How consumers' media usage creates synergy in advertising campaigns

Reference:
Dens Nathalie, De Pelsmacker Patrick, Goos Peter, Aleksandrovs Leonids, Martens David.- How consumers' media usage creates synergy in advertising campaigns
International journal of market research / Market Research Society [London] - ISSN 1470-7853 - 60:3(2018), p. 268-287
Full text (Publisher's DOI): https://doi.org/10.1177/1470785317751333
To cite this reference: https://hdl.handle.net/10067/1494020151162165141

HOW CONSUMERS' MEDIA USAGE CREATES SYNERGY IN ADVERTISING CAMPAIGNS

Aleksandrovs, L.

Dens, N.

De Pelsmacker, P.

Goos, P.

Martens, D.

ABSTRACT

This study proposes a novel methodology, Mixture Amount Modeling (MAM), to investigate cross-media advertising synergy based on consumers' media usage. MAM allows to derive optimal media mixes that can be different for different types of media users. The authors provide a proof of concept by analyzing 46 852 responses to 92 beauty care advertising campaigns from 10 972 respondents from the Netherlands, Belgium, Finland and Hungary, and demonstrating the impact of consumers' combined magazine, television and Internet usage (i.e., how intensively they use media overall, and the relative proportion of each individual medium) on their campaign-evoked brand interest, perceived brand equity and purchase intention for advertised brands. The results suggest that different patterns of consumer media usage result in different responses to advertising campaigns.

INTRODUCTION

In media mix research, the concept of synergy has become increasingly important (Assael 2011). Positive synergy is created when the combined use of two or more media results in a more positive outcome (e.g., higher sales) than single media use; negative synergy (cannibalization) occurs when single media use leads to more positive outcomes than combined media use. Synergy may occur when advertisers invest in multiple media to attempt to enhance the reach and/or the contact frequency of their advertising campaigns (e.g. Aravindakshan *et al.* 2012; Raman *et al.* 2012). Alternatively, synergy may be the result of consumers using different media, as a result of which they can be confronted with advertising in these media (e.g. Enoch & Johnson 2010; Schultz *et al.* 2012; Lin *et al.* 2013). The current study investigates the latter, i.e., synergies created by consumers' media usage.

Several authors have identified the measurement of interactions between media at the consumer levels as an important research topic (Pilotta & Schultz 2005; Wendel & Dellaert 2005; Enoch & Johnson 2010; Schultz *et al.* 2012). Most studies on synergy due to consumers' media usage are experimental, exposing people to advertising stimuli in different media and measuring their responses in terms of attitudes and behavioral intentions (e.g., Danaher & Rossiter 2011; Voorveld *et al.* 2011). These studies often include a single advertising campaign involving a single combination of media. Most of these studies have investigated the effects of combining two media (e.g., radio and television), only a few examined the combination of three or more media (e.g., Chatterjee 2012). In addition, many of the existing studies suffer from a lack of ecological validity, as they are conducted under forced exposure conditions and measure responses immediately after ad exposure.

The present paper shows how synergy effects between three different media (magazines, television and the Internet) depend upon consumers' overall media usage. To this end, we use the mixture-amount regression modelling approach, which has the unique feature that it allows to investigate how the impact of the media usage mix changes with the total amount of media usage. As a result, we can derive different optima and quantify the size of the synergy effect for users with different levels of media usage.

Previously, Dens *et al.* (2016) applied a mixture model to show how brand placements should be mixed within a program to maximize brand attitude and brand recall. However, their optimum consists of a single mixture combination, independent upon the number of times the brand is placed. The addition of the "amount" variable and its interactions with the mixture in the mixture-amount model presented in this paper explicitly allows to detect positive, negative and no synergy within a single data set, depending on consumers' total media usage (e.g., synergy could be positive for heavy media users, but negative for light media users). Mixture-amount models have a long history in industrial statistics, bio-science engineering, medicine and agriculture(Cornell 2002; Smith 2005). Recently, Aleksandrovs *et al.* (2015) presented the first application to marketing. Their results, based on campaign investments and consumer responses to 34 advertising campaigns in magazines and on television for beauty care products, show that the optimal media mix indeed changes as a function of the total number of Gross Rating Points (GRPs) invested. In this article, we apply the mixture-amount methodology in a different way: rather than considering campaign investments as the independent variables, we use consumers' media usage data as predictors. In addition, the model presented here is more complex, as we add a third mixture element (the Internet). The sample of campaigns and respondents is also much larger.

As a proof of concept, we ran the model on real-life data from 92 advertising campaigns that ran in the Netherlands, Belgium, Finland and Hungary. We utilize consumers' magazine, television and Internet usage as the independent variables, and campaign-evoked brand interest (the consumer's interest in the brand as a direct result of the campaign), perceived brand equity (value of the brand) and purchase intention (likelihood of buying) for brands advertised in these media as dependent variables at the individual respondent level (please refer to the "Data" section for more information). This allows us to combine the ecological validity of a real-life advertising context with individual-level data for a large dataset.

LITERATURE REVIEW

Why Synergy Effects Occur

Different theories explain why and how media synergy effects may occur. Positive synergy based on sequential media use can be explained by image transfer (Smith 2004): The information in the second advertising exposure serves as a cue for audiences to retrieve their memory of the first exposure. This occurs mainly when people are exposed to ads in two different media (rather than the same medium twice) (Voorveld *et al.* 2011). Edell & Keller (1989) found that when consumers hear the audio track of a television commercial they watched before, they easily recall the visual scenes of the commercial, causing positive synergy. Also, forward encoding takes place when an ad in the first medium serves as a prime to an ad in the second medium, stimulating a consumer's interest for and attention to, and subsequently deeper processing and easier encoding of the second ad (Voorveld *et al.* 2011). Third, the differential attention hypothesis posits that repeated messages in the same medium are less likely to attract attention than the same message in varied media, which would again indicate positive synergy (Yaveroglu & Donthu 2008). Finally, the multiple source effect (Harkins & Petty 1981) entails that, compared to a repeated argument from a single source, exposure to different arguments from multiple sources results in more thorough processing. This enhanced elaboration leads people to generate more positive thoughts and to more likely comply with the arguments, leading to positive synergy, provided they are exposed to enough sources for synergetic effects to occur. Consumers increasingly also use different media simultaneously. Nielsen (2014) reports that 84% of smartphone and tablet owners use their devices as second-screens while watching TV at the same time. Lin *et al.* (2013) report that people are prone to consume several media (almost) simultaneously. Repetition variation theory (Stammerjohan *et al.* 2005) suggests that pre-cognitive or pictorial cues aid encoding and improve attitudes toward multiple exposures from different media as long as tedium is forestalled. Second, differences in modality (mode of presentation, i.e., visual, audio,…) between different media correspond to differences in available information and the activation of multiple paths in memory (Chatterjee 2012). The encoding variability theory (Appleton-Knapp *et al.* 2005) suggests that when a consumer receives an ad trough several media sources, he or she encodes the ad in memory in different ways, such that the likelihood of recalling information related to the ad is enhanced (Naik & Peters 2009).

Ads encountered through multiple sensory modes have more elements or information available than single sensory mode ads (Chatterjee 2012). However, that may also mean that more effort is necessary for the ad to be processed thoroughly. Humans have limited capacity to process information (Lang 2000). When exposed to multiple messages at once, audiences have to divide their attention and cognitive resources between different media (Pilotta & Schultz 2005). This may affect the thoroughness and efficiency of information processing negatively. If that is the case, simultaneous exposure to different media is likely to result in negative synergy effects. At the same time, however, when audiences do not have enough cognitive ability to process the messages thoroughly, they are more likely to adopt the peripheral route to make judgments based on heuristic cues, such as source credibility and attractiveness (Rucker & Petty 2006). In that case, simultaneous exposure to multiple messages may simply affect the way in which audiences process both messages, which could result in either positive or negative synergy, depending on the advertising content.

Note that sequential or simultaneous advertising exposure in different media entails some form of repetition. As noted in Berlyne's (1970) two-factor theory, repetition may lead to tedium. The negative effects of tedium can overwhelm the gain in communication outcomes from positive habituation (Chatterjee 2012). This would also suggest negative synergistic effects.

Evidence on the Existence of Synergy Effects

A number of studies support the existence of positive synergetic effects when consumers use multiple media (e.g., Edell & Keller 1989). Abraham (2008) reports that consumers who were exposed to both online display and search ads in the same time period generated higher sales revenues than the combined revenues from consumers exposed to display ads only and search ads only. Chatterjee (2012) found that the use of multiple media outperformed single medium repetition in terms of immediate and delayed brand recall and immediate brand attitude. Lin *et al.* (2013) provide evidence that consumers gain additional utility from media multiplexing (the joint use of several media) as opposed to single media use.

At the same time, other studies find no evidence of synergetic effects or even observe negative synergetic effects (also called cannibalization). Dijkstra *et al.* (2005) demonstrate that TV-only campaigns are superior to multiple-media campaigns in evoking cognitive responses, and that print-only campaigns are as effective as multiple-media campaigns for most responses. Stammerjohan *et al.* (2005) found positive synergies between publicity and advertising in terms of the attitude towards the ad and brand, but did not find the expected synergies based on exposure in differing media (print and radio). Danaher and Dagger (2013) developed 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. They find, however, that the addition of pairwise interactions for media synergy does not improve the fit of their model. Taylor *et al.* (2013) document that, when online advertising is added to a television campaign, the extra reach achieved is primarily duplicated. They found no evidence of a synergy in sales impact. If anything, exposure to both media even seems to result in a decline in sales for most brands under study.

These findings raise the question of whether and in what circumstances cross-media use leads to positive synergy and negative cannibalization effects. Evidence from prior studies indicates that the existence of synergy may depend on consumers' brand familiarity, the dependent variable of interest, and the type of media under consideration. Stammerjohan *et al.* (2005) found evidence of positive synergies between exposure to publicity and advertising, but only for a less familiar brand. Chang & Thorson (2004) found that the combined use of television and the web elicited higher attention, higher message credibility, and more positive thoughts. However, their study found no synergetic impact on attitude toward the ad, attitude toward the brand, and purchase intention.

Tsao & Sibley (2004) documented a positive reinforcement effect between Internet advertising on the one hand and billboards, direct mail, magazine, radio, and television advertising on the other. In contrast, they documented a negative displacement effect in the relationship of free community papers and weekly papers with Internet advertising. Daily newspapers and in-store advertising revealed no significant effects of displacement or reinforcement with Internet advertising. While Havlena *et al.* (2007) report positive synergy between TV and print advertising opportunity-to-see on traditional brand metrics and positive perceptions of the brand, they find little or no synergistic effects when online banner advertising is added to the mix. The findings of Schwaiger *et al.* (2010) suggest that while a combination of Internet and print advertising is more effective than only Internet advertising with regard to brand attitude, the advertising effectiveness of the combined media is not better than that of print advertising only. Varan *et al.* (2013) show that synergies in terms of awareness, ad likeability, brand attitude and purchase intention exist between different advertising formats (i.e., interactive and non-interactive), but not across devices (television-sets, PCs, iPods and mobile phones), when the same format is used. The present study aims to contribute to the debate on the existence of advertising synergy by studying whether synergy may depend on consumers' media usage levels. Our mixture-amount modelling approach allows for a systematic estimation of positive and negative synergy effects for different media usage patterns, and provides guidelines for optimization. We apply the approach to survey data on consumer responses to a large selection of real campaigns.

MIXTURE-AMOUNT REGRESSION MODELS

Mixture-amount regression models are inspired by food science and agriculture, where fertilizers and pesticides are commonly used to enhance the yield of a crop, and in medicine, where medical drugs are used to cure patients. Fertilizers, pesticides and medical drugs are mixtures of various ingredients. Statistical models for studying the yield of a crop or the probability of survival do not only use the amount of fertilizer or the drug dose as an independent variable, but also the proportions of the different ingredients. These models are commonly referred to as mixture-amount models, and allow the optimal proportion of the ingredients to depend on the dose of fertilizer, pesticide or drug (Cornell 2002). White *et al.* (2003) state that the mixture-amount modeling paradigm "provides for the first time an effective statistical approach to modeling complex patterns of local synergism, additivity, and antagonism in the same data set, the possibility of including additional experimental components beyond those in the mixture, and the capability of modeling three or more drugs." For the same reasons why we believe mixture-amount modeling is important in the context of advertising too, where mixtures of multiple media are present, and the total amount of media consumption varies across respondents.

A mixture-amount model involves two kinds of explanatory variables. First, proportions of ingredients, defining a mixture. Second, a measure of the amount used of the mixture. A key feature of the model is that it allows for the effect of the amount to depend on the exact mixture used, and vice versa. Modeling these kinds of effects requires the inclusion of interaction terms between mixture proportions and the amount, and between multiple ingredient proportions in the model.

Formally, suppose we have q ingredients in a mixture, and that we 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

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

where η represents an outcome, the regression coefficients β_i and β_{ij} are 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). A coefficient β_i can be considered as the baseline effect of medium i in the event no other media are used, while the coefficient β_{ij} is a baseline interaction effect between medium i and medium j. When a coefficient β_{ij} is sufficiently positive, the synergy between medium i and medium j will be positive. When a coefficient β_{ij} is sufficiently negative, medium i and medium j have a negative synergy. The coefficients γ_i and γ_{ij} describe how the baseline effects β_i and β_{ij} change with the amount A.

The mixture-amount model in Equation (1) is thus a special type of regression model, involving several terms which capture interaction effects between different ingredients and 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 (see e.g., Scheffé 1958).

Mixture models and mixture-amount models are mainly used for prediction and optimization of the proportions of the ingredients for any given total amount (Cornell 2002; Goos *et al.* 2016). The focus on prediction is due to the unavoidable multicollinearity in data sets involving mixtures. As a matter of fact, the different proportions cannot be changed independently since all proportions always sum to 1. The main drawback of multicollinearity is that the regression coefficients cannot be interpreted independently and individual t-tests suffer from a lack of power. However, one can predict and optimize responses perfectly well, even in the presence of multicollinearity (see e.g., Goos *et al.* 2016).

In the context of advertising, q corresponds to the number of media types used, x_i corresponds to the proportion of usage of the ith medium by the consumer (e.g, x_1 = proportion of television usage, x_2 = proportion of magazines usage, x_3 = proportion of the Internet usage). The amount A is a measure of the total consumer's usage of all media.

The mixture-amount modeling approach is generic and can be used for any number of media and any range of consumers' media usage. It also lends itself to a multi-level (= mixed model) analysis with random effects to capture similarities between responses from the same respondent, between responses collected at the same time point, for the same campaign, etc. Table 1 provides an overview of the methodological approaches of previous studies modelling synergy effects, as opposed to the present article. Note that only two of the papers that have used mathematical models on large datasets have used individual-level consumer media usage as the input. The others are all based on advertising spends and aggregated response data. As highlighted, the most notable difference is that mixture amount model presented in the present article uses proportions and explicitly accounts for estimating different synergy effects at different levels of media usage. None of the other models do that.

PLACE TABLE 1 ABOUT HERE

DATA

Advertising campaigns

We selected 92 skin and hair care (shampoo, facial cream, soap) campaigns in Belgium, Hungary, Finland and the Netherlands. A campaign is a series of advertisements that share a single idea and theme, and that appear in different media channels across a specific time frame. The campaigns selected for this research ran in magazines, on television and/or on the Internet (in varying combinations) in the countries under study between June and December 2011. For Belgium, we selected campaigns in two regions: Wallonia, the southern, French-speaking region and Flanders, the northern, Dutch-speaking region. Fifteen of the 92 campaigns ran in Wallonia, Belgium, 18 in Flanders, Belgium, 17 in Hungary, 19 in the Netherlands and 23 in Finland. The campaigns involved 48 brands from 9 mother brands of skin and hair products for women (e.g., the brands Youth Code and Revitalift from the mother brand L’Oréal Paris). The campaigns were selected at five different time points, which we refer to as waves. Some brands had multiple campaigns in the total testing period, but, in that case, the campaigns for any given brand ran at different points in time and/or in different regions.

Data collection procedure and sample

We drafted a unified multinational survey to measure individual consumers' media usage and their responses to the campaigns under study. The universe of the study were women in the age range of 20 to 50 living in the countries under study (which corresponds to the target group of the campaigns). The data were collected online, from the consumer panel of GfK. A simple random sample was drawn in each region (the sampling frame being the GfK consumer panel database) at each wave. the participants were contacted through an email containing a link to an online questionnaire, programmed in 4 languages in the software Qualtrics. Respondents that were selected in a previous wave were excluded from selection in a following wave.

In each wave, about 500 unique respondents were recruited for Wallonia, Flanders, Hungary, the Netherlands and Finland to evaluate between two and five campaigns. This procedure (five measurement points (waves) in five regions times approximately 500 respondents per region per wave) results in final sample of 10972 unique respondents. As each respondent assessed multiple campaigns (all the campaigns that were tested in the same wave), we have repeated measurements for each respondent. The total analyzed dataset contains 46852 responses. The data were not weighed.

Respondents were asked a number of questions, including their media usage and brand equity and purchase intentions for a number of brands (see below, under "measures"), after which they saw the creative executions of the campaign in their original format (i.e., a movie clip for a television ad, a print ad for magazines and/or an online video or banner ad for Internet). They then indicated the degree of campaign-evoked brand interest, for the totality of the campaign.

Measures

First, we measured a number of socio-demographics for the sample description. As independent variables, we captured respondents' TV, Internet and magazine usages. Each of these usages was quantified separately by multiplying the frequency of use with the usage intensity. TV and Internet usage were calculated by multiplying the number of days a respondent watches TV or uses the Internet in a normal week (0 = never watches TV, never uses the Internet, 6 = every day) as a measure of frequency with a measure of how long she watches TV or uses the Internet per day (1 = less than 30 minutes per day, 9 = eight or more hours per day) as an indication of usage intensity. The resulting TV and the Internet usage scores range from 0 (never watches TV, never uses the Internet) to 54 (watches TV, uses the Internet every day for eight hours or more). For example, a level of 20 means that the respondent either watches TV or uses the Internet three or four days a week for 3 to 4 hours, or five or six days a week for 2 to 3 hours. Magazine usage was calculated by multiplying how often a respondent reads magazines (frequency) (0 = never reads magazines, 6 = seven or more magazines per week) with a measure of the thoroughness with which she reads these magazines (usage intensity) (1 = leaf through without actually reading, 5 = read thoroughly from cover to cover). The resulting magazine usage score ranges from 1 (never reads magazines) to 30 (reads several magazines every day from cover to cover). For example, a woman who reads a few magazine articles scans the rest of the magazine less than once a week would score a 6 on magazine usage, while a woman who reads three or four magazines per week from cover to cover would score 20. To construct a correct measure for the total media usage and the media usage proportions per medium type, it is necessary for TV and the Internet usage score ranges to be equal to the magazine usage score range. To that end, the TV and Internet usage scores were rescaled to ensure they have the same range as the magazine usage score, by multiplying the original TV and Internet usage scores by 30/54).

The major limitation of the current dataset is that it does not include information on the actual media vehicles that consumers used (e.g., which particular magazines they read, or which channels they watch) and whether these correspond to the vehicles that the campaigns ran in. We discuss the implications later in the paper.

As dependent variables, we use three consumer responses. Campaign-evoked brand interest was measured using a 10-item 7-point Likert scale (e.g., "This campaign has encouraged me to try the brand") ($\alpha = 0.97$). Perceived brand equity (further shortened as "brand equity") was measured using a 6-item 5-point Likert scale (e.g., "… is a high quality brand") ($\alpha = 0.93$). To obtain a single score for these constructs, we averaged respondents' scores across the items. Purchase intention was measured using a single-item 7-point semantic differential scale (not at all likely - very likely). The full scales can be found at https://docs.google.com/document/d/1DJfOPVSSB-uXwukdzrmXolD-Q_015O1pBgJ8NyuRxdQ/edit?usp=sharing.

Table 2 provides examples of the data for a number of respondents. For instance, the respondent with id 40876 evaluated campaign 1, for brand 1 of mother brand 1 in the Netherlands. The data for that respondent were collected in wave 1. The respondent's overall media usage was 16.3 on a 0-90 scale. The columns labeled x_{mag}, x_{TV} and x_{inet} represent the proportions of magazine, television and Internet usage of this respondent, respectively. 49% of the total media usage of this respondent was magazine reading, 31% TV viewing, and 20% Internet usage. Note that these proportions always sum up to 1.

PLACE TABLE 2 ABOUT HERE

METHOD OF ANALYSIS

The specification of the mixture-amount model utilized in this study (1) recognizes that different total media usage amounts have a different impact on advertising responses, (2) allows for possible interaction effects between magazine, television and the Internet usage (i.e., allows for a (positive or negative) synergistic effect), and (3) allows for a possible interaction effect between the total amount of media usage and the proportion of magazine, television and the Internet usage.

To capture all the dependencies between the responses in the data, we include a number of random effects in the mixture-amount model. First, random effects are included to control for the fact that the data include measurements at different points in time (e.g., to capture the fact that responses during summer holidays may be different from other months). Similarly, random effects are included to model the dependency between answers from the same respondent and to capture the dependency between all answers for the same campaign, the same brand and the same region. Hence, we adopt a multilevel generalized linear model (GLM) approach when estimating the mixture-amount model for campaign-evoked brand interest, brand equity and purchase intention.

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

$$\eta = \eta_{sys} + \eta_{random}. \tag{2}$$

We use the identity link function and assume a normal distribution for the three responses under study here (Hardin & Hilbe 2012). The systematic part of the linear predictor in our GLM models for campaign-evoked brand interest, brand equity and purchase intention is given by

$$\begin{aligned}\eta_{sys} = {} & \beta_{mag} x_{mag} + \beta_{TV} x_{TV} + \beta_{inet} x_{inet} + \beta_{\text{int } i} x_{mag} x_{TV} + \beta_{\text{int } ii} x_{mag} x_{inet} + \beta_{\text{int } iii} x_{TV} x_{inet} \\ & + \beta_{\text{int } iv} x_{mag} x_{TV} x_{inet} + \gamma_{mag} x_{mag} A + \gamma_{TV} x_{TV} A + \gamma_{inet} x_{inet} A + \gamma_{\text{int } i} x_{mag} x_{TV} A \\ & + \gamma_{\text{int } ii} x_{mag} x_{inet} A + \gamma_{\text{int } iii} x_{TV} x_{inet} A + \gamma_{\text{int}} x_{mag} x_{TV} x_{inet} A,\end{aligned} \tag{3}$$

where x_{mag}, x_{TV} and x_{inet} represent the proportions of magazine, television and the Internet usage, respectively, $\beta_{\dots}$ and $\gamma_{\dots}$ represent the regression coefficients, and A is the natural logarithm of the media usage score. Media usage was log transformed to allow for diminishing marginal returns. A comparison of the model with and without the logarithmic transformation showed that the model with transformation fit the data substantially better. The random part of the linear predictor involves all the random effects of the respondent, the wave, the region and the brand.

We used the SAS procedure MIXED to estimate the models. Because of the large number of observations (> 46 000) and the inclusion of random effects for 10972 respondents, we ran the models on a Tier 2 level supercomputer.

RESULTS

Estimates

Three mixture amount models were estimated, one for each dependent variable. The R^2 for brand interest equals 0.60, while that for brand equity is 0.48 and that for purchase intention amounts to 0.45. To measure the performance of our models, we also use 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 0.75, while that for brand equity is 0.65 and that for purchase intention is 0.62. These values indicate a good fit (Vonesh *et al.* 1996). The estimates of the regression coefficients in the mixture-amount models for brand interest, brand equity and purchase intention are displayed in Table 3.

PLACE TABLE 3 ABOUT HERE

To facilitate the interpretation of the model, the identification of synergistic effects and the optimization of the media mix, we visualize the estimated mixture-amount models by using the prediction profiler embedded in the software package JMP (SAS). The prediction profiler is a dynamic tool to plot the simultaneous effects of all independent variables in a regression model. It is especially useful for models with interaction and nonlinear effects. A key feature of the profiler is that the levels of the independent variables can be modified interactively and that the impact of doing so is translated instantaneously into a predicted value for the outcome variable(s) under investigation. Since the optimal solutions are similar for all three outcomes, we selected the option in JMP to optimize the overall desirability based on the average of the three outcomes jointly.

Figure 1 and 2 show two example prediction profilers, built using the coefficient estimates from Table 3. The first scenario (Figure 1) represents a total media usage of 20, which is relatively low, a second scenario (not depicted) is for a total media use of 40 (moderate), and the third scenario (Figure 3) is for a relatively high total media use of 60. The values for the independent variables appear on the horizontal axes, while the predicted values for the dependent variables (brand interest, brand equity and purchase intention) are shown on the three vertical axes. The results are also summarized in Table 4.

PLACE TABLE 4 ABOUT HERE

The figures involves four panes per row, each pane showing the impact of one independent variable on each outcome by means of a solid curve, given the values selected for all other independent variables (which are mentioned on the horizontal axes and indicated by vertical dashed lines). The leftmost pane in each of the figures' rows shows the impact of the proportion of magazine usage on the dependents. The second pane in each row shows the impact of the proportion of TV usage, and the third pane shows the impact of the proportion of Internet usage (recall that, together, these proportions sum up to 100%). Finally, the fourth pane visualizes the effect of the overall media usage.

Figure 1 shows that, in Scenario 1 (a total media use of 20), the brand interest, brand equity and purchase intention is maximized for respondents with media usage proportions of 71% magazines, 13% TV and 16% Internet. Under these optimal media usage proportions, the predicted brand interest is 3.66, while the predicted brand equity is 2.98 and the predicted purchase intention is 3.77. The convex curves in the three leftmost panes of Figure 1 show that different media usage proportions would lead to a drop in the outcomes. The rightmost pane shows that the predicted brand interest, brand equity and purchase intention increase with the total amount of media usage.

PLACE FIGURE 1 ABOUT HERE

When consumers' total media usage increases to 40 (Scenario 2), the maximum predicted brand interest, brand equity and purchase intention increase slightly to respectively 3.89, 3.18 and 4.12. Importantly, the optimal media usage mix changes. While magazines remain the dominant media in this scenario with an optimal proportion of 39%, that is about half compared to the previous scenario. It becomes important that consumers watch almost as much television as they read magazines (37%), and Internet usage gains in importance as well (optimally 24%).

When consumers' total media usage increases further (e.g., to 60, Scenario 3, Figure 2), the maximum predicted brand interest, brand equity and purchase intention continue to increase. Again, the optimal media usage mix shifts, but only slightly. Magazines lose their dominant position, and television takes over. The optimal proportion of Internet usage remains unchanged.

PLACE FIGURE 2 ABOUT HERE

Synergy coefficient

With a few exceptions (e.g., Steele *et al.* 2013; Pynta *et al.* 2014), in previous experimental studies, it has been difficult to reliably quantify synergy effects because the study design always involved only a limited number of media combinations. In the current study, we quantify synergy effects based on cross-media usage by calculating a synergy coefficient. In case of a positive synergistic effect, we define this synergy coefficient as the difference between the predicted value of the dependent variable under the optimal proportions of media usage (τ_{opt}), as indicated by our model, and the maximum predicted value of the dependent variable across the possible situations in which a single medium is used by a consumer. In other words, in order to have positive synergy, the optimal combined media usage should result in a higher score on the dependent variable than the "best" single medium. In case of cross-media cannibalization, we define the synergy coefficient as the difference between the predicted value of the dependent variable for the worst media usage mix ($\tau_{\min}$) and the minimum predicted value of the dependent variable under single medium usage. The mathematical expression for the synergy coefficient is:

$$\varsigma_m = \begin{cases} \tau_{opt} - \max(\nu_1, \nu_2, ..., \nu_i, ..., \nu_n), \tau_{opt} \neq \nu_i \\ \tau_{\min} - \min(\nu_1, \nu_2, ..., \nu_i, ..., \nu_n), \tau_{opt} = \nu_i, \end{cases} \quad (4)$$

where ν_i is the response in the event the consumers use only medium *i*. For example, in Scenario 2 (Table 4, moderate total amount of media usage), the optimal media usage proportions resulted in a predicted purchase intention of 4.12. If a respondent would use only TV (and thus no magazines and no Internet), the predicted purchase intention would be 3.45. As this is the highest possible value for a single medium (the predicted purchase intentions for "magazine usage only" and "Internet usage only" are clearly lower; see Figure 1), the synergy coefficient for purchase intention under this scenario equals 4.12−3.45 = 0.67. This means that, in Scenario 1, cross-media synergy increases the purchase intention by 0.67 points, compared to the situation in which a respondent uses only one medium (in this case, TV).

Figure 3 shows how the synergy coefficient changes as a function of the total media usage. For all outcomes, the synergy is negative for consumers with a low total media usage. The synergy increases with the total media usage and is close to zero when the total media usage is around 30. The largest synergy is observed for consumers with a high media usage.

PLACE FIGURE 3 ABOUT HERE

DISCUSSION

In line with previous studies (e.g., Naik *et al.* 2005;Dertouzos & Garber 2006; Hansen *et al.* 2006), the results of our study support the idea that consumers' usage of a combination of multiple media (television, magazine and Internet) benefits advertising responses over single medium use. However, it should be noted that this positive effect is present only for consumers that are relatively heavy media users. For light media users, we document negative effects of multiple media usage. This finding possibly explains some of the discrepancies between previously published studies on synergy, and indicates that future research has to take consumers' overall media usage into account.

The results might be explained by the multiple source effect that, compared to a repeated argument from a single source, exposure to different arguments from multiple sources results in more thorough processing (Harkins & Petty 1981). This effect might be enhanced with higher media usage and enable people to generate more positive thoughts and to be more likely to comply with the arguments. Light media users' exposure to messages in different media is apparently not sufficient to generate positive effects but, on the contrary, leads to negative effects, possibly due to a lack of processing opportunities and hence confusion.

The maximal predicted campaign-evoked brand interest, brand equity and purchase intention is highest for heavy media users. This could indicate that repeated exposures (either in the same or different media) indeed contribute to consumer responses. In any case, it seems that, for light media users, it is better that they use a single medium relatively more intensively, than that they spread out their media usage across different media. This is because, when using various media superficially, it is unlikely that campaigns are actually encountered. In this sample, when a consumer is an overall light media user, it is best when she uses magazines only (as opposed to television or Internet), as this results in the highest possible campaign-evoked brand interest, brand equity and purchase intention. Compared to television, magazine advertisements are more self-paced, providing readers with an opportunity to more thoroughly process specific information in advertising (Speck & Elliott 1997). This is especially important when consumers only see an advertisement once. Consumers may be less capable of processing an ad on television. The results of Bronner & Neijens (2006) also suggest that television advertising is perceived as relatively more irritating, which may reflect negatively on campaign-evoked responses. While magazine advertisements in general may not be so vivid, they may do a better job at stimulating campaign-evoked brand interest, brand equity and purchase intention. For consumers that more heavily use media overall, the optimal proportion of magazine usage decreases to about 37%. The relative importance of TV, on the other hand, increases with the total media usage.

For both moderate and heavy media users, the optimal proportion of Internet usage is about 24%, which is lower than that of magazines and television. Havlena *et al.* (2007) argued that the Internet is a low reach medium in a cross-platform context. Magazines and television are the primary media for beauty care advertising in the countries under study. The fact that consumers' Internet usage still plays a relatively important role may be attributed to the fact that consumers do not necessarily encounter ads online, but may use it for additional information or deals (Lin *et al.* 2013; Reimer *et al.* 2014). This could help explain the synergetic effect between TV and Internet usage.

These results have managerial implications for differentiating the media mix for consumer groups that vary in their degree of media usage. There is ample evidence that people frequently consume several media (simultaneously) (Lin *et al.* 2013) and advertisers exploit this by using multiple channels to reach their target audience and increase the frequency of their campaigns. Our results provide evidence that campaigns can indeed benefit when consumers use a combination of multiple media (compared to a single medium), but only when their overall media usage is medium to high. We argue that, for this group, it does indeed pay off for advertisers to invest in multiple media in order to capitalize on potential synergy effects. For low media users, however, it would be better to invest in a single medium to avoid spreading the campaign too thinly. In the current sample, the most seems to be gained by targeting magazine users. Based on demographic profiling, the heavy media users in this sample are less likely to have kids (51% of consumers with a media usage score of 60 or higher have kids, compared to 61% of consumers with a media usage score of less than 20). They are also relatively less active in the workforce (49% compared to 77%).

The current dataset therefore holds implications for communications planning in the sense that, when drawing up annual advertising budgets, advertisers usually first decide on how to divide their budget across media in more general terms (x% TV, x% online, …), in function of their target audience. While the current application does not provide concrete guidelines on how to spread budgets across media types, it does suggest that the added value of including more media is higher when the target group's overall media usage is higher, and advertisers would be better off allocating their entire budget to a single medium for light media users.

CONCLUSIONS

As a conceptual and methodological contribution, we proposed and tested a novel modeling approach that provides estimates of the effects of consumers' overall media usage and the distribution of this media usage across magazines, television and the Internet. The major advantage of mixture-amount models over existing models is that they enable researchers to determine different optimal media mixes (and subsequently quantify synergy) for different levels of media usage. Our results illustrate that the optimal media mix indeed differs greatly depending on a consumer's total media usage, a fact that researchers and advertisers should consider in the future. The prediction profilers, shown in Figures 1 through 3, offer an easy-to-use tool to visualize and dynamically simulate the effects.

We view this paper as a proof of concept of the applicability of the mixture-amount modeling technique in an advertising context. While mixture amount models find their origin in experimental designs, the present paper demonstrates that they are applicable to large datasets as well. One of the criteria, however, is that the there is a sufficient spread in the amounts and proportions of the independent variables.

The model can also be applied to other product categories or other types of input data, including consumers' media usage of specific medium vehicles (for example, the specific channel that a consumer watches or individual magazines he or she reads). The model can not only be applied to "optimize" outcomes based on consumers' media usage, which is often outside the control of advertisers, but can also be applied to optimize advertising effort, as demonstrated by Aleksandrovs *et al.* (2015). Dens *et al.* (2016) provide an application of a simpler mixture model to maximize brand placement effectiveness based on how the brand is integrated into the program.

Mixture-amount models can be applied to binary, categorical or continuous dependent variables, and future research could therefore apply the proposed methodology to outcomes such as sales or campaign recognition. One could also add additional interactions with consumers' product category involvement or product category experience, in order to investigate how this further influences the optimal media usage allocations and synergy effects. Finally, while we include three media (magazines, TV, and the Internet) in the present application, the model can easily accommodate generalizations to other media (e.g., radio, newspaper, …).

LIMITATIONS AND SUGGESTIONS FOR FURTHER RESEARCH

The major limitation of the current dataset is that it does not include information on the actual media vehicles that consumers used (e.g., which particular magazines they read or which channels they watch) and whether these correspond to the vehicles that the campaigns ran in. Therefore, we do not have data on actual advertising exposure. However, the target groups for the campaigns under study are relatively narrowly defined, and all campaigns only ran in media (specific magazines and television channels) that the target group is likely to use. Therefore, it is likely that heavy media users have encountered the advertising campaigns in our sample. In contrast, a consumer who is a light magazine user, for example, may actually only read one specific magazine or leaf through a few different ones. It is therefore more likely that she missed a specific campaign under investigation, either because it did not run in the specific magazine that she reads, or because of low attention. The greater the overall media usage of a consumer, the greater the chance that at least one of the media vehicles she uses ran the campaign under investigation. Most previous cross-media research has actually also focused on opportunity-to-see, or on aggregate data on campaign investments. Obviously, the measurement of exposure frequency at the individual respondent level can provide a much more detailed analysis of the effects of advertising frequency and greater insight into how to improve cross media campaigns (Havlena *et al.* 2007).

Future research in other categories could expand the number of media. Particularly, in the context of big data collected in digital environments, researchers could apply the mixture amount modeling technique to investigate potential synergies based on consumers' usage of different types of sites (e.g., brand websites, review sites, social media) or their exposure to several types of online ads (e.g., email, display ads, search ads).

We have also focused on campaign-evoked brand interest, brand equity and purchase intention as outcomes. This approach is customary in campaign evaluation research and is justified by empirical research based on classical hierarchy-of-effects models (Barry 1987; Gordon & Anand 2000) and the theory of planned behavior (Ajzen 1991), which suggest that these variables are often predictive of actual buying behavior in the longer run. Future research could also apply the proposed methodology to outcomes such as sales or campaign recognition. While the fact that the current model required a processing time of two weeks on a supercomputer may seem like a limitation for future applicability, computers are rapidly growing in their powers and new algorithms for estimating multilevel generalized linear models are continuously being developed. For instance, applying the partitioned-samples pseudo-likelihood methodology of Ivanova *et al.* (2015) allows for a substantial reduction of the computing time. We applied our approach to a data set involving more than 46000 responses obtained from 10972 respondents, and the model included many random effects. A supercomputer or new algorithms would not be required for smaller datasets.

Obviously, campaign effectiveness also depends on considerations other than consumers' media usage, such as advertising creativity. However, the mixture-amount model presented here can be extended to include (interactions with) other factors that may impact consumers' optimal media mix.. Finally, the model should be tested further to investigate to what extent the results are context-specific or media usage mix specific, and to what extent they can be generalized to different products, countries and target groups.

ACKNOWLEDGEMENT

Funding: This work was supported by the Research Foundation - Flanders (FWO Vlaanderen).

REFERENCES

Abraham, M. (2008) The off-line impact of online ads. *Harvard Business Review*, **86**, 4, pp. 28.

Ajzen, I. (1991) The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, **50**, 2, pp. 179-211.

Aleksandrovs, L., Goos, P., Dens, N. & De Pelsmacker, P. (2015) Mixed-media modeling may help optimize campaign recognition and brand interest. *Journal of Advertising Research*, **55**, 4, pp. 443-457.

Appleton-Knapp, S.L., Bjork, R.A. & Wickens, T.D. (2005) Examining the spacing effect in advertising: Encoding variability, retrieval processes, and their interaction. *Journal of Consumer Research*, **32**, 2, pp. 266-276.

Aravindakshan, A., Peters, K. & Naik, P.A. (2012) Spatiotemporal allocation of advertising budgets. *Journal of Marketing Research*, **49**, 1, pp. 1-14.

Assael, H. (2011) From silos to synergy. A fifty-year review of cross-media research shows synergy has yet to achieve its full potential. *Journal of Advertising Research*, **51**, 1, 50th Anniversary Supplement, pp. 42-48.
Barry, T.E. (1987) The development of the hierarchy of effects: An historical perspective. *Current issues and Research in Advertising*, **10**, 1-2, pp. 251-295.
Berlyne, D.E. (1970) Novelty, complexity and hedonic value. *Perception and Psychophysics*, **8**, pp. 279-286.
Bronner, F. & Neijens, P.C. (2006) Audience experiences of media context and embedded advertising: A comparison of eight media. *International Journal of Market Research*, **48**, 1, pp. 81-100.
Bruce, N.I., Foutz, N.Z. & Kolsarici, C. (2012) Dynamic effectiveness of advertising and word of mouth in sequential distribution of new products. *Journal of Marketing Research*, **49**, 4, pp. 469-486.
Chang, Y. & Thorson, E. (2004) Television and web advertising synergies. *Journal of Advertising*, **33**, 2, pp. 75-84.
Chatterjee, P. (2012) The role of varying information quantity in ads on immediate and enduring cross-media synergies. *Journal of Marketing Communications*, **18**, 3, pp. 217-240.
Cornell, J.A. (2002) *Experiments with mixtures: Designs, models, and the analysis of mixture data*. New York, NY: Wiley.
Danaher, P.J. & Dagger, T.S. (2013) Comparing the relative effectiveness of advertising channels: A case study of a multimedia blitz campaign. *Journal of Marketing Research*, **50**, 4, pp. 517-534.
Danaher, P.J. & Rossiter, J.R. (2011) Comparing perceptions of marketing communication channels. *European Journal of Marketing*, **45**, 1/2, pp. 6-42.
Dens, N., De Pelsmacker, P., Goos, P. & Aleksandrovs, L. (2016) How to mix brand placements in television programs to maximize effectiveness. *International Journal of Market Research*, **58**, 5, pp. 649-670.
Dertouzos, J.N. & Garber, S. (2006) Effectiveness of advertising in different media. The case of US army recruiting. *Journal of Advertising*, **35**, 2, pp. 111-122.
Dijkstra, M., Buijtels, H. & van Raaij, W.F. (2005) Separate and joint effects of medium type on consumer responses: A comparison of television, print, and the internet. *Journal of Business Research*, **58**, 3, pp. 377-386.
Edell, J.A. & Keller, K.L. (1989) The information processing of coordinated media campaigns. *Journal of Marketing Research*, **26**, 2, pp. 149-163.
Enoch, G. & Johnson, K. (2010) Cracking the cross-media code: How to use single-source measures to examine media cannibalization and convergence. *Journal of Advertising Research*, **50**, 2, pp. 125-136.
Goos, P., Jones, B. & Syafitri, U. (2016) I-optimal design of mixture experiments. *Journal of the American Statistical Association*, **111**, 514, pp. 899-911.
Gopalakrishna, S. & Chatterjee, R. (1992) A communications response model for a mature industrial product: Application and implications. *Journal of Marketing Research*, **29**, 2, pp. 189-200.
Gordon, B. & Anand, K. (2000) Web commercials and advertising hierarchy-of-effects. *Journal of Advertising Research*, **40**, 1, pp. 35-42.
Hansen, F., Olsen, J.K. & Lundsteen, S. (2006) The effects of print vs TV advertising, documented using short-term advertising strength (stas) measures. *International Journal of Advertising*, **25**, 4, pp. 431-446.

Hardin, J.W. & Hilbe, J. (2012) *Generalized linear models and extensions, third edition*. Lakeway Drive, College Station, Texas: Stata Press.
Harkins, S.G. & Petty, R.E. (1981) The multiple source effect in persuasion: The effects of distraction. *Personality and Social Psychology Bulletin*, **7**, 4, pp. 627-635.
Havlena, W., Cardarelli, R. & De Montigny, M. (2007) Quantifying the isolated and synergistic effects of exposure frequency for TV, print, and internet advertising. *Journal of Advertising Research*, **47**, 3, pp. 215-221.
Hung, K., Gu, F.F. & Tse, D.K. (2005) Improving media decisions in China: A targetability and cost-benefit analysis. *Journal of Advertising*, **34**, 1, pp. 49-63.
Ivanova, A., Molenberghs, G. & Verbeke, G. (2015) Fast and highly efficient pseudo-likelihood methodology for large and complex ordinal data. *Statistical Methods in Medical Research*, **online first**.
Lang, A. (2000) The limited capacity model of mediated message processing. *Journal of Communication*, **50**, pp. 46-70.
Lin, C., Venkataraman, S. & Jap, S.D. (2013) Media multiplexing behavior: Implications for targeting and media planning. *Marketing Science*, **32**, 2, pp. 310-324.
Naik, P.A. & Peters, K. (2009) A hierarchical marketing communications model of online and offline media synergies. *Journal of Interactive Marketing*, **23**, 4, pp. 288-299.
Naik, P.A. & Raman, K. (2003) Understanding the impact of synergy in multimedia communications. *Journal of Marketing Research*, **40**, 4, pp. 375-388.
Naik, P.A., Raman, K. & Winer, R.S. (2005) Planning marketing-mix strategies in the presence of interaction effects. *Marketing Science*, **24**, 1, pp. 25-34.
Nielsen. (2014). The digital consumer [Electronic Version] from http://www.nielsen.com/us/en/insights/reports/2014/the-us-digital-consumer-report.html.
Pilotta, J.J. & Schultz, D.E. (2005) Simultaneous media experience and synesthesia. *Journal of Advertising Research*, **45**, 1, pp. 19-26.
Pynta, P., Seixas, S.A.S., Nield, G.E., Hier, J. & Millward, E. (2014) The power of social television: Can social media build viewer engagement? A new approach to brain imaging of viewer immersion. *Journal of Advertising Research*, **54**, 1, pp. 71-80.
Raman, K., Mantrala, M.K., Sridhar, S. & Tang, Y.E. (2012) Optimal resource allocation with time-varying marketing effectiveness, margins and costs. *Journal of Interactive Marketing*, **26**, 1, pp. 43-52.
Reimer, K., Rutz, O.J. & Pauwels, K. (2014) How online consumer segments differ in long-term marketing effectiveness. *Journal of Interactive Marketing*, **28**, 4, pp. 271-284.
Rucker, D.D. & Petty, R.E. (2006) Increasing the effectiveness of communications to consumers: Recommendations based on elaboration likelihood and attitude certainty perspectives. *Journal of Public Policy & Marketing*, **25**, 1, pp. 39-52.
Scheffé, H. (1958) Experiments with mixtures. *Journal of the Royal Statistical Society. Series B (Methodological)*, **20**, 2, pp. 344-360.
Schultz, D.E., Block, M.P. & Raman, K. (2012) Understanding consumer-created media synergy. *Journal of Marketing Communications*, **18**, 3, pp. 173-187.
Schwaiger, M., Cannon, H.M. & Numberger, S. (2010) Is two better than one? The impact of cross-media print and internet advertising in germany. *Communicative Business*, **1**, pp. 7-26.
Smith, G. (2004) Brand image transfer through sponsorship: A consumer learning perspective. *Journal of Marketing Management*, **20**, 3-4, pp. 457-474.
Smith, W.F. (2005) *Experimental design for formulation*. University City Science Center, Philadelphia: Siam.

Speck, P.S. & Elliott, M.T. (1997) Predictors of advertising avoidance in print and broadcast media. *Journal of Advertising*, **26**, 3, pp. 61-76.
Stammerjohan, C., Wood, C.M., Chang, Y. & Thorson, E. (2005) An empirical investigation of the interaction between publicity, advertising, and previous brand attitudes and knowledge. *Journal of Advertising*, **34**, 4, pp. 55-67.
Steele, A., Jacobs, D., Siefert, C., Rule, R. & Levine, B. (2013) Leveraging synergy and emotion in a multi-platform world. *Journal of Advertising Research*, **53**, 4, pp. 417-430.
Taylor, J., Kennedy, R., McDonald, C., Larguinat, L., El Ouarzazi, Y. & Haddad, N. (2013) Is the multi-platform whole more powerful than its separate parts? Measuring the sales effects of cross-media advertising. *Journal of Advertising Research*, **53**, 2, pp. 200-211.
Tsao, J.C. & Sibley, S.D. (2004) Displacement and reinforcement effects of the internet and other media as sources of advertising information. *Journal of Advertising Research*, **44**, 1, pp. 126-142.
Varan, D., Murphy, J., Hofacker, C.F., Robinson, J.A., Potter, R.F. & Bellman, S. (2013) What works best when combining television sets, pcs, tablets, or mobile phones? How synergies across devices result from cross-device effects and cross-format synergies. *Journal of Advertising Research: Vol. 53, No. 2, 201*, **53**, 2, pp. 212-220.
Vonesh, E.F., Chinchilli, V.M. & Pu, K. (1996) Goodness-of-fit in generalized nonlinear mixed-effects models. *Biometrics*, **52**, pp. 572-587.
Voorveld, H.A.M., Neijens, P.C. & Smit, E.G. (2011) Opening the black box: Understanding cross-media effects. *Journal of Marketing Communications*, **17**, 2, pp. 69-85.
Wendel, S. & Dellaert, B.G.C. (2005) Situation variation in consumers' media channel consideration. *Journal of the Academy of Marketing Science*, **33**, 4, pp. 575-584.
White, D.B., Slocum, H.K., Brun, Y., Wrzosek, C. & Greco, W.R. (2003) A new nonlinear mixture response surface paradigm for the study of synergism: A three drug example. *Current Drug Metabolism*, **4**, 5, pp. 399-409.
Yaveroglu, I. & Donthu, N. (2008) Advertising repetition and placement issues in on-line environments. *Journal of Advertising*, **37**, 2, pp. 31-44.

TABLE 1

Overview of prior studies, compared to the current model

Features	Gopalakrishna and Chatterjee (1992)	Naik and Raman (2003)	Naik & Peters (2009)	Bruce *et al.* (2012)	Danaher and Dagger (2013)	Taylor *et al.* (2013)	Aleksandrovs et al. (2015)	Present study
Estimation method	Nonlinear least squares regression	Kalman filter estimation	Hierarchical seemingly unrelated regressions	Bayesian dynamic linear model	Type II Tobit model	(no modelling)	Mixture-Amount Model	Mixture-Amount Model
Dependent variable(s)	Share of account potential obtained	Sales	1. Qualified dealer visits 2. Car configurator visits	Sales revenue	Purchase outcome (dollar sales or profit)	Short-term advertising strength (STAS) based on category purchasing	1. Campaign recognition 2. Brand interest	1. Campaign-evoked brand interest 2. Perceived brand equity 3. Purchase intention
Input variables	Advertising and personal selling expenditure	Advertising expenditure	Advertising expenditure	Advertising expenditure, WOM volume and valence	Consumer media exposure	Television viewing Online browsing	Advertising effort (GRPs)	Consumer usage of magazines, TV and Internet
Interactions	Advertising by personal selling	Print by TV advertising	All two-way interactions between TV, radio, magazine, and newspaper. Online by offline media.	WOM by advertising	Pairwise interactions for advertising in 10 media	(none)	Magazine by TV advertising	Consumers' usage of magazines by TV by Internet
Advertising effort x media mix interaction	No	No	No	No	No	No	Yes	No
Consumers' overall media usage x per media usage interaction	No	No	No	No	No	No	No	Yes
N-media generalization	No	Yes	Yes	No	Yes	No	Yes	Yes
Synergy effect quantified	No	Yes	Yes	No	No	No	Yes	Yes
Brands in dataset	1	1	1	360	1	10	24	48

TABLE 2
Data examples

Respondent ID	Campaign	Brand	Mother Brand	Region	Wave	Overall media usage	Proportion of magazine usage x_{mag}	Proportion of TV usage x_{TV}	Proportion of Internet usage x_{inet}
40876	1	1	1	the Netherlands	1	16.3	0.49	0.31	0.20
39344	3	3	4	the Netherlands	2	65.8	0.43	0.10	0.47
40546	4	5	1	the Netherlands	4	1.1	0	0	1
...	...	...	...	...	...	...	...	...	...
24882	19	1	1	the Netherlands	5	28.8	0.21	0.52	0.27
5914	20	4	2	Flanders	1	25.0	0.8	0	0.2
1289	22	6	8	Flanders	3	14.4	0	0.46	0.54
4803	23	19	2	Flanders	4	4.4	0	1	0
...	...	...	...	...	...	...	...	...	...
16470	37	24	1	Flanders	5	90.0	0.29	0.36	0.35
5585	38	10	4	Wallonia	1	57.4	0.14	0.24	0.62
6381	40	15	2	Wallonia	4	50.0	0.30	0.47	0.23
16031	41	18	3	Wallonia	5	33.0	0.25	0.40	0.35
...	...	...	...	...	...	...	...	...	...
16416	52	26	1	Wallonia	5	65.8	0.43	0.10	0.47
15356	53	10	7	Finland	4	43.0	0.18	0.36	0.46
56578	55	22	6	Finland	2	33.3	0.30	0.35	0.35
14419	58	36	2	Finland	3	66.7	0.15	0.4	0.45
...	...	...	...	...	...	...	...	...	...
15032	75	38	2	Finland	4	25.0	0.8	0	0.2
26180	76	27	9	Hungary	2	50.0	0.2	0.2	0.6
26180	83	42	5	Hungary	4	65.8	0.43	0.10	0.47
4676	92	48	8	Hungary	5	4.4	1	0	0
...	...	...	...	...	...	...	...	...	...

TABLE 3
Mixture-amount model coefficient estimates

	Brand interest		**Brand equity**		**Purchase intention**	
Model Term	**Coefficient Estimate**	**Standard Error**	**Coefficient Estimate**	**Standard Error**	**Coefficient Estimate**	**Standard Error**
$\beta_{mag} x_{mag}$	5.1431	0.7398	4.1727	0.6553	8.0500	1.4411
$\beta_{TV} x_{TV}$	3.1604	0.3810	3.1081	0.6369	2.9437	1.3363
$\beta_{inet} x_{inet}$	3.6212	0.3210	3.0943	0.3804	4.0747	0.7970
$\beta_{\text{int}i} x_{mag} x_{TV}$	-4.7786	2.8055	-6.3432	2.9244	-11.9313	6.3034
$\beta_{\text{int}ii} x_{mag} x_{inet}$	-2.9196	2.2642	-2.8335	2.2210	-14.0899	4.7812
$\beta_{\text{int}\,iii} x_{TV} x_{inet}$	-1.9766	1.3390	-0.7142	1.9947	2.1753	4.1579
$\beta_{\text{int}iv} x_{mag} x_{TV} x_{inet}$	-17.1216	10.2638	-8.2077	9.7833	-6.3974	21.0311
$\gamma_{mag} x_{mag} A$	-0.5207	0.2362	-0.4034	0.2069	-1.3865	0.4542
$\gamma_{TV} x_{TV} A$	0.02578	0.1200	-0.06019	0.1997	0.1378	0.4208
$\gamma_{inet} x_{inet} A$	-0.1967	0.09765	-0.1456	0.1197	-0.3049	0.2516
$\gamma_{\text{int}i} x_{mag} x_{TV} A$	1.9045	0.8969	2.0538	0.9258	3.9092	1.9978
$\gamma_{\text{int}ii} x_{mag} x_{inet} A$	1.3424	0.7353	1.1656	0.7094	4.6506	1.5304
$\gamma_{\text{int}\,iii} x_{TV} x_{inet} A$	0.9411	0.4315	0.3314	0.6300	-0.3525	1.3209
$\gamma_{\text{int}} x_{mag} x_{TV} x_{inet} A$	5.3229	3.1396	2.9216	2.9920	3.8467	6.4370

TABLE 4

Optimal proportions, maximum predicted outcomes and synergy coefficients for three different media usage amounts

Scenario	**1**	**2**	**3**
Media usage amount	20 (low)	40 (moderate)	60 (high)
Magazine usage proportion	71%	39%	37%
TV usage proportion	13%	37%	39%
Internet usage proportion	16%	24%	24%
Brand interest	3.66	3.89	4.07
Brand equity	2.98	3.18	3.31
Purchase intention	3.77	4.12	4.34
Brand interest synergy coefficient	0.08	0.64	0.81
Brand equity synergy coefficient	0.02	0.29	0.45
Purchase intention synergy coefficient	-0.13	0.67	0.83

FIGURE 1

Prediction profiler for a low media usage amount (Scenario 1 in Table 4)

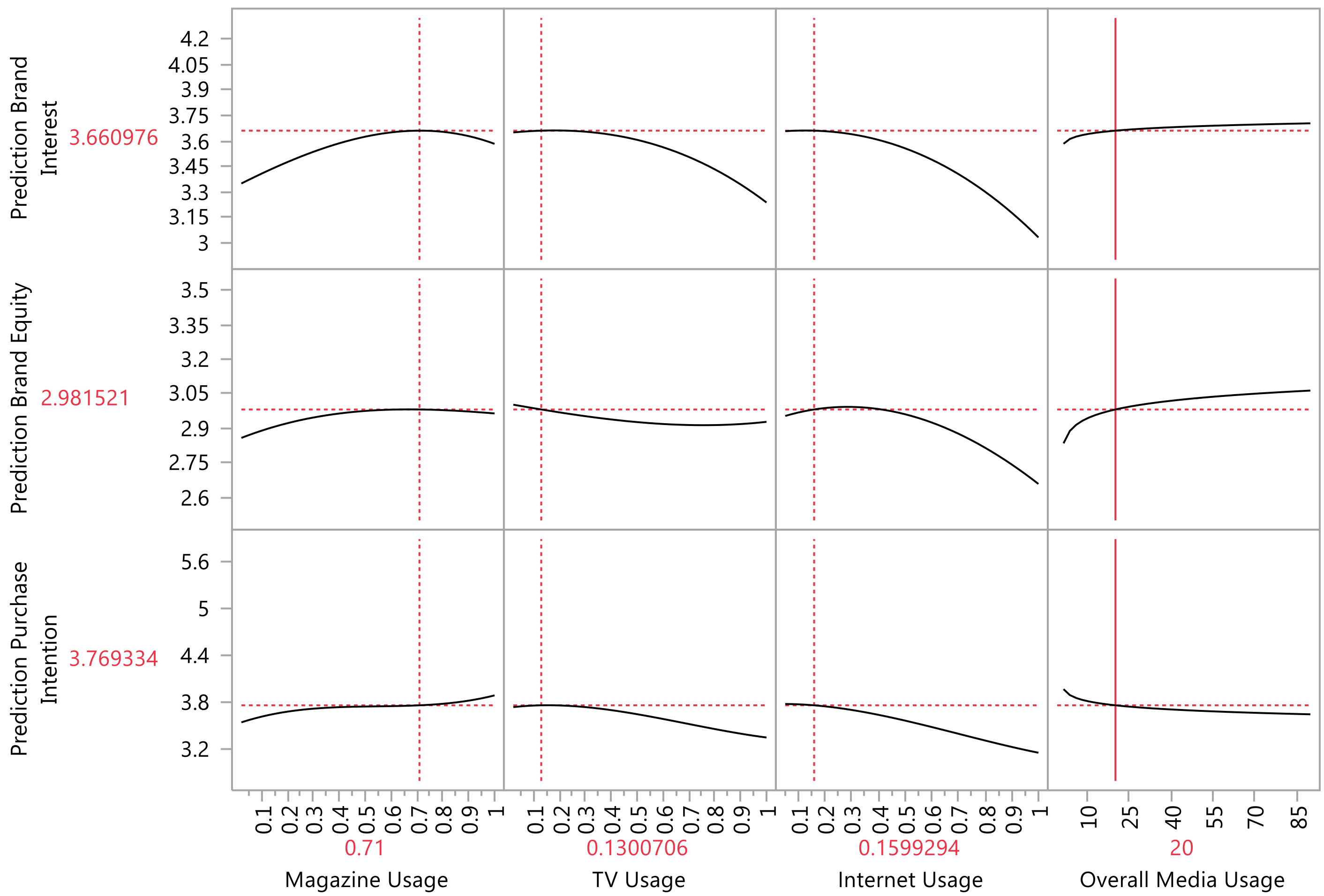

FIGURE 2

Prediction profiler for a high media usage amount (Scenario 3 in Table 4)

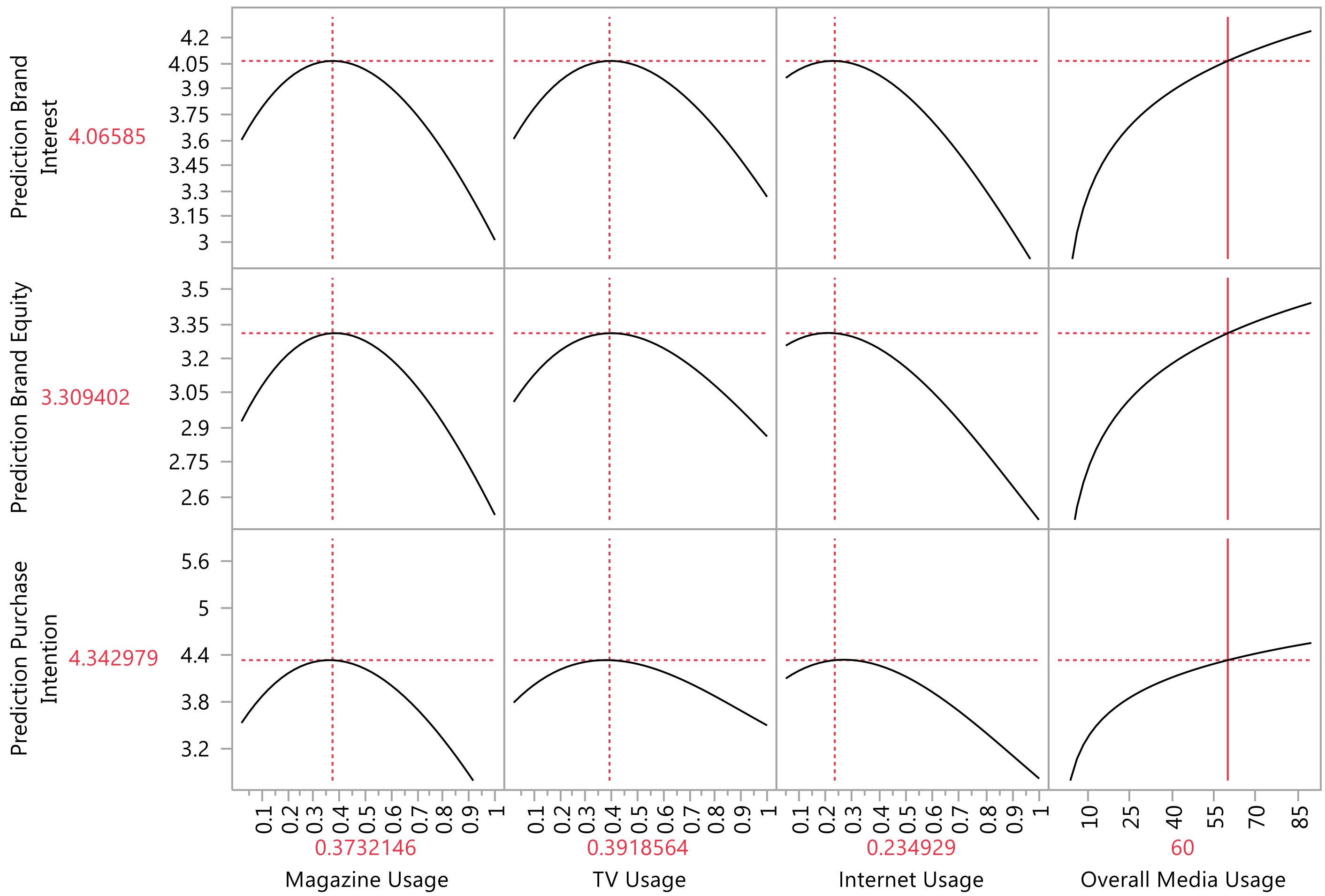

FIGURE 3

Synergy coefficient for brand interest, brand equity and purchase intention as a function of