EFFECTS OF MULTIPLE MODELS AND GROUP DIVERSITY IN SOCIAL MEDIA ADVERTISING

ABSTRACT

This study examines digital video advertising, focusing on the impact of single versus multiple models on social media responses and the role of group diversity (age, gender, ethnicity) in international ads. Using theories of information utility, message repetition, and cue-diagnosticity, it analyzes 234 YouTube and Instagram campaigns with 38,774 consumer comments via machine learning-based facial recognition. Results show that social media ads with multiple models outperform single-model ones in driving responses, consistent with theoretical predictions. However, group diversity within ads shows no significant effect. The study offers theoretical, managerial, and methodological insights, highlighting future research opportunities on diversity in advertising.

Keywords: diversity, machine learning, facial recognition, social media

Advertisers have responded to the trend toward greater diversity and inclusion in many Western societies by including models with diverse characteristics that deviate from the characteristics of the majority groups in society (Eisend et al., 2026). Here, we define a model as any identifiable human figure appearing in an ad, regardless of celebrity status, thereby distinguishing models from endorsers whose persuasive effects typically derive from prior fame, credibility, or brand association. As the portrayal of a minority model (e.g., a member of an ethnic minority group) may not resonate with the expectations of a society's majority, diversity in advertising leads to positive social effects (e.g., reduced stereotypes and prejudices) but can have negative commercial effects (Eisend, Muldrow, & Rosengren, 2023). Extant research on diversity in advertising has examined the effects of minority models in advertising on consumers and has focused on the use of a single model belonging to a specific minority group (e.g., Rößner, Gvili, & Eisend, 2021; Plotkina & Saurel, 2020; Zúñiga, 2016).

Although studying a single model has certain advantages, particularly in establishing internal validity in experimental research, it poses several challenges regarding the external validity and practical applicability of the results. Consequently, existing research provides limited insights into how audiences respond when multiple models appear simultaneously within a single advertisement, which is increasingly common in contemporary campaigns. First, as our research reveals, most advertisements depict more than one model to show diversity (71% in our sample); therefore, research on single models lacks external validity. Second, prior research usually singles out a particular diversity dimension, thus ignoring the fact that diversity refers to multiple dimensions that coexist (e.g., age, ethnicity, gender) and simultaneously influence consumers. Second, advertisers who aim to be more diverse and inclusive run the risk of discriminating against other minority groups in society by selecting only a single model who belongs to a particular minority group. Third, focusing on specific minority models to increase diversity might work well in national campaigns, but may not work in international campaigns on social media, where the same model (e.g., a young African woman) is either a minority or a majority group member depending on the country of the recipients.

The multiple-model advertising literature has traditionally examined campaigns using different ads with single models across executions, rather than multiple models appearing together within a single advertisement. The purpose of multiple-model advertising is to leverage congruence effects by appealing to a wider audience (Choi & Rifon, 2012). However, research has neglected situations in which different models appear together as a group within a single ad, particularly when portraying diversity. Group diversity occurs when the individual members forming a heterogeneous group differ from each other in terms of a single or various diversity dimensions (Blau, 1977). Multi-model diversity ads can counter negative effects of minority display in international campaigns, particularly on social media, because various minority groups can be addressed to serve audiences from various countries that have different minority-majority group compositions. This study investigates the effects of group diversity in international social media ads using multiple models who differ along three main diversity dimensions and their interactions. More specifically, we scrutinize the age, ethnicity, and gender of human models in YouTube and Instagram advertisements of leading brands and investigate the effects of multiple models, group diversity dimensions, and their interactions on consumers' responses.

This study makes three primary contributions to advertising research. First, we advance advertising theory by shifting the analytical focus from individual models or endorsers to the number of models appearing within a single advertisement. This perspective moves beyond mainstream endorsement research (e.g., Chaihanchanchai, 2025) by treating advertisements as configurations of co-present models rather than as vehicles for individual sources (Brennan, Ilicic, & Kennedy, 2026). We examine whether model multiplicity itself—independent of individual characteristics—shapes consumer responses in social media environments. To this end, we conceptualize group diversity as heterogeneity among multiple co-present models across three demographic dimensions, a perspective that has received scant attention. Existing research provides little evidence on whether group diversity in multi-model ads influences consumer responses. We examine how diversity among co-present models operates in international social media advertising. Using real-world international campaigns, we provide a high-external-validity test of diversity effects that complements prior experimental research.

Second, we extend diversity research in advertising from traditional media contexts (e.g., print, television) to international social media advertising, where audiences are heterogeneous and responses are publicly observable at scale (Eisend, Muldrow, & Rosengren, 2023). In doing so, we examine the responses as expressed by textual and pictorial content (e.g., emojis).

Third, we employ a computational approach that integrates deep learning-based facial recognition, enabling simultaneous analysis of multiple communication dimensions of advertising content (i.e., text and pictures) in large-scale datasets. This approach reflects a growing trend in the analysis of text and pictorial user responses (e.g., Shahbaznezhad, Dolan, & Rashidirad, 2021; Unnava & Aravindakshan, 2021).

CONCEPTUAL FRAMEWORK

Figure 1 shows the conceptual model used in this study. We investigate the influence of single vs. multiple models in social media campaigns and the effects of group diversity of multiple models in terms of three diversity dimensions as well as their interactions. To that end, we review the research on multiple models, diversity in advertising, and explain our concept of group diversity. Finally, we discuss the concept of social media responses as our focal dependent variable.

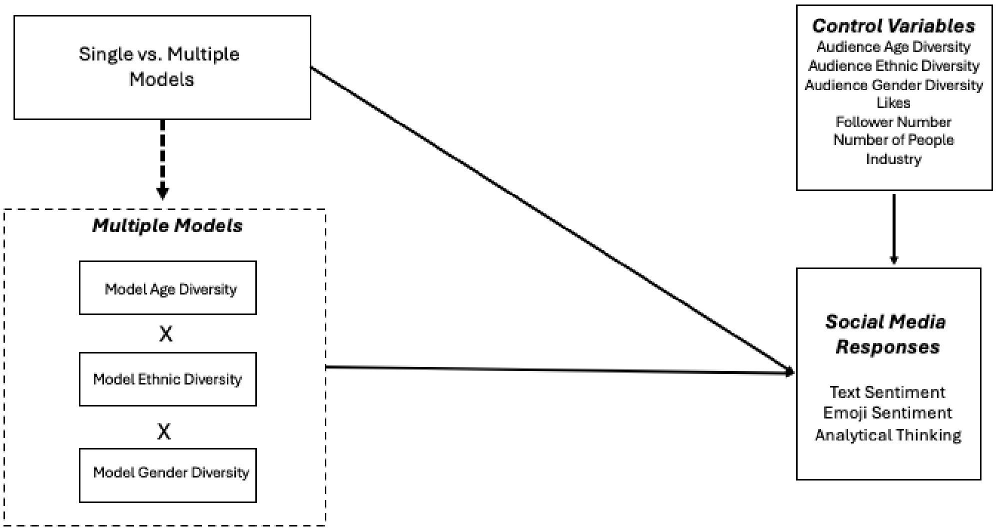

Figure 1. Conceptual model

Multiple Models in Advertising

To date, scholars paid limited attention to the effects of multiple models appearing simultaneously within a single ad. Recent work by Brennan et al. (2026) examines multi-celebrity endorsement, defined as featuring two celebrities together in an ad. Drawing on social impact theory, the authors demonstrate that using multiple celebrity endorses within a single ad is more effective than distributing them across separate ads, leading to more favorable brand attitudes, behavioral intentions, and willingness to pay. Endorser credibility serves as a crucial moderator.

Although empirical research on multiple models remains limited, related theoretical perspectives have been examined in adjacent contexts involving multiple information sources. For example, Moore et al. (1994), using information utility theory, found that when audiences perceive source as unpaid, multiple sources generate more favorable attitudes than a single source due to a multiple-source effect—enhancing information utility by increasing motivation for information processing. Similarly, Rice et al. (2012) apply Elaboration

Likelihood Model (ELM; Petty & Cacioppo, 1986) to test how the number of endorsers, source congruence, and involvement jointly shape persuasion outcomes. They reveal that persuasion differs across processing routes. Under low involvement (peripheral route), multiple models exert more favorable brand attitudes, regardless of source congruence, provided that individual source cues are positive. Under high involvement (central route), however, multiple models enhance brand attitudes only when source congruence is strong.

Another relevant perspective is cue-diagnosticity theory. Diagnosticity refers to the extent to which information is perceived as useful for evaluating a brand or an ad (Martin et al., 2009). Assuming impression formation as a categorization process, the theory posits that a greater the number of diagnostic cues leads to more favorable evaluations. Byun et al. (2021) show that, as long as the review contents are consistent, a larger number of product reviews from multiple sources is perceived as more reliable and convincing. Extending this logic to advertising, we argue that multi-model ads, compared to single-model ads, elicit stronger social media responses due to greater perceived informational value.

Diversity in Advertising

Diversity refers to the individual differences between people with distinct attributes and to the recognition, understanding, and appreciation that each individual is unique and differs from others in terms of various attributes (Bernstein, Bulger, Salipante, & Weisinger, 2020). Research on diversity in advertising often adopts an unidimensional approach by referring to one of three main dimensions: age, ethnicity, or gender (Eisend et al., 2023).

First, research on age diversity in advertising has yielded inconsistent findings (Eisend, 2022). Some studies find a "next-younger" effect, whereby senior consumers prefer young but mature models who are considered more credible and likable than same-age models (e.g., Bristol, 1996; Chevalier & Lichtlé, 2017). Other studies have found no effects of using older versus younger models (e.g., Greco & Swayne, 1992; Skurpin, Beldad, & Tempelman, 2019).

Second, ethnic diversity research often explores the perception of minority group representation by the targeted ethnic minority group and general ethnic majority audience. For example, a study found that ethnic majority consumers prefer ethnic majority models and respond negatively to ethnic minority models (Aaker, Brumbaugh, & Grier, 2000). Another showed that the use of racial minority models in an advertisement attracts members of that racial group but deters those of the racial majority in the country in which it is presented (Avery, 2003). Other scholars have found that most consumers respond equally well to majority and minority models (e.g., Appiah, 2007). Zúñiga (2016) examined how the targeted minority group evaluates ethnically primed ads and found no statistically significant difference in responses when comparing high black cultural ethnic primed ads with low and high white cultural ethnic primed ads.

Finally, with regard to gender diversity, the extant research shows that gender depictions in advertising are most effective when they are congruent with consumers' existing social and cognitive schemata and in line with their gender-role expectations and values (Orth & Holancova, 2004; Putrevu, 2004). That is, more diverse and inclusive depictions of women and men lead to more positive responses by consumers with a nontraditional gender-role ideology and vice versa. Regarding audience gender effects, men and women process advertising information differently (Putrevu, 2001). In particular, traditional and nondiverse gender portrayals lead to more favorable responses among men than among women (Eisend, Plagemann, & Sollwedel, 2014; Whipple & Courtney, 1985).

Multiple Models and Group Diversity

The studies in the preceding section have examined diversity unidimensionally, typically from a single national perspective (mostly Western) and a characteristic of a lone model, but this means largely overlooking group diversity in international multi-model ads, which are more prevalent than single-model ones. Here, diversity refers to differences among co-present models within the same advertisement, rather than representation by a single minority model.

To date, empirical research on the multi-model ads is rare, with four exceptions. Mohan, Ferguson, and Huhmann (2022) examined business-to-business magazine advertisements that included both single and multiple models. However, the authors were more interested in model–product fit (from the perspectives of gender and age) and thus did not specifically discuss diversity of multiple models. Ryu, Park, and Feick (2006) showed a superior effect of ads with two models from different nationalities compared with those with two models of the same nationality. Owing to its facial recognition approach, An and Kwak's (2019) paper is of particular interest to the current research. Their study examined multiple diversity dimensions in social media advertising and showed that gender and racial diversity vary considerably across brands, white models outnumber other races, and interracial and cross-sex interactions in advertising are underrepresented. However, An and Kwak (2019) did not provide any insights on group diversity in relation to advertising effects or effects on social media responses. Cowart, Yu, & Ding (2024) experimented with two-model ads with different manipulations on models' racial background and gender. Their aim was to explore consumer perceptions on monoracial versus multiracial models. Findings suggested that the level of inclusiveness was perceived to be similar whether the two models were monoracial nondominant models, or interracial models. Consumers tended to be more wary of a company's ulterior motives when they see ads with two interracial models as compared with ads with two monoracial nondominant models.

Group diversity as a concept appears in organizational literature in relation to advantages and disadvantages of diverse teams (e.g., Joshi & Roh, 2009; Stahl, Maznevski, Voigt, & Jonsen, 2010; Van Dijk, van Engen, & van Knippenberg, 2012). Such studies have assessed group diversity using Blau's (1977) index, which computes diversity by aggregating the number of group members (e.g., the number of people per ethnicity) and the number of groups (e.g., ethnic groups). The index represents diversity as heterogeneity of people within a group. This is a different approach to assess diversity than depicting a person belonging to one or multiple minority groups in society. For instance, from a group-diversity perspective, a single young African woman would be considered less diverse than a group of two White men who differ in age. Although this might appear counterintuitive from a narrow national perspective (typically Western), it is reasonable in an international context, where the same individual may belong to either a minority or a majority group depending on the target audience's country. Accordingly, group diversity offers a more appropriate framework for assessing diversity in international advertising campaigns on social media platforms.

Social Media Responses

Researchers have explored the influence of various content formats including advertising on social media platforms including Instagram, Facebook, and YouTube on users' engagement behavior (e.g., Shahbaznezhad et al., 2021; Unnava & Aravindakshan, 2021). Social media engagement has been described as having various levels of involvement, from viewing a video, to contributing by clicking on 'like', to creating content by posting images or text (Schivinski, Christodoulides, & Dabrowski, 2016). In our study, we investigate three different types of social media responses of engaged users. We do this by exploring the sentiment and analytical thinking within the content created by consumers (e.g. comments or emojis in response to the video advertisement). Analytical thinking reveals the extent to which the author employs formal, logical, and hierarchical patterns in their writing (Pennebaker, Chung, Frazee, Lavergne, & Beaver, 2014). Sentiment determines whether a text exhibits a negative, neutral, or positive emotional state (Oc et al., 2023; Pennebaker et al., 2014).

Advanced machine learning and artificial intelligence (AI) techniques have been developed to analyze the vast amount of unstructured data generated by social media platforms (e.g., Büschken & Allenby, 2016). For example, researchers can perform sentiment analysis—a technique that leverages machine learning to identify and measure emotional tone in emojis (Novak, Smailović, Sluban, & Mozetič, 2015). Similarly, Linguistic Inquiry and Word Count (LIWC) software (Pennebaker, Boyd, Jordan, & Blackburn, 2015) employs computational linguistic analysis to leverage an inbuilt dictionary to gain insights into the quality of social media interactions. This allowed researchers to explore analytical thinking and emotional tone (Kietzmann & Pitt, 2020; Oc, Plangger, Sands, Campbell, & Pitt, 2023). By leveraging these instruments, marketing professionals can discern patterns in unstructured data more effectively, assess the effects of social media advertising campaigns, and compare various outcomes (Kübler, Colicev, & Pauwels, 2020). Past research suggests that comments and consumer attitudes towards social media advertisements impact financial performance (Yoon *et al.,* 2018).

Based on the foregoing theoretical arguments, advertisements featuring multiple co-present models should elicit stronger audience responses than those featuring a single model. This is because multiple models provide a greater number of information cues, increasing the perceived informational value and diagnosticity of the advertisement. In addition, the simultaneous presence of multiple models may enhance message salience and perceived relevance, leading to stronger engagement. Accordingly, we hypothesize that

H 1: Advertisements featuring multiple models generate stronger social media responses than advertisements featuring a single model.

Within advertisements featuring multiple models, heterogeneity among co-present models may also shape audience responses. Therefore, we posit that:

H2: Greater diversity among models within multi-model advertisements is associated with stronger social media responses.

METHOD

Data

We collected our data on YouTube and Instagram, which are the most frequently used social media platforms and providers of video content—the predominant type of content on social media platforms (SimilarWeb, 2023). Our dataset consists of 234 social media brand campaigns (videos) and 38,774 consumer comments on these campaigns. Of these campaigns, 166 featured multiple models, accounting for 27,252 comments.

For the campaign data, we selected the video posts of the top 100 global brands listed on the Interbrand website (Interbrand, 2022) from Instagram and YouTube. Using Interbrand's top 100 brands is a common choice in advertising studies (e.g., Ashley & Tuten 2015; Chu & Keh 2006; Peterson & Jeong 2010), as they encompass various industries, product categories, and countries of origin. This selection represents a sample of brands deemed diverse and representative, as indicated by other advertising studies (e.g., Araujo, Neijens, & Vliegenthart, 2015; Mangiò, Pedeliento, & Andreini, 2021). We chose brands' video campaigns over five years (2017–2021) that had a detectable human face for the purpose of facial recognition analysis. We defined campaign videos as the social media advertising videos that showcase a brand's products. We selected campaigns if they received more than 50 comments. For each brand, we identified at least one campaign and no more than three campaigns in the brand's official channel on YouTube and Instagram; this eliminated the potential dominance of certain brands with multiple campaigns. Examples of brand campaign videos examined in this study are listed in the Web Appendix Table A.

We sampled up to 600 of the most recent comments per campaign. This limit eliminated the risk of brand dominance in the dataset of comments as some campaigns have a large number of comments (i.e., more than 5000). Comments were extracted by applying a self-developed Python algorithm that uses open-source application programming interfaces (APIs) and libraries to scrape data. In total, 44,538 comments were obtained. Coders manually checked for spam comments (i.e., the same comment being posted several times) and deleted them (Li & Xie, 2020). Subsequently, non-English comments, including uninterpreted characters such as @ and & signs, and comments with fewer than two words were deleted unless they included emojis.

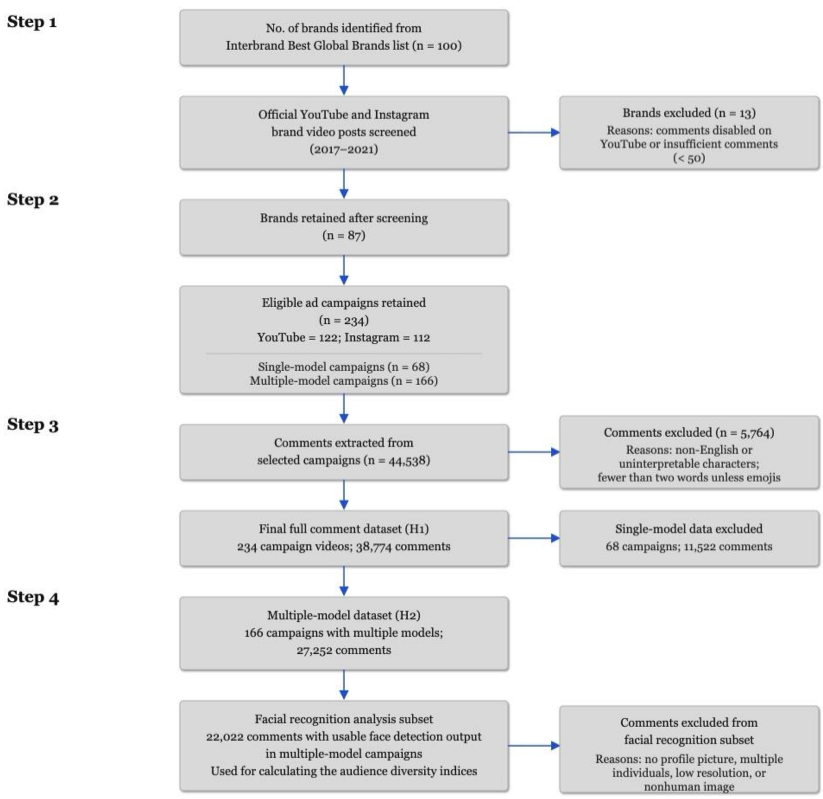

Figure 2. Construction of analysis samples for the study

We could include only 87 from 100 brands on Interbrand's list because some brands such as Apple do not allow comments on YouTube and other brands do not have enough comments per campaign (less than 50 comments). After applying these selection criteria, the dataset comprised 234 (122 posted on YouTube and 112 posted on Instagram) campaigns and 38,774 comments. The comments included 10.07 words (SD = 12.41) on average, ranging from 2 to 616 words. The emoji dataset included 11,549 comments containing either emojis only or text plus emojis. Figure 2 describes the construction of the sample.

Measures

Table 1 provides an overview of the variables, definitions, and operationalizations used in this study.

Single vs. Multiple Models. We coded people in a campaign as "models" if they were identifiable and actively appeared in the advertisement. Individuals with blurry faces, very brief background appearances, or no discernible role in the advertisement were not counted. This operationalization differs from the concept of an endorser. Whereas endorsers are typically defined by their persuasive function, prior recognition, credibility, or explicit association with the brand, our coding captures the visible presence of human figures in the advertising execution. We adopted this broader term because many social media video advertisements include human figures who contribute to the creative execution without necessarily functioning as formal endorsers. Thus, the variable "model type" distinguishes between advertisements featuring one identifiable human figure and those featuring more than one identifiable human figure.

Model and Audience Diversity. To assess the diversity of the models in the campaigns as well as the audience who commented on those campaigns, we used a facial recognition algorithm to determine the age, ethnicity, and gender of the models and individuals who left a public comment. Facial recognition technologies involve a combination of neural network, machine learning, and deep learning approaches. Creating facial recognition software requires network configuration and training as well as testing stages involving large datasets. We used a reliable commercial API, Clarifai, which has been proven valid in previous studies (e.g., Nanne et al., 2020). Audience diversity measures are derived from publicly available profile images associated with user comments. Diversity scores are computed only when a detectable human face is present in the profile image. Profiles without identifiable human faces are excluded from these calculations. Importantly, we do not treat profile images as verified measures of users' sociodemographic backgrounds. Rather, these measures capture perceived demographic cues available to other users and to the platform environment. Because profile images may be absent, outdated, symbolic, nonrepresentative, or selected for impression-management purposes, audience diversity based on profile images should be interpreted cautiously as a proxy for perceived audience composition, not as confirmed demographic diversity. This operationalization introduces potential measurement noise; however, such noise would bias estimates toward zero rather than inflate effects.

Analyzing all of the audience's profile pictures was not feasible. Some users did not have profile pictures, whereas others had multiple individuals in their photos, thus making it difficult to identify the account holder. In some cases, the image resolution was too low for analysis. Additionally, there were instances of users choosing nonhuman images. There was no observable pattern in missing profile pictures. Consequently, the dataset for facial recognition analysis was reduced to 32,209 comments with profile pictures from 234 campaigns. Of these comments, 22,022 were from campaigns with multiple models (see Figure 2). We employed these comments with profile pictures of the audience to compute the audience diversity indices for each campaign. As a result, each campaign was assigned a diversity index score describing the diversity of models appearing the ads along three dimensions (age, ethnicity, and gender) and a diversity score describing the diversity of the audience along the same dimensions. The diversity index describes group diversity and is computed based on the Blau index. Blau's (1977) index of heterogeneity is a common measure of diversity. The index is calculated as $(1 - \sum P_i^2)$, where P_i is the proportion of group members in category *i*. This index considers the number of group members and the number of different groups. For instance, if a population of 40 people consists of three different ethnic groups, with 20 people from one ethnic group and 10 people each from the other ethnic groups, the index is computed as: $1 - (0.5^2 + 0.25^2 + 0.25^2) = 0.625$.

Dependent Variables: Text Sentiment, Emoji Sentiment, Analytical Thinking. We employed automated text analysis methods using machine learning algorithms to generate three dependent variables from the comments. We used a bottom-up sentiment extraction library—the TextBlob natural language processing (NLP) library in Python (Micu, Micu, Geru, & Lixandroiu, 2017)—to process textual data and measure the variable *Text sentiment*. We used a Python library developed by Novak et al. (2015) to calculate the sentiment score for emojis (*Emoji sentiment*). The average score of *Emoji sentiment* was taken if there was more than one emoji in the comment. After naturally processing a comment, LIWC automatically counts and calculates the percentage of words associated with various significant psycholinguistic concepts including thinking styles, emotions, and social concerns. We used this LIWC process to compute the *Analytical thinking* variable.

Control Variables. We included several control variables to account for differences across brands and campaigns that could influence engagement and commenting outcomes. At the brand level, we controlled for the size of the brand's social media audience using the natural log of follower count. At the campaign level, we controlled for the complexity of the creative using the number of people appearing in the video, and for campaign reach and popularity using the number of views and likes recorded at the time of data collection. We also included industry fixed effects by dummy-coding nine industry categories to account for systematic differences in communication norms and audience responses across sectors. Finally, to address potential selection bias due to comment inclusion criteria, we added the inverse Mills ratio (IMR) computed using Heckman's (1979) two-step procedure.

Table 1. Variables, definitions, and operationalization.

Variable	Definition	Operationalization/data description
Model Type	Whether the campaign features one identifiable model or more than one identifiable model.	Binary variable: single-model campaign = 0, multiple-model campaign = 1. Of the 234 campaigns, 68 were single-model campaigns and 166 were multiple-model campaigns.
	Dependent variables	
Text sentiment	Sentiment valence based on comments' polarity ratings.	TextBlob Natural Language Processing (NLP) library in Python; calculates scores between −1 (most negative) and 1 (most positive).
Emoji sentiment	Emoji valence based on emojis' polarity ratings.	Python library developed based on Novak et al. (2015); calculates scores between −1 (most negative) and 1 (most positive).
Analytical thinking	Level of *Analytical thinking* in the comment.	Derives a score between 0 (lowest) and 100 (highest) from LIWC2015 (Pennebaker et al., 2015).
	Independent variables	
	Models and Audience Diversity Variables	
Model age diversity *Model ethnic diversity* *Model gender diversity*	Age diversity of multiple models. Ethnic diversity of multiple models. Gender diversity of multiple models.	Facial recognition analysis of multiple models appearing in video advertising. Diversity scores calculated according to the Blau index (Blau, 1977). Scores range from 0 (no diversity) to 1 (high diversity).
Audience ethnic diversity *Audience age diversity* *Audience gender diversity*	Ethnic diversity of the audience. Age diversity of the audience. Gender diversity of the audience.	Facial recognition analysis of all users commenting on a single campaign based on the users' publicly available profile pictures. Diversity scores calculated according to the Blau index (Blau, 1977). Scores range from 0 (no diversity) to 1 (high diversity).
	Control Variables	
Follower count	Number of followers on the brand's social media account.	Natural log of the follower count.
Number of people	Number of human characters.	Min = 1, max = 66
Views	The number of views that the campaign video had at the time of data collection.	Min = 1,574, max = 105,586,389, mean= 3,677,673
Likes	The number of likes that the campaign video had at the time of data collection.	Min = 70, max = 579,000, mean = 63517
Industry	Industries of the selected brands.	Dummy-coded for nine industry categories.[a]
IMR	Inverse Mills ratio to address nonselection bias.	Calculated based on Heckman (1979).

NOTES:

[a] Dummy-coded industry categories are entertainment, retail, automotive, information technologies, alcohol, restaurants, consumer-packaged goods, finance, and energy (as the base category).

Analysis

Difference Between Single- versus Multi-model Campaigns. To find an answer to the first hypothesis, we explored the distinctions between single-model and multi-model campaigns by applying an analysis of covariance (ANCOVA) to each dependent, controlling for the control variables (views, likes, follower counts and industries). We used a binary categorization because our theoretical focus is the contrast between single-model and multiple-model advertising, rather than the marginal effect of each additional model. This distinction is also necessary because the group diversity indices are meaningful only when more than one model is present. We therefore treat model type as a theoretically motivated threshold variable and examine the role of model diversity separately within the multiple-model subsample. We estimate the following model for all campaigns:

$$DV_{ij} = \mu + \beta_1 \, Model\ Type_i + \beta_2 \, Views_{ij} + \beta_3 \, Likes_{ij} + \beta_4 \, Follower\ Count_{ij} + \beta_{5\text{–}13} \sum Industry\ Dummies_{ij} + \epsilon_{ij}$$

where DV_{ij} represents either of three dependent variables (*Text sentiment, Emoji sentiment, Analytical thinking*) for the *j*-th observation in the *i*-th group. *"μ"* is the overall mean of the dependent variable. B_1 represents the effect of Model Type (single vs. multiple models). $\beta_{2\text{-}13}$ are the regression coefficients for the respective covariates. ϵ_{ij} is the random error term. We refrain from adding the diversity variables in this analysis, as the inclusion of single-model campaigns confounds the group diversity measure (i.e., single model who make up about a fourth of the sample all have a group diversity score of zero). The crucial variable is model type and we test whether this variable has an influence on any of the three dependent variables.

Influence of Group Diversity in Multi-model Campaigns. To answer the second hypothesis, we explored the factors that affect the dependent variables in multi-model campaigns, including all independent variable from Table 1 in three statistical models for the three dependent variables each

Our data indicate a nested structure with multiple comments nested within campaigns and the variables in our model referring to either the comment- or campaign-level. We applied a mixed effects generalized least squares regression model in R with campaign level (indicated by subscript "c") and individual comment level (indicated by subscript "i") parameters for 166 multi-model campaigns:

$DV_i = \beta_0 + \beta_{01}\ Model\ age\ diversity_c + \beta_{02}\ Model\ ethnic\ diversity_c + \beta_{03}\ Model\ gender\ diversity_c + \beta_{04}\ Audience\ age\ diversity_c + \beta_{05}\ Audience\ ethnic\ diversity_c + \beta_{06}\ Audience\ gender\ diversity_c + \beta_{07}\ Views_c + \beta_{08}\ Likes_c + \beta_{09}\ Follower\ Count_c + \beta_{10}\ Number\ of\ People_c + \beta_{11\text{–}19} \sum Industry\ Dummies_c + \beta_{20}\ Model\ age\ diversity_c \times Model\ ethnic\ diversity_c + \beta_{21}\ Model\ age\ diversity_c \times Model\ gender\ diversity_c + \beta_{22}\ Model\ ethnic\ diversity_c \times Model\ gender\ diversity_c + \beta_{23}\ IMR_i + \delta + \varepsilon_{ic},$

where DV = (a) *Text sentiment*, (b) *Emoji sentiment*, and (c) *Analytical thinking*

We included campaign and brand random effects to capture unobserved differences across campaigns and brands (Bart, Stephen, & Sarvary, 2014; Good, Hughes, & Wang, 2021). Because we excluded very short comments, we applied Heckman's (1979) two step correction for potential selection bias. We first estimated a probit model on all comments to predict inclusion based on word count and computed the inverse Mills ratio. We then included this ratio in the main models. Its significance indicates that correcting for selection was necessary. Appendix Table B presents the descriptive statistics and correlations for all measures in the multiple-model campaigns, none of which exceeded 0.5. We further assessed collinearity using the variance inflation factor (VIF) scores that across all models were less than 3.1. These results suggest that there are no multicollinearity problems (Kennedy, 2003).

RESULTS

Difference Between Single- vs Multi-model Campaigns

As shown in Figure 3 and Table 2, campaigns featuring multiple models differ significantly from single model campaigns in terms of social media comment responses. For text sentiment, there was a statistically significant increase, $F(1, 38{,}773) = 30.84$, $p < .001$, with mean sentiment rising from 0.09 (single model) to 0.11 (multiple models). This pattern is also evident within each platform subsample, with significant effects on YouTube, $F(1, 11{,}270) = 26.05$, $p < .001$, and Instagram, $F(1, 27{,}502) = 54.97$, $p < .001$. The effect remains significant in the Instagram only subset, $F(1, 11{,}548) = 6.91$, $p < .01$. For emoji sentiment, there was likewise a statistically significant increase, with mean emoji sentiment rising from 0.46 (single model) to 0.48 (multiple models), and the overall difference was highly significant, $F(1, 38{,}773) = 105.80$, $p < .001$. The emoji sentiment effect is also significant on YouTube, $F(1, 11{,}270) = 63.06$, $p < .001$, and on Instagram, $F(1, 27{,}502) = 39.81$, $p < .001$. Taken together, these results answer RQ1 by showing that multi model campaigns elicit systematically more positive comment sentiment, both in text and emojis, compared to single model campaigns, after accounting for views, likes, follower count, and industry.

Analytical thinking shows the same pattern. As shown in Figure 3 and Table 2, comments posted under multi model campaigns exhibit significantly higher analytical thinking scores (0 to 100 scale) than comments posted under single model campaigns. The overall difference is statistically significant, $F(1, 38{,}773) = 105.80$, $p < .001$, with the mean increasing from 53.8 (single model) to 57.0 (multiple models). This effect is also significant within platform subsamples, including YouTube, $F(1, 11{,}270) = 63.06$, $p < .001$, and

Instagram, F(1, 27,502) = 39.81, p < .001, indicating that multi model campaigns are associated with more analytically framed language in user comments, controlling for views, likes, follower count, and industry. The results support Hypothesis 1.

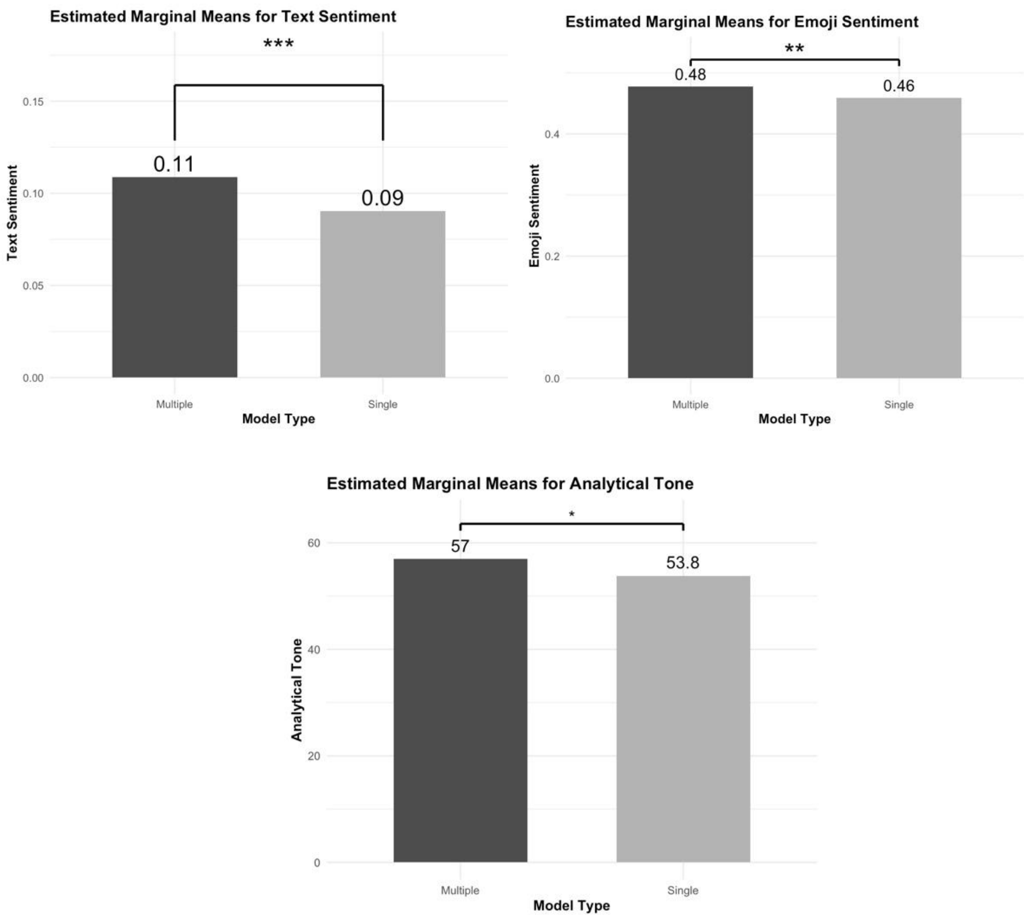

Figure 3. Estimate marginal means for social media responses

Table 2. Single vs. multiple model effects on social media responses (F-values)

Predictor variable[a]	*Text sentiment*			*Emoji sentiment*	*Analytical thinking*		
	Total	***You Tube***	***Instagram***	***Instagram***	***Total***	***You Tube***	***Instagram***
Model type	30.84***	26.05***	54.97***	6.91**	105.80***	63.06***	39.81***
Other Parameters							
Views	261.48***	3.23*	20.63***	8.40**	1.42	8.13**	14.87***
Likes	69.70***	6.74**	12.15***	30.34***	0.46	0.73	19.66***
Follower count (log)	102.98***	6.81**	60.47***	65.77***	591.65***	29.50***	373.46***
Industry[a]	52.52***	23.88***	49.20***	51.00***	30.27***	19.12***	28.58***
# of comments	38,774	11,271	27,503	11,549	38,774	11,271	27,503
# of campaigns	234	122	112	112	234	122	112

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
[a] Variables with multiple dummy variables. Statistical significance is reported for the overall significance test across the parameter estimates of the dummy variables.

Influence of Group Diversity in Multiple Model Campaigns

As reported in Table 3, we find no evidence that model group diversity within multiple model campaigns shapes audience responses, rejecting Hypothesis 2. Model age diversity, model ethnic diversity, and model gender diversity are not significantly associated with text sentiment or Instagram emoji sentiment. For analytical thinking, there is some evidence that higher model ethnic diversity is associated with higher analytical thinking, but only in YouTube comments ($\beta = 12.31$, SE = 7.13, $p < 0.05$), while the corresponding effects are not significant in the pooled sample or on Instagram.

In contrast, audience ethnic diversity shows a clearer pattern. It is negatively related to Instagram emoji sentiment ($\beta = -1.21$, SE = 0.40, $p < 0.01$) and positively related to analytical thinking in the pooled sample ($\beta = 38.86$, SE = 16.15, $p < 0.05$) and on YouTube ($\beta = 30.25$, SE = 12.26, $p < 0.05$). Interaction effects are largely not statistically significant, although the model ethnic diversity by model gender diversity interaction is marginal for analytical thinking on YouTube ($\beta = -24.02$, SE = 13.35, $p < 0.10$). Overall, the results do not provide consistent support for direct effects of model diversity on social media responses.

Regarding control variables, follower count is positively associated with text sentiment in the pooled sample ($\beta < 0.01$, $SE < 0.01$, $p < 0.05$) and on Instagram ($\beta = 0.02$, $SE < 0.01$, $p < 0.05$), and it is also positively related to Instagram emoji sentiment ($\beta = 0.03$, $SE = 0.01$, $p < 0.05$). However, follower count is negatively associated with analytical thinking in the pooled model ($\beta = -2.46$, $SE = 0.58$, $p < 0.001$), with a marginally negative effect on Instagram ($\beta = -2.45$, $SE = 1.29$, $p < 0.10$). Likes show a small positive association with text sentiment on YouTube ($\beta < 0.01$, $p < 0.05$), while views are positively related to analytical thinking on YouTube ($\beta < 0.01$, $p < 0.05$). The inverse Mills ratio is statistically significant in most specifications, including all text sentiment models ($\beta = 0.18$ to 0.21, $p < 0.001$), Instagram emoji sentiment ($\beta = -0.01$, $SE < 0.01$, $p < 0.05$), and analytical thinking for the pooled and YouTube models ($\beta = -2.82$, $SE = 0.33$ and -7.58, $SE = 0.49$, both $p < 0.001$), which supports the use of the selection correction. Industry controls are included in all models.

Table 3. Influence of model and audience diversity dimensions on consumer responses.

Predictor variable[a]	***Text sentiment*** B (SE)			***Emoji sentiment*** B (SE)	***Analytical thinking*** B (SE)		
	Total	***YouTube***	***Instagram***	***Instagram***	***Total***	***YouTube***	***Instagram***
Model age diversity	-0.01 (0.08)	0.02 (0.06)	-0.03 (0.19)	0.07 (0.20)	-6.88 (10.01)	-6.10 (7.85)	-27.36 (25.92)
Model ethnic diversity	0.04 (0.07)	0.07 (0.06)	-0.03 (0.18)	0.02 (0.18)	-1.30 (8.94)	12.31* (7.13)	-21.77 (23.94)
Model gender diversity	-0.10 (0.09)	-0.07 (0.08)	-0.15 (0.18)	< 0.01 (0.20)	10.06 (11.24)	-3.85 (9.55)	31.36 (24.28)
Other Parameters							
Intercept	-0.02 (0.12)	-0.13 (0.13)	-0.03 (0.39)	0.95* (0.44)	72.70*** (15.55)	48.48*** (13.77)	61.24 (53.23)
Audience age diversity	-0.03 (0.08)	< 0.01 (0.07)	0.08 (0.24)	< 0.01 (0.27)	-2.61 (10.10)	5.28 (7.97)	3.95 (32.31)
Audience ethnic diversity	0.06 (0.12)	0.07 (0.10)	-0.30 (0.35)	-1.21** (0.40)	38.86* (16.15)	30.25* (12.26)	58.22 (48.04)
Audience gender diversity	-0.09 (0.08)	< 0.01 (0.07)	-0.09 (0.26)	-0.13 (0.29)	-7.07 (10.13)	-9.66 (7.66)	-8.21 (34.93)
Views	< 0.01 (< 0.01)	< 0.01 (< 0.01)	< 0.01 (< 0.01)	< 0.01 (< 0.01)	< 0.01 (< 0.01)	< 0.01* (< 0.01)	< 0.01 (< 0.01)
Likes	0.01 (< 0.01)	< 0.01* (< 0.01)	< 0.01 (< 0.01)	< 0.01 (< 0.01)	< 0.01 (< 0.01)	< 0.01 (< 0.01)	< 0.01 (< 0.01)
Follower count (log)	< 0.01 * (< 0.01)	< 0.01† (< 0.01)	0.02* (< 0.01)	0.03 * (0.01)	-2.46*** (0.58)	-0.22 (0.69)	-2.45† (1.29)
Number of people	< 0.01 (< 0.01)	< 0.01 (< 0.01)	< 0.01 (< 0.01)	< 0.01 (< 0.01)	0.07 (10.10)	-0.02 (0.08)	-0.01 (0.25)
Industry[b]	Included	Included	Included	Included	Included	Included	Included
Inverse Mills ratio	0.19*** (0.00)	0.21*** (< 0.01)	0.18*** (< 0.01)	-0.01* (< 0.01)	-2.82*** (0.33)	-7.58*** (0.49)	-0.21 (0.42)
Interaction Effects							
Model age diversity × Model ethnic diversity	0.02 (0.13)	-0.01 (0.10)	0.20 (0.32)	0.18 (0.35)	16.28 (16.81)	0.90 (13.05)	62.57 (43.85)
Model age diversity × Model gender diversity	0.07 (0.15)	0.08 (0.14)	< 0.01 (0.29)	-0.23 (0.31)	-15.93 (19.21)	1.93 (17.01)	-21.73 (40.01)
Model ethnic diversity × Model gender diversity	-0.01 (0.13)	-0.03 (0.11)	0.09 (0.28)	-0.03 (0.30)	-19.77 (16.51)	-24.02† (13.35)	-43.56 (37.46)
R^2	0.35	0.27	0.23	0.23	0.10	0.04	0.02
# of comments	27,252	8,488	18,764	7,895	27,252	8,488	18,764
# campaigns	166	96	70	70	166	96	70

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

[a] See Table 1 for variable definitions.

[b] Variables with multiple dummy variables. Statistical significance is reported for the overall significance test across the parameter estimates of the dummy variables.

DISCUSSION

This study attempts to address two hypotheses regarding the effects of number of models and diversity in social media advertising. The first hypothesis relates to the effects of multiple models and we find that multiple models lead to stronger effects than a single model. The second hypothesis concerns the effects of group diversity in advertisements featuring multiple models and we find no evidence for an advantage of diversity in social media advertisements. In this section, we discuss the implications of the findings as well as the novel methodological approach that we contribute to this research stream.

Theoretical Implications

The findings of this study have important theoretical implications. First, this study serves as a steppingstone in the research on multiple models in advertising. To date, limited empirical work has examined the effects of multi-model ads, with important exceptions (e.g., Moore et al., 1994; Rice et al., 2012). Consistent with our conceptual framework, our findings corroborate the greater impact of showing multiple models, compared with showing just one. From the theoretical perspectives such as information utility, persuasive message repetition, and cue-diagnosticity theory, we can interpret that, because multiple models can increase the usefulness of the alternative information inputs, consumers may perceive advertising as more informative, credible, and persuasive, and thus be more likely to engage on social media.

By addressing the multiplicity of both model presence and diversity in an ad, our study contributes to the research on the role of group diversity in brand endorsement research, which has been neglected despite the ubiquity of group diversity in advertisements. As such, this study answers the call by Gopaldas and Fischer (2012: 404) to examine whether and how marketers feature multiple marginalized groups in their brand campaigns and, more recently, that by Rosa-Salas and Sobande (2022: 184) to explore "the interconnected nature of racism, sexism, classism, misogyny, and other interrelated forms of oppression that exist within marketplaces, marketing institutions, and commercial representations." Yet, a fact that we found no significant findings for communicating group diversity and the interactions between different diversity dimensions seems to demonstrate the limited impact of multidimensional group diversity. The findings imply that the demographic categories of group diversity may have been perceived as weak by viewers. This encourages researchers to explore the conditions under which group diversity produces stronger effects on advertising responses.

By focusing on group diversity instead of single diversity, we provide results that better reflect current advertising practices, as 71% of all ads in our dataset use multiple models. Although recent research on diversity in advertising indicates positive diversity effects in current advertisements (Eisend et al., 2023), our findings paint a different picture of null effects. These contradictory findings are especially relevant given the fact that the current data related to international social media campaigns show high external validity compared with prior diversity research, which has mostly applied single-model stimuli in classroom experiments in a particular national context to examine the effect of minority models in advertising.

Managerial Implications

Portraying multiple models perform better than portraying one model. Advertisers may therefore assume that increasing the number of models in an ad will have cumulative benefits on audience responses. However, our findings suggest that randomly increasing heterogeneity in diversity groups within a single campaign may not enhance social media responses. Therefore, advertisers should be cautious about overemphasizing diversity for the purpose of increasing social media responses. In addition, congruence between the model and the audience is easier to establish in single-model campaigns. We find that the same congruence effects become complex in group diversity ads.

Prior research on diversity in advertising responses has mainly focused on advertising in traditional media in a particular national context, thus overlooking the differences in international audiences between media platforms and the idiosyncratic dynamics of social media. Our results support advertisers in understanding that diversity does not play a major role in determining the influence of advertising on social media, which is not necessarily a disappointing result, as diversity in advertising is often said to jeopardize advertising's influence on the audience. In an era of data-driven decisions, marketers and advertisers can utilize advanced technologies to decipher the age, ethnicity, and gender of their social media followers, thereby enabling better segmentation and targeting in their campaigns (An & Kwak, 2019; Eisend, 2019; Eisend et al., 2023; Putrevu, 2001). Various dimensions of diversity, different response measures, and AI-driven audience profiling can empower advertisers to strategically incorporate diversity in their international campaigns without jeopardizing intended commercial effects on the (national majority) audience (Chevalier & Lichtlé, 2017; Eisend et al., 2014).

Methodological Implications

In this study, we leveraged an innovative approach to explore the effects of using multiple models and model and audience diversity on various response metrics by employing a machine learning-enabled facial recognition technique. Drawing upon the findings of Xiao and Ding (2014), who demonstrated the potential impact of facial recognition in advertising, our AI-based methodology facilitated the efficient identification of social media users' age, ethnicity, and gender. This offers researchers a robust method for measuring diversity.

Facial recognition uses the same logic as other biometric recognition systems, which is based on the fact that "human beings have been created with a completely matchless and unique touch" (Yaman, Rattay, & Subasi, 2021: 203). Furthermore, machine learning is a powerful tool for analyzing large amounts of data. Although the scope of our research was limited to images, machine learning can explore rich insights from audio, large-scale networks or tracking data, and hybrid data (e.g., a combination of text, image, and structured data; Ma & Sun, 2020). Because diversity relates to people with distinct attributes, employing complex data is the optimal approach for exploring the intertwined nature of diversity. For example, analyzing not only individual appearances (e.g., diversity by skin color) but also voices (e.g., diversity by accent) may produce a different picture of diversity.

Another significant contribution of our study is our analysis of emoji sentiment. This approach has been underutilized in research despite its potential to offer nuanced insights into audience responses, especially given its increasing usage on platforms such as Instagram and TikTok. There are cases where text comments are sparse or non-existent, and emojis play a crucial role in conveying emotional reactions. By integrating this analysis into our methodological framework, we were able to extend our understanding of audience responses. This represents a promising avenue for future research that encourages a deeper exploration of nonverbal cues in digital communication.

Limitations and Future Research Directions

Despite the valuable insights gained from this study, three limitations should be acknowledged. First, our operationalization of models captures the number and demographic diversity of identifiable human figures appearing in social media video advertisements, but it does not distinguish between the narrative roles these figures play within the advertisement. In dynamic video advertising, human figures may occupy central roles in the storyline, act as peripheral background characters, or appear primarily as visual elements that support the creative execution. Although we excluded blurry or indistinct background figures and focused only on identifiable human figures actively appearing in the advertisement, our coding does not capture the extent to which each model functions as a central persuasive cue, a peripheral cue, or a narrative character. This is an important limitation because the persuasive meaning of single versus multiple models may depend not only on the number of models but also on their role in the storyline, screen time, prominence, dialogue, product interaction, and relationship to the brand. Future research should therefore extend our approach by coding the narrative centrality and functional role of each model, for example by distinguishing focal models, supporting characters, background figures, and explicit endorsers.

Second, we employed AI- and machine learning-enabled facial recognition techniques to determine social media users' age, ethnicity, and gender by analyzing their profiles. Although this approach is innovative and potentially more accurate than traditional computerized content analysis, it may still be subject to identification errors, particularly for individuals with ambiguous facial features or those using profile pictures that are not representative of their true appearance. Although we excluded profiles without identifiable human faces from these calculations, we cannot verify whether the remaining images accurately represent the account holders. This limits the strength of conclusions that can be drawn from the audience diversity variables. Future research should aim to improve the accuracy of these techniques and explore the possibility of combining alternative methods, such as self-reported demographic information or a combination of different data sources, to measure audience diversity.

Third, our research focuses primarily on YouTube and Instagram as platforms for analysis. Although these platforms are widely used and provide a rich source of data, the findings may not be directly applicable to other social media platforms with different user demographics and interaction patterns, such as Facebook and TikTok. Future studies should examine the effects of models and audience diversity on consumer responses across various social media platforms to provide a more comprehensive understanding of this phenomenon.

Our study provides the foundations for a deeper understanding of the role of single vs. multiple models and model and audience diversity in social media advertising. Future research should build on these findings by addressing their limitations and exploring new directions to contribute to a more comprehensive and actionable knowledge base for advertisers and marketers. Further investigation is needed to clarify the interrelationships between diversity characteristics from the model and audience perspectives. For example, research on diversity characteristics in group settings can open a dialogue on other crucial aspects of group diversity such as intersectionality.

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The dataset can be accessed via below doi address.

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WEB APPENDIX

Table A. Examples of brand campaign videos.

Brands	Industry	Example video link	Endorser Type
Adidas	Retail	https://www.instagram.com/p/CLo_sOOnssr/	Multiple
Adobe	Information Technology	https://www.instagram.com/p/B0ghQ04nVna/	Multiple
Allianz	Finance	https://www.instagram.com/tv/CL_bLkcIV14/	Multiple
Amazon	Retail	https://www.instagram.com/p/CMxDb7DnZHj/	Multiple
BMW	Automotive	https://www.youtube.com/watch?v=9rx7-ec0p0A	Multiple
Canon	Information Technology	https://www.youtube.com/watch?v=e11uTz_-9yk	Multiple
Cartier	Retail	https://www.youtube.com/watch?v=AGkE4WZKDk0	Single
Caterpillar	Automotive	https://www.youtube.com/watch?v=DWc8dUl7Xfo	Multiple
Chanel	Retail	https://www.youtube.com/watch?v=KYVVGj6b-G4	Multiple
Citibank	Finance	https://www.youtube.com/watch?v=jS3k89Ph2sw	Multiple
Corona	Alcohol	https://www.instagram.com/tv/CHNl3O6Bk3J/	Multiple
Dior	Retail	https://www.instagram.com/tv/B7C2JqJomMo/	Multiple
Disney	Entertainment	https://www.youtube.com/watch?v=KR7aSbEdpHo	Multiple
eBay	Information Technology	https://www.instagram.com/p/CHYKwM6jNQZ/	Multiple
Facebook	Information Technology	https://www.youtube.com/watch?v=JRkAmEl2vdI	Single
FedEx	Information Technology	https://www.instagram.com/tv/CL9FmxNDXY-/	Multiple
Ferrari	Automotive	https://www.youtube.com/watch?v=EXbdcdxv93c	Single
Google	Information Technology	https://www.youtube.com/watch?v=Qyiautg41h8	Multiple
Gucci	Retail	https://www.youtube.com/watch?v=78wHAsOPNRs	Multiple
Heineken	Alcohol	https://www.instagram.com/p/BvGlG8eoM1A/	Single
Hennessy	Alcohol	https://www.youtube.com/watch?v=z2vqJBLD6g8	Single
Hermes	Retail	https://www.instagram.com/p/CFAI6XMAquC/	Single
Honda	Automotive	https://www.instagram.com/p/CMNNfNpHY7V/	Single
HP	Information Technology	https://www.instagram.com/p/CCBlHNBDOGt/	Multiple
HSBC	Finance	https://www.instagram.com/p/CMhfSs1IYuD/	Multiple
Huawei	Information Technology	https://www.instagram.com/p/CDi1VvABhrC/	Single
Hyundai	Automotive	https://www.youtube.com/watch?v=33qjeTyBswM	Multiple
IKEA	Retail	https://www.instagram.com/tv/CAOJiKOg6zk/	Single
Instagram	Information Technology	https://www.youtube.com/watch?v=gxJtbbgKBb0	Multiple
Kia	Automotive	https://www.youtube.com/watch?v=AkPqC6OSEtI	Multiple
Land Rover	Automotive	https://www.youtube.com/watch?v=ALtGqSdt-4w	Multiple
LEGO	Retail	https://www.youtube.com/watch?v=SU6a7FdSrH4	Multiple
L'oréal	Retail	https://www.instagram.com/p/CNnFn7NAu_y/	Single
Louis Vuitton	Retail	https://www.instagram.com/p/CMwPZS9royF/	Single
Mercedes Benz	Automotive	https://www.instagram.com/tv/CMh-NTbHJ0d/	Multiple

Microsoft	Information Technology	https://www.youtube.com/watch?v=lBeepqQBpvU	Multiple
Nestle	Consumer-Packaged Goods	https://www.instagram.com/p/Bw4VtalHHGi/	Single
Netflix	Entertainment	https://www.youtube.com/watch?v=yGgbNCkJqSM	Multiple
Nintendo	Entertainment	https://www.youtube.com/watch?v=If-tK57epLc	Multiple
Nissan	Automotive	https://www.youtube.com/watch?v=51f9eFe8-Uk	Multiple
Pampers	Consumer-Packaged Goods	https://www.instagram.com/p/B8utXdxJnuw/	Multiple
Pepsi	Consumer-Packaged Goods	https://www.instagram.com/p/B73e6tNngw9/	Multiple
Philips	Retail	https://www.instagram.com/p/CBxgF6qnsTd/	Multiple
Porsche	Automotive	https://www.youtube.com/watch?v=52AMJwF7P0w	Single
Prada	Retail	https://www.youtube.com/watch?v=RB8MKyBawxs	Single
Samsung	Retail	https://www.youtube.com/watch?v=NlMeE7QX5Tc	Single
Siemens	Retail	https://www.instagram.com/p/CFzPmc8KF9n/	Multiple
SONY	Retail	https://www.youtube.com/watch?v=6kxqEkpMi5M	Single
Spotify	Entertainment	https://www.instagram.com/p/B4QOF32HtO9/	Multiple
Tesla	Automotive	https://www.youtube.com/watch?v=UjenHNz-MRI	Single
Tiffany & Co.	Retail	https://www.youtube.com/watch?v=QtKkY5Q3jB8	Multiple
Toyota	Automotive	https://www.instagram.com/tv/B-MeLeepwqE/	Single
Uber	Information Technology	https://www.instagram.com/tv/B1cDMdQHzgq/	Multiple
UPS	Information Technology	https://www.instagram.com/p/CKwekysnuZw/	Single
YouTube	Information Technology	https://www.instagram.com/p/CNYX1vvpwOk/	Single
ZARA	Retail	https://www.instagram.com/p/CMcZAJpCW4v/	Single

Note. Campaigns in the full dataset were coded as either single-model or multiple-model campaigns. The full dataset included 68 single-model campaigns and 166 multiple-model campaigns.

Table B. Correlation matrix with descriptive statistics.

	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1 *Text sentiment*	0.12	0.30	1												
2 *Emoji sentiment*	0.47	0.27	0.09	1											
3 *Analytical thinking*	57	41	−0.04	−0.08	1										
4 *Model age diversity*	0.49	0.24	0.03	−0.06	−0.02	1									
5 *Model ethnic diversity*	0.47	0.25	0.04	−0.02	−0.01	0.16	1								
6 *Model gender diversity*	0.35	0.20	−0.05	−0.09	−0.01	0.23	0.26	1							
7 *Audience age diversity*	0.63	0.08	< 0.01	−0.09	0.02	0.12	−0.11	0.04	1						
8 *Audience ethnic diversity*	0.73	0.05	< 0.01	−0.16	0.06	0.20	< 0.01	0.11	0.07	1					
9 *Audience gender diversity*	0.44	0.08	−0.08	−0.04	−0.02	0.03	0.17	0.21	−0.10	−0.09	1				
10 Views	3677673	1180330	-0.04	0.02	-0.11	-0.23	-0.21	-0.11	0.10	0.08	0.01	1			
11 Likes	63517	88380	-0.05	0.01	-0.10	-0.05	-0.11	0.03	0.06	0.02	-0.09	0.79	1		
12 *Follower count* (log)	7	7	−0.08	0.05	−0.12	0.31	0.01	0.01	0.10	−0.12	0.03	0.63	0.67	1	
13 *Number of people*	8	9	0.05	−0.06	−0.01	0.23	0.24	0.11	−0.04	−0.04	< 0.01	0.14	0.03	−0.07	1