How to mix brand placements in television programmes to maximise effectiveness

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HOW TO MIX BRAND PLACEMENTS IN TELEVISION PROGRAMS TO MAXIMIZE EFFECTIVENESS

ABSTRACT

Based on 20 brand placement campaigns for 17 brands in 11 Belgian entertainment programs, and responses of 3 884 viewers, we use the Mixture Modeling research technique to identify the optimal mix of brand placement types in a program. We determine the optimal proportions of prop placements (branded products that are put on display during the program, without active interaction between the product and a person), interactive placements (placements that entail interaction between a branded product and a person), and look-and-feel placements (branding elements that are visually incorporated in the scenery of the program) to maximize brand attitude and brand recall. Controlling for program connectedness, brand attitude is maximized when all brand placements in a program are interactive. The optimal mix for brand recall is more diverse, and changes for consumers with different viewing frequencies. For light viewers, 39% interactive and 61% prop placements should be used. For consumers with high viewing frequency, a relatively larger proportion should be allocated to interactive placements (44%).

Purpose of the study

The increasing penetration of digital television and online pay-per-view and streaming services is putting the traditional advertising-funded business model of commercial television under pressure. Hybrid advertising formats that merge commercial content, i.e., brand identifiers or branded products, with media content, such as television programs or online news articles (product or brand placement), are becoming increasingly popular (Verhellen *et al.* 2013; PQMedia 2015). Famous examples of well-known brand placements include James Bond's outspoken preference for certain brands of alcoholic beverages and fast cars, American Idol's longstanding arrangement with Coca-Cola and Carrie (Sarah Jessica Parker) and co.'s adoration of Louis Vuitton handbags, Manolo Blahnik shoes and other high-end designers in the "Sex and the City" series and movies.

Although the phenomenon of brand placement in motion pictures and television is as old as the industry itself (Newell *et al.* 2006), in recent years, it is taking up an increasing share of advertising budgets. In 2014 brand placement in all its forms and in all audiovisual media was estimated to be worth $73.3 billion, a 6.3% gain compared to the year before (PQMedia 2015). In 2007, the European parliament promulgated a revised version of the Audiovisual Services Directive, that legalized brand placement in the European Union. In Belgium, the setting of the present research, a content analysis of 210 hours of programming on Belgian commercial television registered 1029 placements, the equivalent of one placement every 12 minutes (Wouters & De Pelsmacker 2011).

The rise of brand placement as a promotional tool has resulted in a vast body of academic research (e.g., Russell 1998; Karrh *et al.* 2003; Van Reijmersdal *et al.* 2009; Wilson & Till 2011). According to this research, brand placement can have beneficial effects on brand recall (Bressoud *et al.* 2010), brand image (e.g.: Van Reijmersdal *et al.* 2007), brand preference (Auty & Lewis 2004) and even stock prices (Begy & Talwar 2015). Recent studies demonstrate that these effects vary depending on placement characteristics (Dens *et al.* 2012), consumer characteristics (e.g., Lehu & Bressoud 2008) and contextual factors (Cowley & Barron 2008). However, brand placement is constantly evolving, and there is much more to learn about how it operates.

Audiovisual content producers and creative professionals are reluctant towards giving advertisers a free stage to promote their brands within their productions. Production and/or broadcasting companies increasingly offer standardized placement package-deals and, consequently, brand placement campaigns are usually a mix of different and often pre-defined types of placement. One of the challenges of brand placement strategy and operationalization is to decide what the optimal mix of these (pre-defined) brand placement types is to ensure maximum brand placement effectiveness. To the best of our knowledge, there is as yet no study or methodology that systematically assesses the impact of different 'mixes' of brand placement types on the overall effectiveness of a brand placement campaign. The main contribution of the present study is to develop and test a model by means of which viewer responses to different brand placement type mixes in television programs can be assessed and a placement mix can be determined to maximize brand recall or brand attitude. To that end, the current study uses Mixture Modelling, an analytical approach that is novel in advertising research, and that allows to predict advertising outcomes for any combination of brand placement types in a program, and derive brand placement type allocation to optimize any advertising outcome. Our research approach combines brand placement content analysis with mixture modeling based on quantitative response data collected from a large amount of viewers of Belgian television programs in which brands were placed in various ways, and we estimate the effect of campaigns consisting of different blends of brand placement types on brand recall and brand attitude. We closely cooperate with the largest commercial media company in Belgium that operates a number of television and radio channels, and is actively using brand placement as part of its business model.

A limitation of most existing brand placement research is the scarcity of field studies that explore how brand placement works in real-life settings. The external validity of most placement research is restricted by a number of methodological shortcomings. Apart from a few noteworthy exceptions (e.g., Russell 2002; Dens *et al.* 2012), most previous studies were conducted in non-naturalistic laboratory settings that are not representative of real-life exposure to brand placement (e.g., Homer 2009). Second, many studies are based on exposure to unrealistically short and edited stimuli (e.g., Yang & Roskos-Ewoldsen 2007). Lastly, a large majority of placement studies rely on student samples instead of real consumers (Gupta & Gould 2007). These limitations compromise the external validity of previous brand placement research. The present study addresses these limitations by conducting a field study on the effects of several season-long placement campaigns that ran in television programs that were broadcast on Belgian commercial television, on actual viewers.

Our study contributes to market research and advertising practice in that understanding what (combinations of) placement types work best allows advertisers to develop customized campaigns that can maximize the achievement of specific objectives. Our methodological approach allows market research agencies to assess brand placement effectiveness in a valid way. In addition, these insights also contribute to an estimation of the value of a placement campaign, and to develop relevant placement business models.

The placement mix

Placement criteria: Prominence and plot connection

Brands can be placed in editorial content in a number of ways, and can be categorized on the basis of a number of criteria. Russell (1998) proposed a 'Tripartite Typology' of placement formats. Visual and auditory placements correspond to what Russell calls screen placements and script placements, respectively. This criterion is referred to as the "modality" of the placement (e.g., Russell 2002; Brennan & Babin 2004). Placements in both modalities can be more or less obvious, central, or emphasized. Gupta and Lord (1998) define this as "prominence", the extent to which the brand placement possesses characteristics designed to make it a central focus of audience attention. While modality can be easily determined in individual scenes, prominence is a more relevant dimension in the context of an entire movie or TV show, as these may include multiple placements of the same brand in different modalities (Dens *et al.* 2012). Studies indicate that while prominence improves brand recognition and recall, it can be detrimental for brand attitude and choice (e.g., Van Reijmersdal 2009; Dens *et al.* 2012; Verhellen *et al.* 2015). The third dimension of placements according to Russell (1998) are plot placements, which indicates the extent to which a placed brand is "plot connected", i.e. becomes part of the plot, taking a major place in the story line or building the persona of a character. Plot connection generally benefits both brand recognition and brand attitude (Dens *et al.* 2012; Verhellen *et al.* 2015).

Placement typology used in practice

Media companies often offer advertisers the opportunity to place brands in their programs using pre-determined formats. The media company that was involved in the current research distinguishes between three formats.

- *'Look and feel' placements:* Brand identifiers of the advertiser (e.g., logo's, colors, etc.) are incorporated in the scenery of the program, such that the scenery represents the "look and feel" of the brand. For example, participants of talent contests are interviewed in a custom-designed area that is decorated in the brand's color scheme, and resonates with the style and feelings that the brand wants to convey (e.g., trendy, high-tech, etc.). This format consists of visual brand identifiers only. 'Look and feel' placements are relatively subtle (i.e. not prominent). Their presence is restricted to the background, and the brand name itself is usually not shown or mentioned. They are also lowly plot connected, as the brand identifiers do not have any functional role in the show (e.g.; the interview could be done anywhere else without affecting the storyline), and there are no brand interactions with any of the characters. Due to the lack of both prominence and plot connection, this type of placement should hamper brand recall. The lack of plot connection will also not contribute a great deal to brand attitude, either. The restriction of the brand's presence to brand identifiers only may also be too subtle to allow for any positive attitudinal effects to occur. We thus expect that look and feel placements will play a relatively minor role in the optimal placement mix for both brand recall and brand attitude.

- *Props:* Branded products are put on display at various instances during the program, without active person-product interaction. For example, during one of the programs the presenters interviewed contestants at a table on which several bottles of a branded soft drink were displayed. Like look and feel placements, prop placements are visual only, but include the actual product and the brand name is usually clearly visible. The products are often in the foreground. Prop placements are lowly plot connected (e.g., if the interview table would be empty, this would have no impact on the program). Based on the lack of plot connection, combined with a relatively higher degree of prominence, we expect that prop placements will not play a major role in the optimal placement mix for brand attitude. The prominence of this type of placements, however, may make them relatively appropriate for stimulating brand recall.
- *Interactive placements:* These placements entail relevant interaction between a branded product and a person (character, presenter, contestant). The interaction can be visual (e.g., a cook adding a branded ingredient to a dish), auditory (e.g., mentioning the brand as the prize for a competition) or both. Interactive placements are thus more plot connected than the passive prop and look and feel formats. They are usually at least moderately prominent, because the interaction draws attention to the product. Of the three types of standard brand placement formats, this is the only type that contributes to plot connection. Therefore, we expect that this placement type is especially suited to stimulate brand attitude and will therefore make up a major part of the optimal placement mix for brand attitude. As plot connection also contributes to brand recall, we also expect that interactive placements will be present in the optimal placement mix for brand recall.

Besides the placement mix, we include viewers' degree of program connectedness as a covariate. Connectedness refers to the intensity of the relations that viewers develop with television programs and their characters (Russell *et al.* 2004). Russell *et al.* (2004) demonstrated that connectedness positively impacts viewers' attitudes toward brands that are placed in the program. In a study by Russel (2009), connectedness, however, did not influence brand recall.

We also add viewing frequency as a moderator. Verhellen *et al.* (2015) found that viewing frequency was positively related to brand recall. However, the moderating role of viewing frequency on placement (mix) effectiveness has not been explored yet. Nevertheless, it may have an impact in that, for instance, prominent placements may be noticed better at low viewing frequency, leading to higher brand recall, or prominent non-plot connected placements may have a more negative effect on brand attitudes as viewing frequency increases.

Method

The purpose of the analysis is to predict recall of and attitude towards brands placed in television programs as a function of the mix of three types of placements used, viewers' level of viewing frequency as a moderator, and program connectedness as a covariate. To that end, we estimate two Mixture Models (one for each dependent variable). Mixture models have been used in various research areas. Sahrmann *et al.* (1987) for instance, describe mixture experiments for the optimization of a recipe for a cocktail, while Schrevens & Cornell (1993) discuss the use of mixture models to study the composition of nutrients for plants in hydroculture and Roush et al. (2004) use a mixture experiment to optimize the diet of broilers. Piepel (2007) describes an experiment for modeling the properties of mixtures for nuclear waste glass. De Ketelaere *et al.* (2011) discuss a mixture experiment with an additional amount variable for the optimization of the taste of a specific kind of bread. White *et al.* (2004) apply a mixture-amount model to data from an *in vitro* study of the combined effect of Trimetrexate (TMQ) and AG2034 on the inhibition of cancer cell growth. As far as we are aware of, so far, these models have not been applied to marketing communications optimization, except in one study on advertising media mix optimization (Authors 2015).

In general, Mixture Models take the following form (Cornell 2002). Suppose we have q ingredients (placement types) in a mixture, and denote the proportion of the ith ingredient by x_i, than a Mixture Model allowing for mixing effects among the q mixture components, can be formulated as follows:

$$\eta = \sum_{i=1}^{q} \beta_i x_i + \sum\sum_{i<j}^{q} \beta_{ij} x_i x_j + \sum\sum_{i<j<k}^{q}\sum \beta_{ijk} x_i x_j x_k + \ldots, \tag{1}$$

where η represents an outcome and β_i , β_{ij} and β_{ijk} represent the effects of the mixture composition. In this study, η is the predicted outcome for brand recall (binary) and brand attitude (interval scale). The interaction terms help us understand how changing the proportion of one or multiple mixture components impacts the effects of the other mixture components. The Mixture Model in Equation (1) is a special type of regression model, because it is based on proportions. Regression models for mixture data do not have an intercept because the sum of all ingredient proportions equals 1. Mixture Models are characterized by a large degree of multicollinearity, due to the fact that the ingredient proportions sum to 100%. This makes most conventional significance tests for individual coefficients useless. The models are, however, useful for making predictions and for determining the optimal proportions of the ingredients.

The Mixture Models in the current study predict brand attitude and brand recall as a function of the proportions of the three placement types used, and introduces viewing frequency as a moderator. The resulting model is akin to mixture-process variable models such as in Næs *et al.* (1998), Cornell (2002), Kowalski *et al.* (2002), Smith (2005) and Goos and Jones (2011). An appropriate model for the impact of q ingredient proportions and l process variables z_1, …, z_l on a response η is given by

$$\eta = \sum_{i=1}^{q} \beta_i x_i + \sum_{i=1}^{q-1} \sum_{j=i+1}^{q} \beta_{ij} x_i x_j + \sum_{k=1}^{l} z_k (\sum_{i=1}^{q} \gamma_{ik} x_i + \sum_{i=1}^{q-1} \sum_{j=i+1}^{q} \gamma_{ijk} x_i x_j), \quad (2)$$

In the context of the present study, the process variable z_k correspond to the respondents' viewing frequency. The Mixture Model in the present study allows for (a) look and feel, prop and interactive placement proportions to have a different impact on the outcomes, (b) interaction effects between look and feel, prop and interactive placements to capture potential synergies, and (c) interactions between the proportions of look and feel, prop and interactive placements, on the one hand, and respondents' viewing frequency on the other. This means that, this specific situation, the mixture-process variable model can be written as:

$$\begin{aligned} \eta &= \beta_{ive} x_{ive} + \beta_{lf} x_{lf} + \beta_{prop} x_{prop} + \beta_{\text{int}} x_{ive} x_{lf} + \gamma_{\text{int}} x_{ive} x_{prop} + \lambda_{TV} x_{lf} x_{prop} \\ &+ p(\beta_{ive} x_{ive} + \beta_{lf} x_{lf} + \beta_{prop} x_{prop} + \beta_{\text{int}} x_{ive} x_{lf} + \gamma_{\text{int}} x_{ive} x_{prop} + \lambda_{TV} x_{lf} x_{prop}) + \theta d_{conn}, \end{aligned} \quad (3)$$

where x_{ive}, x_{lf} and x_{prop} represent the proportions of interactive, look and feel and prop placements (the multiplications represent the 2-way interactions between the different proportions), p represents respondents' viewing frequency and d_{conn} represents respondents' program connectedness, which we include as a covariate. Due to the binary nature of brand recall, we use the logit link function to connect the linear predictor to the probability of brand recall and assume a Bernoulli distribution for the response. As brand attitude is measured on a five-point scale (see below), we treat this as an interval dependent. Within the current data set, the full model containing the interactions with viewing frequency did not converge for brand attitude. Therefore, for brand attitude, we estimate a simpler model excluding the interactions with viewing frequency, while preserving program connectedness as a covariate.

To estimate the brand recall and brand attitude models we use the SAS procedures GLIMMIX for the brand recall model and MIXED for the brand attitude model.

Data Collection

Sample

We collected data for 20 different brand placement campaigns for 17 brands that ran in 11 reality entertainment programs on Flemish commercial television between 2011 and 2013. The list of programs contains all the major reality entertainment shows that ran on the main commercial television channel in that period. The majority of these programs are local talent competitions (singing, cooking, dancing contests), with the exceptions of “Sofie’s Kitchen”, which is an instructive cooking show (cfr. “Nigella’s Kitchen”) and “Let’s Get Fit”, which is a reality show aimed at promoting a healthy lifestyle. For each program, the major sponsors that had paid brand placements in the program were identified in cooperation with the television network. Six brands invested in multiple programs, and as a result, are included in the analyses twice (Table 1).

Table 1 about here

For each of the 20 campaigns, consumer responses were measured in a sample from the online consumer panel of a Belgian market research agency. Individual sample sizes per campaign ranged between n = 332 and n = 465. Each sample consisted of approximately 50% non-viewers and 50% viewers of the program in question, and was collected using a quota sampling procedure (quota were based on age and gender), in order to be representative of the television network’s viewer profile. For two campaigns, the sample consisted of only female respondents, and for six campaigns, only 15-34 year olds were selected, consistent with the target groups of the placed brands. Respondents were contacted one day after the final episode of a certain show was broadcast, and given a week to complete the survey. The outcome of this procedure yielded a sample of 3 884 viewers of the programs across the 20 brand placement campaigns, and 3756 non-viewers. The sample consists of 43.2% male and 56.8% female respondents. In terms of age, 30.07% was between 15 and 24 years old, 35.34% between 25 and 34, 16.10% between 35 and 44, and 18.49% between 45 and 54.

Placement type proportions: Content analysis

To determine the proportions of each of the placement types, a content analysis was performed on the 11 programs listed above. Each episode of the programs was coded by two independent coders based on a standardized coding scheme. Before performing the coding task, both coders received a 3 hour training session that focused on distinguishing the three placement types across the different program formats. The coding scheme required the coders to classify each placement into one of the three placement categories that are defined above, i.e., look and feel placement, prop placement and interactive placement. To ensure independence between the coders, all placements that were missed by one coder, but not by the other one, were grouped in two files (one per coder) and completed by the coder who originally missed the placements. This procedure yielded a total of 1660 coded placements. Cohen’s Kappa coefficient of the two data series was κ = .919. With a value of 1 indicating perfect agreement, and .60 being the most widely used cutoff value for the acceptability of the inter-coder reliability, we found high consistency between the coders’ ratings (Verhellen *et al.* 2014). In line with the procedure recommended by Perreault and Leigh (1989), a third coder, who received the same training, was asked to solve the few disagreements between the initial coders’ ratings. For each campaign, we calculated the relative proportion of placements across the three placement types, by adding up the number of placements of all three placement types and calculating the percentage occurrence of each placement type.

The distribution of the placement type mixtures present in the dataset across the three mixture components is visualized using a triangular plot (Figure 1). For a given mixture, the position of the dot in the triangle represents the percentage proportion of placements for that mixture. The left axis represents the percentage proportion of look and feel placements, the right axis represents the proportion of prop placements for any given mixture dot, and the horizontal axis represents the proportion of interactive placements. For the mixture models to generate accurate predictions, there needs to be a decent spread of the dots across the triangular plot of the mixture diagram. This implies that the model can draw from different, heterogeneous mixtures. If the mixtures are too homogeneous, this limits the predictive capabilities of the model in areas where no mixture data are available. Figure 1 shows a good spread of dots in most areas of the diagram. The area where the model has no predictive ability (because there are no observations) is shaded. For the campaigns in the present dataset, the maximum proportion of plot placements did not exceed 83.5%, and the present dataset contains only one interactive placement proportion that exceeds 67%. This implies that predictions that include a prop placement proportion higher than 83.5% or an interactive placement proportion higher than 67% have limited validity.

Figure 1 about here

Measures

Viewing frequency was measured using a 7-point Likert scale ('1' indicates that the respondent did not watch the program, '7' indicates that he or she watched all episodes). The respondents that indicated '1' constituted the non-viewers group. For program viewers, program connectedness was measured by means of a 4-item, 5-point Likert scale based on Russell *et al.* (2004) (e.g., 'I would like to participate in [program] myself', α = .888). The effectiveness of the brand placement campaigns was measured using two variables: brand recall (e.g., Gupta & Gould 2007; Bressoud *et al.* 2010) and brand attitude (e.g., Cowley & Barron 2008; Homer 2009). Brand recall was measured with viewers only, using an open ended question (i.e., 'Please write down which brand(s) you saw in the program'). The answers were converted into a dummy variable ('1' indicates correct recall of the brand). Brand attitude was measured in both the viewers and the non-viewers group, using a 4-item 5-point Likert scale ('I like ___', '___ is a good brand', 'I feel good about ____' and 'My opinion on ___ is positive', *α* = .919) based on Sengupta and Johar (2002). Per brand, summated brand attitude scores were calculated separately for the viewers and the non-viewers (control groups). We subtracted the control group's mean attitude score for the corresponding brand from each viewer's individual brand attitude score (cfr. Russell 2002; Dens *et al.* 2012). This resulted in a brand attitude difference measure that expresses the shift in brand attitude due to the exposure to the program. These scores are used in the subsequent analyses.

Table 2 provides an excerpt of the final data file, which combines the 20 placement mixtures with the individual-level data (brand recall, brand attitude, program connectedness and program viewing frequency) per campaign.

Table 2 about here

Results

Model estimation and fit

We estimated two mixture models, one with brand attitude and one with brand recall as the dependent variable. Due to the multicollinearity in the data, a typical problem for regression models involving proportions (Cornell 2002), it is neither useful to interpret individual estimates nor to focus on individual p-values. However, the estimated regression model is suitable for making predictions concerning ad recall and brand attitude. Indeed, multicollinearity typically has little impact on the accuracy of a prediction (Verbeek 2012). For the model with the binary brand recall variable as the dependent, the estimation was performed using a generalized linear mixed model and a logit link function. For the model with the continuous brand attitude variable as the dependent, a generalized linear mixed model with an identity link function has been used. The model estimates from a generalized linear mixed model are maximum likelihood estimates obtained through an iterative process. As a result, they are not calculated to minimize variance, so the OLS approach to goodness-of-fit does not apply. To quantify the predictive model performance of the models, we used the McFadden Pseudo-R^2 (Hagle & Mitchell 1992) because it can be interpreted analogously to an ordinary least squares coefficient of determination for models with binary and continuous outcome. The ratio in Pseudo-R^2 is indicative of the degree to which the model parameters improve upon the prediction of the null model (intercept only). A value between .2 and .4 is considered to evidence good model performance, anything above signals excellent predictive performance (Windmeijer 1995). The analysis yields a value of .503 for the brand attitude model and .497 for the brand recall model, which indicates that both mixture models have excellent predictive power. In addition to Pseudo-R^2, we used a likelihood ratio test that allows to compute a p-value to decide whether to reject the null model in favor of the alternative (mixture-amount) model. The outcomes of this likelihood ratio test are significant for both the brand attitude and brand recall models ($p < 0.001$), again indicating a good fit.

To interpret the outcomes of the models, we use the prediction profiler embedded in the software package JMP Pro 12, developed by the SAS Institute. The prediction profiler demonstrates the change in the predicted responses as a function of mixture components proportions, connectedness and viewing frequency. In the figures below, the vertical axis represents the predicted value for the dependent variable, either brand attitude or brand recall. The horizontal axes show the respective proportions of the three mixture variables in the mixture model, the moderator viewing frequency (for brand recall), and the covariate connectedness. The leftmost pane shows the effect of different proportions of interactive placements, the second pane from the left shows the effect of different proportions of look and feel placements and the third pane shows the effect of prop placements on predicted brand attitude or brand recall. The fourth pane of the brand attitude model shows the effect of connectedness as a covariate. The fourth pane of the brand recall model shows the effect of viewing frequency, and the fifth pane the effect of connectedness. The solid curves in the first three panels show how the value of the dependent variable changes as a function of the proportion of interactive, look and feel and prop placements. In each pane, dashed vertical lines indicate the selected levels of the explanatory variables.

Brand attitude model

Figure 2 shows that 100% of interactive placements lead to the highest possible brand attitude. However, since our actual observations only sufficiently range up to 67% interactive placements, we limit our attitude prediction to that maximum. In case of average program connectedness (score=4), a placement mix with 67% interactive placements leads to a brand attitude difference score of 0.99. Other allocations lead to a lower brand attitude. As program connectedness is considered as a covariate, the optimal placement "mix" does not change with different levels of connectedness. However, as expected, brand attitude increases with increasing levels of program connectedness. In case of low connectedness (score=1), the maximum predicted brand attitude is 0.57; for high connectedness (score=7), the maximum increases to 1.41. The prediction profiler also allows us to predict the value of the dependent variable for other placement mixtures. For instance, suppose an advertiser places his or her brand approximately equally frequently across all placement types (~33%), with an average level of program connectedness the predicted brand attitude would be only 0.23.

Figure 2 about here

Brand recall model

Figure 3 shows that, for frequent program viewers (score=7), an allocation of 44% interactive, 56% prop and 0% look and feel placements leads to the highest predicted brand recall probability (56%). Any other allocation leads to a lower brand recall. Connectedness has a low overall effect on the brand recall probability, but it does improve the overall model fit compared to when we would exclude it. For low frequency viewers (score=2), Figure 4 shows that an allocation of 39% interactive, 61% prop and 0% look and feel placements leads to the highest predicted brand recall probability (31%). Any other allocation would lead to a lower brand recall.

Figures 3 and 4 about here

Discussion, limitations and suggestions for future research

Regardless of the placement mix, as expected, stronger program connectedness leads to more positive brand attitudes and consumers with higher levels of viewing frequency show higher brand recall.

A placement mix that maximizes brand attitude consists of 100% interactive placements, no prop placements and no look-and-feel placements. Interactive placements are the most plot-connected of the three types, and, as previous studies have shown, plot connection is an important driver of positive brand attitudes (Russell 2002; Dens *et al.* 2012). Interactive placements are usually moderately prominent, but as mentioned, the brand name itself is not always prominent. Apparently, the potential negative effects of prominence on brand attitudes are neutralized by the meaningful connection of the brands to the programs due to their interactive nature.

For optimal brand recall, interactive and prop placements should be used, and look-and-feel placements should be avoided. Previous studies indicated that plot connection and prominence improve brand recall (Russell 2002; Dens *et al.* 2012). This may explain the positive effect of interactive placements. Prop placements are usually less plot-connected, but relatively prominent, which explains their positive effect on brand recall. Look-and-feel placements, as argued, are more implicit as neither the brand nor the product are actually shown or mentioned. This may limit their effect on brand recall.

Consumers' viewing frequency moderates how brand placements should be allocated to maximize brand recall. For consumers with low viewing frequency 39% interactive and 61% prop placements should be used. For consumers with high viewing frequency, a relatively larger proportion should be allocated to interactive placements (44%). This could be due to the fact that prop placements are usually more prominent than interactive placements and, hence, prop placements are relatively more effective in generating recall in case of less exposure to the program. Additionally, consumers with higher viewing frequency may show higher acceptability of product placements (Gupta & Gould 1997; Gould *et al.* 2000; McKechnie & Zhou 2003) and as a result might be more open and attentive to interactive placements than consumers with lower viewing frequency.

An important contribution of this study is that it introduces mixture models as a promising novel research method to identify brand placement strategies that optimize placement outcomes in a real-life setting. Mixture models combine brand placement campaign characteristics and individual responses to these brand placement campaigns. We consider the present study as a proof of concept of the applicability of the mixture modeling research technique in a brand placement context. Mixture models are a flexible tool to help advertisers and market researchers determine brand placement effectiveness, for different proportions of different types of brand placements, and for different target groups. The model allows to include other dependent or moderating variables. Moreover, the model can generate reliable results with data on relatively few campaigns.

The present study offers guidelines for advertising and market research practitioners. Brand placement business models are usually based on exposure time and prominence. The methodology presented here can be a starting point for more fine-grained business models that also take placement characteristics into account. Market research based on mixture models can also inform advertisers and media professionals to develop placement campaigns that are tailored to campaign objectives (e.g. a different mix for brand attitude development than for boosting brand recall). One of the remarkable conclusions of the present study is that look-and-feel placements should be avoided since they negatively affect both outcomes compared to the other two types. Look-and-feel placements are one of the standard brand placement formats offered by television channels and, as such, are an important component of the current brand placement business model. Television channels and advertisers should reconsider their placement mix and, more particularly, the use of look-and-feel placements.

In this study we focused on interactive, look and feel and prop placements, connectedness as a covariate and self-reported viewing frequency as a moderator. Viewing frequency could be measured more precisely by use of relatively novel technology (e.g., Sheridan 2012). In addition, mixture modeling allows the inclusion of any other relevant variable. For instance, more or different types of brand placements can be integrated as independent proportion variables. Other moderators or control variables can also be integrated in the model, such as consumer characteristics, program or product type, program liking, product category involvement, or brand familiarity. Besides brand attitude and brand recall, other outcomes can be measured and modeled. For example, research points out the importance of brand likeability (Nguyen *et al.* 2015), brand choice (Marchant *et al.* 2012) and of course ultimately sales (Trinh & Anesbury 2015). Finally, the present study is a "proof of concept". It illustrates a method that is new in the context of marketing communications optimization. Obviously, the results are specific for the context and the data used in this empirical study, and are, as such, not generalizable across all types of marketing communications tools and media and in different contexts and markets. Therefore, there is a need for repeat studies in different markets, with different brands, programs and outcome variables, to corroborate our findings. These are all avenues for further research.

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Table 1. Overview of campaigns per program

Program	Program type	Brand	Product category
1. The Best Hobbychef of Flanders (2011)	Cooking competition	Brand 1	FMCG (food)
2. Minute to Win it (2011)	Entertainment, competition	Brand 2	FMCG (food)
3. The Voice (of Flanders) (2012)	Singing competition	Brand 3 Brand 4 Brand 5 Brand 6 Brand 7	Consumer electronics Retail (phone services) FMCG (personal care) FMCG (personal care) Automotive
4. Belgium's Got Talent (2012)	Talent competition	Brand 8 Brand 9	OTC vitamins Retail
5. So You Think You Can Dance (2012)	Dance competition	Brand 10	FMCG (food)
6. Masterchef (2012)	Cooking competition	Brand 11	Consumer electronics
7. Sofie's Kitchen (2013)	Cooking tutorial	Brand 12	Retail (supermarket)
8. Junior Masterchef (2013)	Cooking competition	Brand 11	Consumer electronics
9. The Voice (of Flanders) (2013)	Singing competition	Brand 3 Brand 9 Brand 13 Brand 14	Consumer electronics Retail (clothing) FMCG (food) FMCG (soft drinks)
10. Let's Get Fit (2013)	Health and lifestyle competition	Brand 15 Brand 16	FMCG (food) Utilities
11. In fashion	Lifestyle program	Brand 17	Retail (fashion)

Note: The information concerning the sponsoring brands is bound by a confidentiality agreement that does not allow disclosure of the sponsoring brands.

Table 2. Data structure

Respondent ID	**Campaign**	**Look and feel**	**Props**	**Integrated**	**Connectedness**	**Viewing frequency**	**Brand recall**	**Brand attitude**
1	1	.30	.40	.30	2	1	0	4
2	1	.30	.40	.30	4	5	1	2
…	…	…	…	…				
205	2	.80	.15	.05	7	4	0	1
206	2	.80	.15	.05	2	7	0	5
…	…	…	…	…				
n	*c*	*p1*	*p2*	*p3*	*K*	*e*	*r*	*v*

Figure 1: Mixture diagram for brand placement mixes

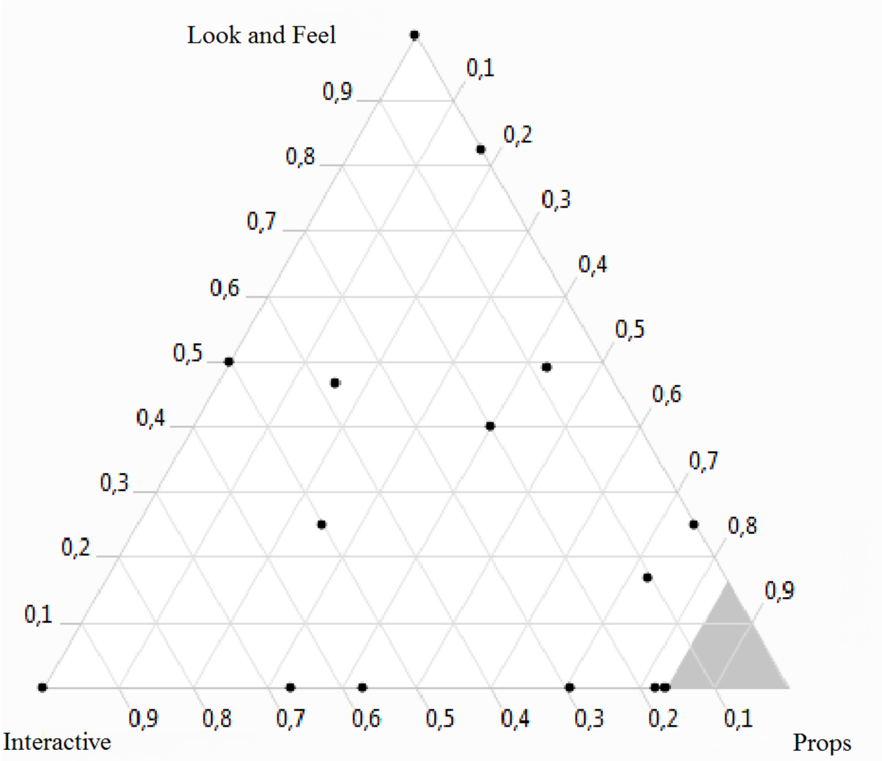

Figure 2: Prediction profiler plot for the solution with maximum brand attitude.

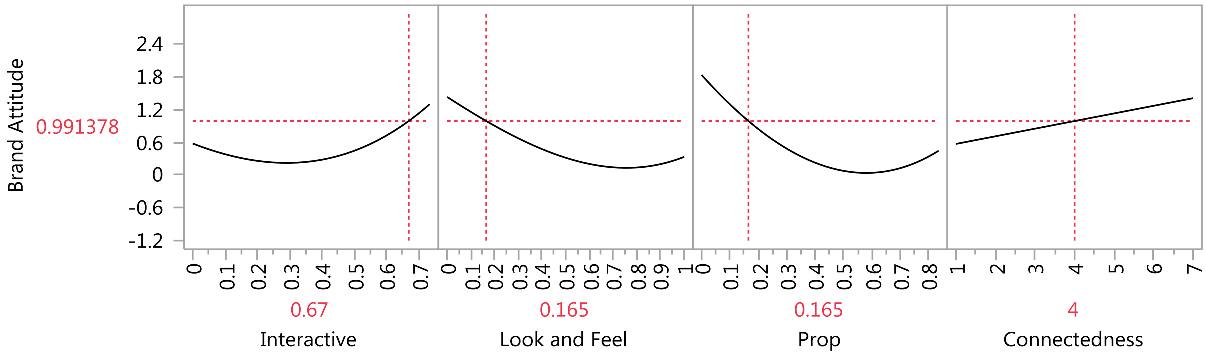

Figure 3: Prediction profiler for the brand recall probability with high viewing frequency (7)

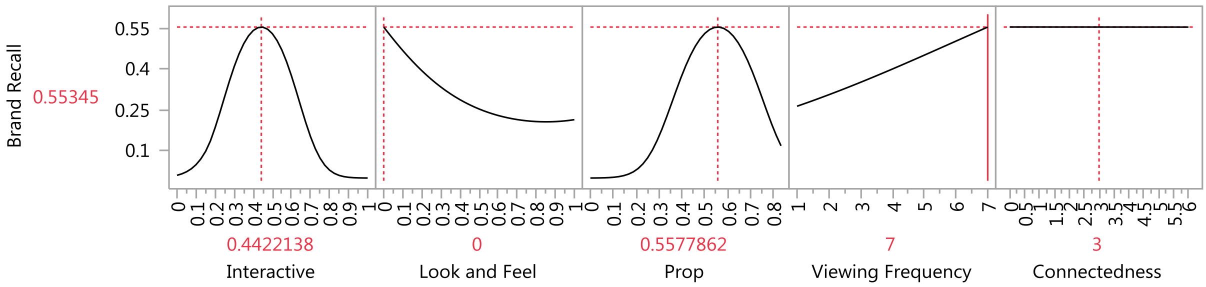

Figure 4: Prediction profiler for the brand recall probability with low viewing frequency (2).