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Original Paper

Using Consumer-Generated Social Media Posts to Improve Forecasts of Television Premiere Viewership: Extending Diffusion of Innovation Theory

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Abstract

This research investigated how social media can be quantified and used as an input to improve audience forecasts for television show premieres. There were two key findings. First, Twitter activity (volume of tweets and retweets) drives viewership of shows that are unscripted (i.e., reality or competition shows). From a practical perspective, Twitter activity improved prediction accuracy beyond that of forecasting inputs typically employed by the industry. The second key finding was the interaction of media attention given to a show and audience size of the show leading into (i.e., preceding) the premiere. One practical implication for network scheduling and promotion efforts is to use strong lead-in shows along with large mass media efforts for a television season's "flagship" series that are most important for a network's success. This research also extends Diffusion of Innovation theory (Rogers, 2003) and diffusion modeling to television entertainment consumption. Diffusion of Innovation theory predicts the importance of information dispersion across heterophilous groups (i.e., groups that are diverse). The Bass (1969) diffusion model, a statistical model introduced to describe the diffusion of innovation, also predicts that media presence (an external factor) in conjunction with consumer eWOM (an internal factor) drive premiere ratings.

Keywords

social media, Twitter data analysis, electronic word of mouth, eWOM, entertainment media industry, predicting audience, diffusion of innovations, diffusion model, early adopters, nielsen television ratings, forecasting viewership

1. Introduction

This study explored the relationship between Nielsen ratings of television premieres and consumer-generated social media posts about those shows. Television show ratings for target marketing demographics are the basis for setting the price of television advertising prior to that shows' premieres. Ratings are also the metric by which a show's success is assessed post-premiere. Therefore, improved forecasts facilitate more accurate, informed transactions between advertisers and media companies. We attempted this by incorporating consumer enthusiasm for a show expressed on social media.

Mass media presence, lead-in audience and show genre, factors that are typically included in television industry forecasts, were considered in this research. Unlike previous work in the area, their relationship with social media was explored in a cross-sectional manner (52 series premieres across multiple genres). Furthermore, temporal sequence of the data (i.e., Twitter posts and stories in the media about the show in the 14 days leading up to its premiere) provided robust evidence of a causal effect on television premiere ratings.

Media companies and advertisers benefit from making more accurate, less subjective transactions when it comes to purchasing commercials appearing during new television series premieres in order to reach a target demographic. Models to help with forecasting decision support are not widely used in the television entertainment media industry, nor do they generally incorporate consumer enthusiasm for a new show (Dellarocas, Zhang & Awad, 2007). This can be a disconnect given a studio's investment in creating and marketing a new show, which is itself a vehicle for commercials advertisers purchase to reach target demographics.

Fifty-two primetime series premieres were analyzed, which appeared on five US broadcast television networks from 2018 to 2021. They included comedies, dramas, and unscripted (i.e., "reality") genres. The analysis yielded four key results. First, a statistically significant effect was found for Consumer eWOM as a mediator of the relationship between Media Presence and Premiere Performance, but this was contingent on Unscripted Genre. For Unscripted shows, Media Presence had a positive effect on Premiere Performance via Consumer eWOM; this relationship, however, did not hold for other genres. Second, a significant interaction was found for Media Presence and Lead-In Audience such that, for strong Lead-Ins (shows with A18-34 ratings around 1.3), Media Presence had a positive effect on Premiere Performance. This relationship disappeared for moderate and weak Lead-Ins. Third, for Unscripted programs, we observed a highly significant linear trend for Consumer eWOM, and a highly significant quadratic trend for Media Presence in the fourteen days leading up to the television show premiere. Fourth, the regression model was used to predict performance for three unscripted television series premiering in early 2022, and incorporating eWOM achieved compelling improvement in forecast accuracy.

This study demonstrated consumer-generated social media posts have a role in driving television premiere viewership for unscripted shows and can be incorporated into a forecasting model to improve accuracy beyond variables that are typically included in television industry forecasts. Significant longitudinal trends were found in the 14 days prior to premiere dates. In addition, a significant interaction was found for Media Presence and Lead-In Audience. For shows with strong Lead-In audiences (shows with A18-34 ratings around 1.3), Media Presence had a positive effect on Premiere Performance.

Entertainment industry executives recognize there is a dearth of tools for forecasting decision support, especially with new television series (Dellarocas, Zhang & Awad, 2007). Based on this research, it is possible to develop a model for unscripted television show premiere ratings that incorporates consumer enthusiasm, which can allow more accurate forecasts. This relationship exists as early as 14 days prior to the premiere. This removes a degree of uncertainty from transactions between advertisers and media companies prior to a show's premiere when commercials are purchased to reach a target demographic.

Consumer-generated social media posts have a role, not only in predicting, but also in driving television premiere viewership for unscripted shows. Temporal sequencing provided strong evidence for causality. This has many marketing implications for Unscripted shows, such as making sharable content available to encourage posting and retweets.

Importantly, the influence of lead-ins was found to be contingent on media attention. This has implications for network television program scheduling and promotion. Networks make the best use of resources by saving strong lead-ins and mass media efforts for their high priority "flagship" premieres. Shows that are lower priority can be scheduled to follow less-strong lead-ins, and the impact of mass media efforts is negligible if the goal is to drive viewership.

2. Research Question

How can consumer-generated social media posts improve forecasts of television premiere viewership? A quantitative analysis was conducted to test the statistical model in Figure 1 from which four hypotheses were generated.

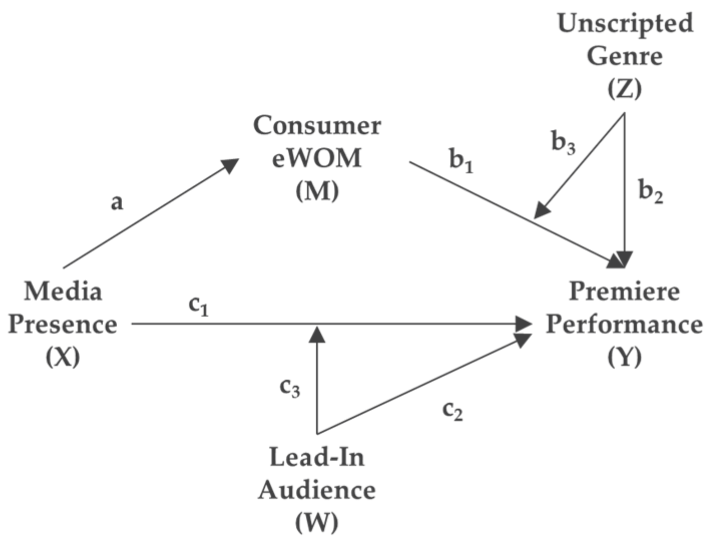

Figure 1. Conditional Process Mediation Model

H_1: Media Presence (X) has a positive indirect effect on Premiere Performance (Y) via generating Consumer Online Buzz (M).

H_2: Media Presence (X) has a positive direct effect on Premiere Performance (Y).

H_3: Lead-In Audience (W) has a positive direct effect on Premiere Performance (Y).

H_4: Unscripted Genre (Z) has a negative direct effect on Premiere Performance (Y).

Although there is a great deal of literature on using eWOM to forecast film (i.e., motion picture) box office revenue, fewer studies use eWOM to predict Nielsen ratings for television programs. These studies, and how this research builds on them, are summarized in Table 1.

Table 1. Summary of Literature on Television Program Forecasts with eWOM

Reference	Outcome Variable(s)	eWOM Variable(s)	Findings Regarding eWOM
This Research	Nielsen ratings (A18-34)	**Volume** (tweets, unique users), **Dispersion** (retweets), **Sentiment** (positive, negative), **Topics** (via LDA)	eWOM variables are combined with other predictors already in use for entertainment industry forecasting to demonstrate whether it is possible to gain additional accuracy.
Crisci, et al. (2018)	Television program Nielsen data (audience persons age 2+)	**Volume** (unique users, total tweets), **Dispersion** (retweets), **Sentiment** (positive, negative)	Various longitudinal (multi-episode) predictive models of unscripted program audience predicted by volume of tweets, retweets, unique users, and positive or negative sentiment.
Nielsen Media Research (2013b)	Live television Nielsen ratings	**Volume** of tweets	In 44% of competitive reality episodes measured, tweets caused ratings changes; 37% in comedy program episodes; 28% in sports; 18% in drama
Godes & Mayzlin (2004)	Television program Nielsen ratings of households watching premiere	Usenet newsgroup **volume** (number of posts) and **dispersion** (number of newsgroups in which program mentioned)	Dispersion significantly related to television program premiere's Nielsen ratings. No consistent support was found for Volume of eWOM; no measure of sentiment valence was included.

Crisci, et al. (2018) used longitudinal analysis to predict audiences for three Italian reality shows (e.g., *X Factor*) based on tweets, retweets, distinct Twitter accounts and sentiment (positive or negative) by training a model using social media data during the first ten episodes of the season and then using the model to predict viewership for the final three episodes.

Nielsen Media Research (2013b) published a white paper describing a time series analysis tracking live television ratings and volume of tweets minute-by-minute for 221 primetime episodes. They found that, overall, in 29% of the episodes, tweets influenced ratings. They also found that influence differed by genre. Tweets drive consumers to tune in to a program for 44% of competitive reality shows, 37% of comedies, 28% of sports episodes, and 18% of drama shows.

Godes & Mayzlin (2004) used Usenet newsgroup conversations, rather than Twitter, to predict Nielsen ratings for shows during the 1999-2000 seasons. Usenet is a collection of thousands of newsgroups with diverse topics (e.g., rec.arts.tv). They found that dispersion (diffusion of information across heterogeneous groups of consumers) was a critical explanatory factor, suggesting the importance of eWOM spreading across heterogeneous communities rather than remaining concentrated within a small set of communities.

Taken together, the studies indicate that Volume (number of tweets), and Dispersion (degree to which heterogeneous groups are engaged; retweets) are each viable predictors of Nielsen ratings. Furthermore, genre is related to the degree to which tweets drive ratings (competitive reality shows being most responsive, and dramas least).

Selection of measures was guided by our theoretical framework. Diffusion of Innovation theory (Rogers, 2003) posits that a measure of heterophilous communication be employed to capture dispersion of information across diverse groups. This was operationalized by retweets, consistent with Crisci, et al. (2018). In addition, the Bass (1969) diffusion model includes two key parameters: external channels and internal channels. Media presence operationalized an external channel; consumer Twitter activity was the construct that operationalized an internal channel. To test the hypotheses, regression analysis was used.

The data frame was comprised of (1) Nielsen television ratings for shows and their lead-ins, (2) consumer Twitter activity—volume of tweets and retweets, (3) media presence—number of stories mentioning shows in newspapers, periodicals, and television news transcripts via Dow Jones Factiva, and (4) show genre from IMDbPro.

3. Data Collection and Analysis

A total of 52 series premieres (i.e., shows designated at episode 1 of season 1) were analyzed. The shows and their lead-ins aired on broadcast networks (ABC, CBS, NBC, FOX, The CW) from 2018 to 2021 in primetime (i.e., 8p to 11p ET). Regression analysis applied in line with current standards of mediation analysis (Hayes, 2013) tested the indirect effects of the predictor variable (media presence) via a proposed mediator (Twitter tweets and retweets) plus additional direct effects from lead-in audience and genre using bootstrapping. This is especially appropriate given the limited sample size for this study (Preacher & Hayes, 2004).

Nielsen television ratings are the basis for billions of dollars of advertising transactions between media companies and advertisers every year. Forecasts of viewership help to establish the cost of advertising in advance of a show's premiere (Nielsen, 2017). For instance, a 30-second commercial during a Super Bowl is expensive by virtue of the size and demographics of the audience the networks and advertisers expect. As such, networks seek to deliver a large audience within demographic groups that are attractive to advertisers (e.g., adults age 18 to 34) so advertisers can achieve their marketing objectives. If a show fails to perform to expectations, then "make-goods" are offered by the network—additional commercials in other shows—to ensure an ad is seen by the viewers that was agreed to. Make-goods, however, often do not fit the advertiser's media plan as well as the shows originally purchased. Reliable forecasts help media companies and advertisers make more accurate, less subjective transactions.

The television entertainment industry invests millions of dollars in creating (writing, production, cast) and marketing a product with little data-driven evidence regarding how many consumers will be interested in it. Thus, this industry is fertile ground for improved forecasting models that provide a decision support system serving as a "second opinion". Hoffmann-Stölting, Clement, Wu and Albers (2017) found that forecasting models of German movie, music and book categories can outperform management judgement in most instances. The exception was top-selling products, which usually receive more attention during development and marketing.

Forecasting viewership can be challenging because it is difficult to incorporate consumer enthusiasm for a new program into a forecasting model as a quantifiable variable. Social media, or electronic word of mouth (eWOM), can be a means of assessing this enthusiasm. Importantly, the model in this research also includes variables that are already the foundation of viewership forecasting in the entertainment industry. In this way, we will demonstrate whether it is possible to improve accuracy beyond what is already widely used in the entertainment industry.

Findings

A total of 71,543 tweets were downloaded across all 52 shows. Non-consumer accounts were removed manually. As displayed in Table 2, although these accounts represented only 2% of total Unique Accounts, they accounted for 50% of total Twitter posts. Non-consumer accounts averaged 63.2 tweets per account (median=6) versus 1.5 tweets per account (median=1) for consumer accounts.

Table 2. Twitter Statistics of Consumer Accounts vs. Non-Consumer Accounts

	Total Tweets		Unique Accounts		Average # Tweets	Median # Tweets
Consumer Accounts	35,732	50%	23,927	98%	1.5	1
Non-Consumer Accounts	35,811	50%	566	2%	63.2	6
Total	71,543		24,493			

The 52 shows comprised three major genres: Unscripted (e.g., competition or reality shows), Comedy and Drama. Ratings by the three major sales demos (Adults age 18 to 34, Adults age 18 to 49 and Adults age 25 to 54) are displayed in the figure below (Figure 2).

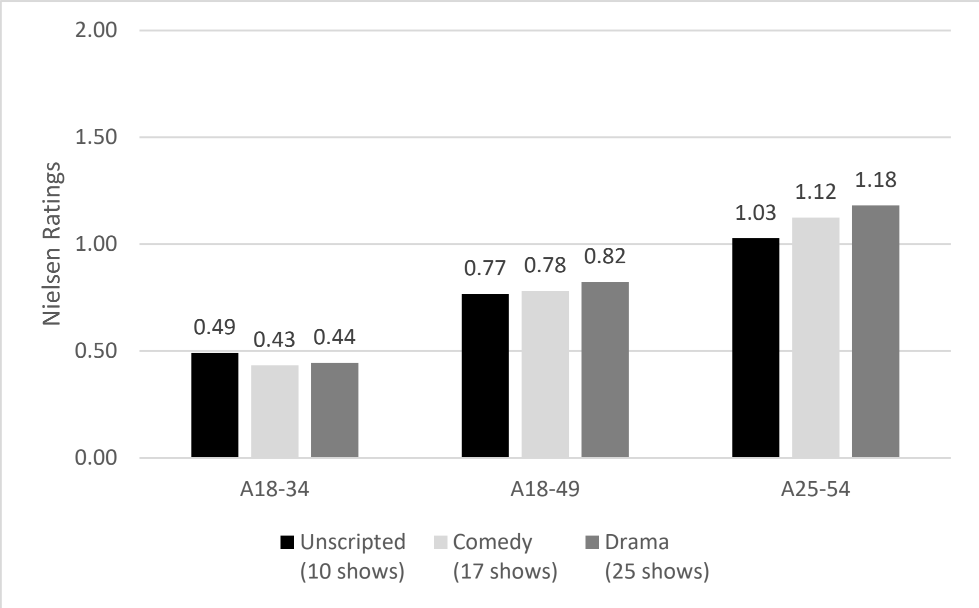

Figure 2. Premiere Performance by Genre

Hypothesis Tests via Conditional Process Regression Analysis

Each of the features of the regression model is described in Table 3, with means, standard deviations and ranges; zero-order correlations are also presented. A log transformation was used on Measure 3, Total # of Consumer Tweets + Retweets, to reduce the variability of the data. Note only Lead-In Audience has a highly-significant zero-order correlation with Premiere Performance.

Table 3. Means, Standard Deviations, Ranges and Correlations

	Mean	Std. Deviation	Range	1	2	3	4
1. Premiere Performance (A18-34)	0.45	0.23	0.04-1.20	-			
2. Lead-In Audience (A18-34)	0.71	0.43	0.10-2.10	0.74**	-		
3. LOG Total # Consumer Tweets + Retweets	2.84	0.61	1.08-3.99	0.26	0.13	-	
4. Media Presence (# mentions)	39.79-	27.83--	0-164	0.23	0.11	0.43**	-
5. Genre (1=Unscripted/0=Comedy or Drama)	0.19	0.40	0-1	0.09	0.13	-0.31*	-0.45**

Note. N=52, * Significant (p<0.05), ** Highly significant (p<0.01).

Table 4 displays a summary of the regression model, with overall model statistics toward the bottom of the panel.

Table 4. Conditional Process Model Summary

	Consequent											
	Consumer eWOM (M)						Premiere Performance (Y)					
		Coeff	SE	t	p-val			Coeff	SE	t	p-val	
Media Presence (X)	a	0.010	0.003	3.407	0.001	*	c_1'	0.002	0.002	1.228	0.226	
Consumer eWOM (M)		–	–	–	–		b_1	0.011	0.041	0.268	0.790	
Lead-In Audience (W)		–	–	–	–		c_2'	0.117	0.112	1.040	0.304	
Unscripted Genre (Z)		–	–	–	–		b_2	-0.4760	0.225	-2.11600	0.040	*
Interaction (X by W)		–	–	–	–		c_3'	0.006	0.002	2.538	0.015	*
Interaction (M by Z)		–	–	–	–		b_3	0.232	0.088	2.642	0.011	*
	R^2 = 0.19						**R^2 = 0.67**					
	F(1, 50) = 11.61, p < 0.01**						**F(6, 45) = 15.45, p < 0.01****					

Note. N=52, *Significant (p<0.05), **Highly significant (p<0.01).

H_1: Media Presence (X) has a positive indirect effect on Premiere Performance (Y) via generating Consumer eWOM (M).

Conditional support was found for Hypothesis 1. As shown in Table 7, there was a significant positive relationship between Media Presence (X) and Consumer eWOM (M), $t(50)=3.407$, $p<0.01$. Although the relationship between Consumer eWOM (M) and Premiere Performance (Y) did not achieve significance, $t(45)=0.268$, $p>0.10$, the effect of Consumer eWOM on Premiere Performance was contingent on Unscripted Genre, $t(45)=2.642$, $p<.05$.

Figure 3 (below) shows that, for Unscripted shows, Consumer eWOM had a positive effect on Premiere Performance. However, this relationship did not hold for the other genres (comedies or dramas). This interaction accounts for 5.1 percent of variance in the model ($\Delta R^2=0.051$), $F(1, 45)=6.98$, $p=0.01$.

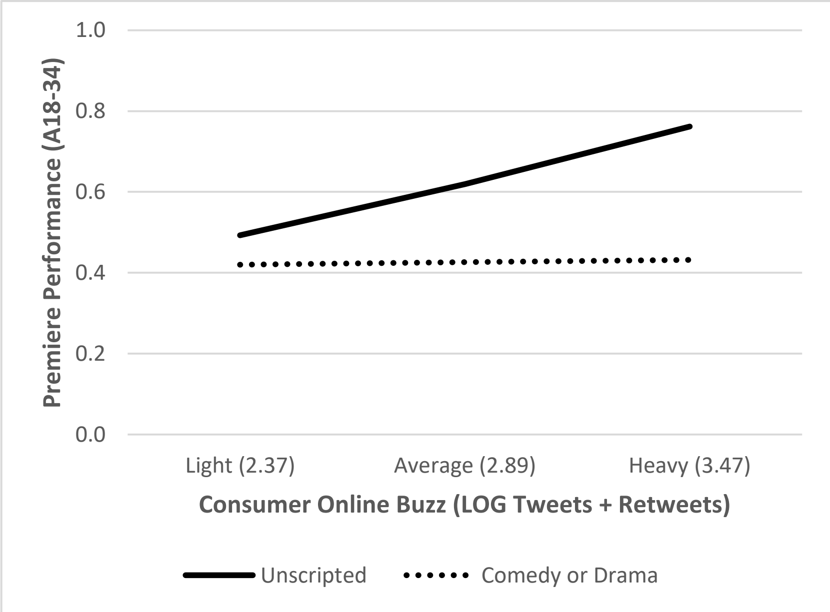

Figure 3. Interaction of Consumer Online Buzz (M) by Premiere's Genre (Z)

H_2: Media Presence (X) has a positive direct effect on Premiere Performance (Y).

H_3: Lead-In Audience (W) has a positive direct effect on Premiere Performance (Y).

Hypothesis 2 and Hypothesis 3 are considered together because conditional support was found for both. The direct effect of Media Presence (X) on Premiere Performance (Y) was not significant, $t(45)=1.228$, $p>0.10$. Similarly, the direct effect of Lead-In Audience (W) on Premiere Performance (Y) did not achieve significance, $t(45)=1.040$, $p>0.10$. However, a significant interaction between Media Presence (X) and Lead-In Audience (W) was found, $t(45)=2.538$, $p<0.05$. Figure 4 shows that, for strong Lead-Ins (with A18-34 ratings around 1.3), Media Presence had a positive effect on Premiere Performance. However, this relationship disappeared for moderate and weak Lead-Ins (with A18-34 around 0.6 and below). The interaction accounts for 4.7 percent of variance in the model ($\Delta R^2=0.047$), $F(1, 45)=6.44$, $p=0.02$.

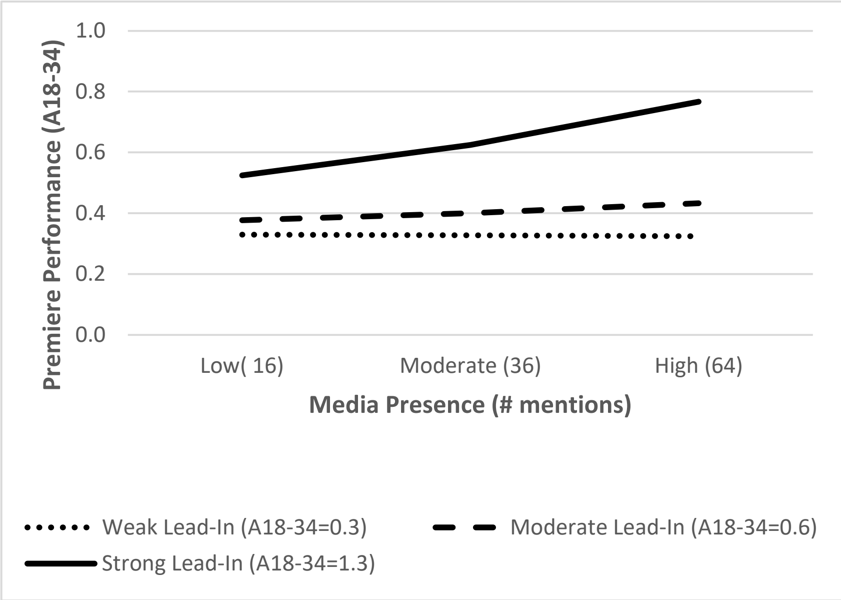

Figure 4. Interaction of Media Presence (X) by Lead-In Audience (W)

H_4: Unscripted Genre (Z) has a negative direct effect on Premiere Performance (Y).

Hypothesis 4 was supported by the data. Genre (Z) had a significant direct effect on Premiere Performance (Y), $t(45)=-2.116$, $p<0.05$. Unscripted shows tended to have lower Premiere Performance than other genres of shows, such as comedies or dramas.

4. Longitudinal Analysis

To further explore the temporal relationship between Consumer Online Buzz and Media Presence, Unscripted Program totals were broken out by the 14 days leading up to each premiere. There was a significant lagged correlation between Media Presence and Consumer Online Buzz, indicating a causal relationship between the two, $r(10)=0.81$, $p<0.01$.

Further, one-way ANOVA contrasts show a highly significant linear trend for Consumer Online Buzz, $F(1, 12)=10.32$, $p<0.01$ and a highly significant quadratic trend for Media Presence, $F(1, 11)=28.03$, $p<0.01$. See Figure 5, below.

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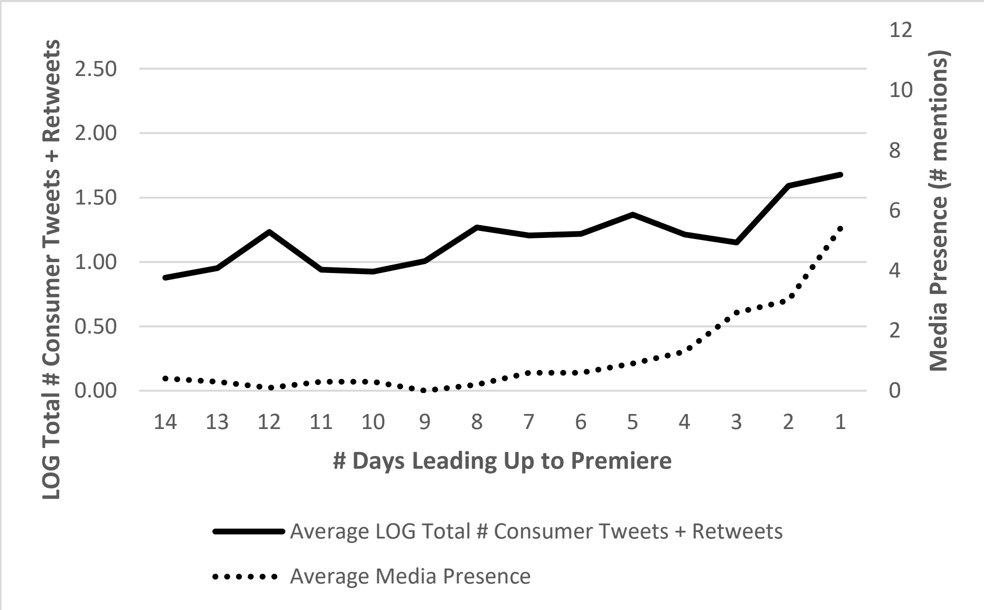

Figure 5. Consumer Buzz vs Media Presence, 14 Days Prior to Premiere (10 Unscripted Shows)

The conditional process regression model in Table 7, based on programs from 2018 to 2021, was then used to predict performance for three unscripted shows premiering in early 2022. Results are reported in Table 5, which shows actual A18-34 rating and compares the model *with* eWOM and *without* eWOM. Mean absolute percentage error (MAPE), summarized at the bottom, *with* eWOM was 26% compared to 80% MAPE *without* eWOM. This MAPE approach is consistent with extant literature in this area.

Table 5. Comparison of Unscripted Show Prediction Mean Absolute Percentage Error (MAPE) with and without eWOM in Model

				Absolute Percentage Error	
Unscripted Show Title	**Network**	**Premiere Date**	**A18-34 Rating**	**With eWOM in Model**	**Without eWOM in Model**
To Tell The Truth	ABC	2/22/2022	0.17	25%	78%
Who Do You Believe?	ABC	5/3/2022	0.10	12%	80%
That's My Jam	NBC	1/3/2022	0.20	40%	82%
Mean				**26%**	**80%**

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5. Lessons for Practice

Above and beyond variables that are typically included in television network entertainment show forecasts (i.e., lead-in and mass media presence), consumer-generated social media can further hone forecast accuracy—in this instance, for unscripted programs. This model may be used for predictions as early as 14 days leading up to the premiere. In addition, the model shows predictive validation with a number of 2022 unscripted shows. Use of this model helps remove uncertainty from transactions between advertisers and media companies when purchasing commercials to reach a target demographic.

Consumer-generated social media posts have a role in not only predicting, but also driving television premiere viewership for unscripted shows. This has many marketing implications for Unscripted shows. For example, make sharable content available to encourage posting and retweets.

Importantly, the influence of lead-ins was found to be contingent on media attention. This has implications for network television program scheduling and promotion. Networks make the best use of resources by saving strong lead-ins and mass media efforts for their high priority “flagship” premieres. Shows that are lower priority can be scheduled to follow less-strong lead-ins, and the impact of mass media efforts is negligible if the goal is to drive viewership.

6. Contributions to Theory

Diffusion of Innovation theory (Rogers, 2003) and diffusion modeling (Bass, 1969) were fruitfully applied to frame this study on television entertainment consumption. The importance of information about a television show being dispersed across diverse groups (as opposed to dispersion to other groups that are similar in terms of age, socioeconomic status, interests, etc.) is a key aspect of Diffusion of Innovation theory. This was operationalized by retweets, consistent with extant literature in this area. Granovetter (1973) asserted that “weak ties” facilitate this, and Twitter, unlike other social networking sites, is predisposed to this type of connection (Virk, 2011). Two key parameters in the Bass (1969) diffusion model describing diffusion of innovation, external and internal channels, are also captured in this study. Media presence (an external channel) can drive premiere ratings. In addition, consumer eWOM (an internal channel) drives premiere ratings for certain shows.

There were a few unavoidable limitations of the study imposed by the data sources available. The showbuzdaily.com site is an exceptionally reliable source of information for broadcast network ratings in primetime. However, it limited the current analysis to four broadcast networks (ABC, CBS, NBC, FOX, and the CW). Including series premieres on cable networks would increase the amount of data available for analysis and improve the generalizability of the current model. Additionally, although media salience (number of mentions in media during the days leading up to premiere) was an informative variable, a separate but related construct would be the level of promotion or advertising for new series (e.g., commercials promoting the new series during the days leading up to premiere). With this additional data, the model could predict when additional promotion (which has monetary cost or opportunity cost for a studio or network) would be helpful.

7. Conclusions and Next Steps

Several next steps for further exploration are clear. First, recall that 50 percent of total tweet volume came from non-consumer Twitter accounts (although they represented only 2% of total Unique Accounts). These included marketing accounts (e.g., “@MaskedSingerFOX”) networks and studios (e.g., “@CBS” or “@CBSTVStudios”), television stations (e.g., “@FOX5Atlanta” or “@CW11Seattle”), entertainment news (e.g., “@TVGuideMagazine” or “@TVInsider”). It would be useful to understand whether there is a place in the current model for non-consumer social media activity to add to our understanding of social media marketing. Second, this analytic approach can be applied to series appearing on digital streaming services (e.g., Netflix, Amazon Prime, Disney +, HBO Max). These tend to have younger audiences who are more engaged with social media. Beyond understanding viewership, such insight could be applied to increase subscriptions or to make streaming service “sticky” which would prevent subscription cancelation.

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