising.

There are three main explanations for positive media-mix synergy effects:

- Different media may attract a different target audience, therefore increasing the reach of a campaign (Havlena, Cardarelli and De Montigny, 2007).
- Some studies relate synergy to audience duplication between media and to enhanced repetition (Havlena, Cardarelli and De Montigny, 2007; Schumann, Petty and Clemons, 1990).
- There is ample evidence that people frequently consume several media (simultaneously)—including using online- and mobile-based platforms—(Lin, Venkataraman, and Jap, 2013) and advertisers exploit this by using multiple channels to increase the frequency of a campaign. Heavy users of one medium tend to be heavy users of many media (Enoch and Johnson, 2010). Therefore, they are exposed more frequently to the same advertising campaign in different media.

The third explanation of synergy also is related to the different cognitive processing of different types of stimuli and its reinforcing effect on advertising outcomes. Media contribute differentially to the route to persuasion and in that sense complement each other (Dijkstra, Buijtels and van Raaij, 2005).

The dual-coding principle (Paivio, Clark and Lambert, 1988) asserts that verbal and non-verbal systems process information using two different cognitive subsystems, one for language (verbal information, such as words) and one for non-verbal objects (*e.g.*, pictures, motion). Because more resources are activated to process both the verbal and the nonverbal information, processing will be more extensive when two representation formats (*e.g.*, television and magazine advertising) are used than when only one is used.

Three psychological processes that contribute to positive synergy for cross-media campaigns, particularly the first two of the three cited below (Voorveld, Neijens and Smit (2011):

- forward encoding (*i.e.*, the advertisement in the first medium primes interest in the advertisement in the second medium);
- multiple-source perception (*i.e.*, believing the brand is good and popular because of the amount of advertising);
- image transfer (*i.e.*, mentally replaying the ad previously viewed during exposure to the ad in the second medium).

The synergy results uncovered in the current dataset are opposing for campaign recognition and brand interest: While the synergy for campaign recognition drops as the invested GRPs increase, the synergy for brand interest increases with the GRP value. The decrease in synergy for campaign recognition for larger campaigns may be explained by ceiling effects: Larger campaigns more likely would be noticed, but at some point, everyone who would notice the campaign would have noticed it in either of the media, and so the added value of optimizing the allocation across the two media would decrease.

As noted also, campaign recognition requires a fairly large share of television advertising either way, and for large campaigns, the optimum amounts to 80 percent. The difference in recognition with campaigns that would invest 100 percent on television, is small (See Figure 2). For smaller

campaigns, more can be gained by lowering the proportion of television advertising, and truly finding the optimal media mix becomes more important.

In terms of brand interest, advertisements in two media can be complementary, which may be explained by dual coding theories (Sadoski and Paivio, 2012). In that case, increasing the amount of GRPs can increase the chance that consumers notice the advertisements in both media, and this produces the strongest effects on brand interest.

IMPLICATIONS AND FUTURE RESEARCH

Mixture-amount models have the potential to assist advertisers in deciding how much to spend on advertising campaigns and how to allocate these efforts across media to maximize campaign effectiveness. The major advantage of mixture-amount models over existing media-mix models is the possibility to identify the optimal media mixes for different levels of advertising effort. A key feature of the models is that they quantify to what extent the optimal allocation of advertising efforts changes with campaign weight.

To the authors' knowledge, there currently are no other models that capture such effects. The prediction profiler offers an easy-to-use tool for advertisers to dynamically simulate the effects of different advertising efforts and media mixes. A global survey by McKinsey & Co. (Doctorow, Hoblit, and Sekhar, 2009) reported that advertisers tend to allocate spending based on historical allocations and rules of thumb far more than quantitative measures. The optimization of the media mix is especially important because the optimal allocation of advertising effort across media could boost campaign recognition by up to 33 percent, and can improve brand interest scores by up to .19 scale points in the current dataset. Some even have suggested that an optimal allocation can enhance a firm's profitability by as much as 400 percent (Raman *et al.* 2012).

When considering the spread in media allocation in the current dataset, it is obvious that, in practice, a number of advertisers still bet on single-media campaigns, thereby foregoing potential positive synergy effects.

The results presented in this paper illustrate that the optimal media mix, indeed, differs greatly depending on the total advertising effort, a fact that advertisers should take into account when planning advertising campaigns.

In addition, the optimal allocation also largely depends on the objective of the campaign. For small budgets, when the objective is to boost campaign recognition, a substantial part of the budget should be allocated to magazine advertising. For larger budgets, the largest share should be spent on television. Future research could use the same model to determine allocations for online advertising and other media, the current authors believe.

If brand interest is the primary objective, increasing the budget has a relatively small effect, but for larger budgets, a more substantial share should be spent on magazine advertising. Importantly, although the results derived based on this particular dataset are not necessarily generalizable, the model can be estimated in other contexts and with more or different types of media as well.

In general, the model should be tested further to investigate to what extent the results are context-specific or media-mix specific, and to what extent they can be generalized to different products, countries and target groups. Due to a limited availability of data, the illustration of the model applicability presented in the current study includes television and magazine advertising only. While this may be justified by the fact that television and magazines are still the two major media employed for beauty-care advertising in the country under study, further research should try to expand the model with other media, such as radio, newspaper and/or the Internet—and other product categories.

Especially given the increasing importance of online advertising today (Peterson, 2014), the Internet is a medium that should be taken into account. Although the current authors have argued that GRPs ought to be preferred over advertising budgets as a measure of campaign weight, studies could also consider starting from advertising budgets.

At the same, the use of GRPs as an input variable also represents a limitation of the application presented here. GRPs are an indication of "campaign weight" and are defined as reach times frequency. Therefore, it is not possible to disentangle the effects of reach and frequency on advertising responses in the current dataset.

In future research, the authors also intend to study other advertising effectiveness measures, such as:

- word-of-mouth effects;
- brand attitudes;
- purchase intention and moderating effects of consumers' media usage and product category experience.

The authors selected campaign-recognition and brand-interest evaluations because these are important process variables that often are measured in campaign evaluation research. Moreover, research based on traditional hierarchy-of-effects models and on the theory of planned behavior shows that cognitive or memory responses (*i.e.*, campaign recognition) and evaluative responses (*i.e.*, brand interest) often are antecedents of buying behavior, and thus predictive of sales (Ajzen, 1991; Barry, 1987).

Most existing advertising-response models are calibrated on sales data (*e.g.*, Danaher and Dagger, 2013; Luan and Sudhir, 2010). The research team did not have access to such data, but mixture-amount models could be applied to all sorts of possible binary, categorical, or continuous dependent variables.

Obviously, campaign effectiveness also depends on considerations other than advertising budgets and media allocation. Future research should try to include these other factors, such as advertising creativity, originality, the quality of advertising executions, or specific information or selling propositions used. For instance, the inclusion of a price level or promotion may have an impact brand interest or other advertising outcomes, such as buying intention (Zoellner and Schaefers, 2015). A content analysis shows that none of the campaigns in the current sample mentioned a price or promotion. Nevertheless, future research should try to control for the potentially confounding effects of different advertising executions.

The model presented in this article allows to capture individual brand campaign differences using random effects, but it is not clear how specific campaign properties affect synergy: How will a more creative campaign execution on television and/or in magazines affect synergy and optimal media-mix allocation? Certain outcomes, such as brand interest or purchase intention, also could be indirectly affected by other responses to the advertisements, such as advertisement likeability. It might be useful, therefore, to explore the possibilities of using mixture-amount models in mediation frameworks to better understand the mechanism behind the effects found.

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