The Journal of Social Media in Society
Spring 2021, Vol. 10, No. 1, Page 79-99
thejsms.org

Modeling Social Television Analytics and Twitter-Enabled Audience Engagement – A Study of Cross-Platform Television Audience in Nigeria

Femi Abikanlu[1*] **and Tunde Aina**[2]
[1]Department of Media and Communications, University of Canterbury, New Zealand
[2]StarTimes Television Network, Nigeria and Harbin Institute of Technology, China
*Corresponding Author: femi.abikanlu@gmail.com

The shift to multi-platform television means that an understanding of the social interactions of television audience and measurement of audience engagement across all television viewing platforms are necessary to understand the behavioural pattern of television audience. The study is an attempt to bridge the gap in the scholarship of social television analytics and industry practice of understanding television audience by proposing an analytical model to audience research of digital television. As a result, the study asks what are the connections between audience experience on television and extended engagement of social media-enabled communication by television services? To understand the relationship between television viewership trends of the selected demography and social interactions of television audience on social media, we used correlation and regressions models to examine the relationship between television audience ratings and Twitter data of audience engagement. The results of the correlation analysis are indicative of an entangled relationship between audience ratings and social interactions of television audience on Twitter. Also, in the context of the selected demography, the regression analysis implies that a change in the value of audience ratings may not necessarily affect social interactions of television audience or the pattern of content consumption on social media.

Keywords: Social Television Analytics, Twitter, Television Ratings, Audience Measurement, Nigeria

---

Due to digital convergence and technological innovations, the methods of measuring the value of a television audience are changing and require a new approach beyond traditional methods. Equally, the user-defined features of multi-platform television services, the shifting nature of audience behaviour, and social interactions of television audience on social media prompted a shift from the traditional practices of audience measurement, such as the Nielsen ratings, to social television analytics (Batrinca et al., 2015; Buschow et al., 2014; Gallego, 2013; Hu et al., 2014; Kosterich & Napoli, 2016a; Pensa et al., 2016; Pynta et al., 2014). Social television analytics integrate the inherent value in the social interactions of television audience on social media as a performance metric for understanding the behavioural patterns of the digital television audience (Kosterich & Napoli, 2016). This approach to understanding audience behaviour helps in identifying the distinctive performance of a specific television content relative to other programs in a television channel, monitor performance trends, analyse the significant patterns of television market and determine advertising rates across a television channel.

In the context of the Nigerian digital television environment, there is an absence of a national recording standard for digital television services and limitation in data accessible to understand the existing connections of audience behaviour from the digital television medium and the corresponding communicative attempts on social media. In response to this limitation and deficit of information available to understand the performance of digital television content, the Nigerian government recently appointed a task team to design and recommend an industry framework for an audience measurement system, with a primary goal of ensuring that advertising revenues are equitably distributed across the Nigerian television industry (Oyeyemi, 2020). For equitable distribution of advertising revenue, social television analytics offer an "analytical alternative" in understanding the market terrain of digital television (Kosterich & Napoli, 2016, p. 255) and the underlying factors that may affect audience behaviour and the performance of television programs.

Primarily, this study attempts to bridge this limitation of the industrial practice of social television analytics by proposing an analytical model for social television analytics. Our approach to this analytical model is a complete deviation from current audience measurement practices such as those involving the use of quantitative research methods—evaluation survey of audience sample, focus groups, demographic analysis, opinion polls, recruitment of panelists, etc. While acknowledging the fluidity and infrastructural impediments of measuring audience behaviour in the emergence of digital television, we believe that a cross-disciplinary approach to audience research is crucial to understanding the performance trends of television content. Likewise, the process of data collection, integration and analysis from the audience measurement systems on digital television networks and social media platforms require multi-disciplinary coordination and input of different skillsets.

Social Media and Social Television Measurement Practices

The technological shift to multi-platform television reduced the accuracy of traditional audience measurement practices and posed a challenge to understanding the performance of television content (Kosterich & Napoli, 2016b; Méadel, 2015). Equally, the shift to multi-platform television means that an understanding of the social interactions of television audience and measurement of audience engagement across all television viewing platforms are necessary to understand the behavioural pattern of television audience. Beyond social interactions, online spaces and social media platforms, such as Facebook and Twitter, have become a public sphere in which the television audience reacts, responds and reinforces existing ideologies or viewpoints on television programs. The real-time attributes of these audience social interactions, depending on the platform, include comments, shares, likes, retweets and replies. The analysis of these audience interactions driven by the need to understand the underlying connections between the television medium and social media resulted in Social Television Analytics. Based on this data-centric approach, the concealed behavioural pattern of television audience and performance of a television program is understood to be inherent in the relationship between data from social media and viewership trends (Hu et al., 2014).

Beyond exposure to television content, the emergence of social television analytics presents an analytical mechanism to understand audience behaviour based on the existing overlap between social media-enabled interactions of television audience and measured performance of television content. Simply put, social media analytics integrates “the collection, analysis and interpretation of social media data to support effective decision-making" (Bekmamedova & Shanks, 2014, p. 3729) and has been widely understood to play a crucial role when measuring the inherent values of television programs and the extent by which television audience are engaged (Kosterich & Napoli, 2016). Through an intensive analysis and interpretation of data from social interactions on social media platforms, the behavioural pattern of television audience can be deduced to create values. Also, for corporate organizations, social media analytics provide an alternative channel to track and understand trends in customer perception, and to conduct strategic and low-cost targeted marketing campaigns. Much is known about the organizational benefits of social media analytics but there are very limited studies to understand the dynamic capabilities of social media analytics to the shifting television landscape.

The traditional audience measurement practices based on the survey of television audience—such as the audimeter and peoplemeter—are mostly limited to data measured from the internal mechanism of the television set. At their very best, as Méadel (2015, p. 40) noted, these traditional audience measurement practices are limited to the viewing patterns of "televiewers" (a contraction of television and viewers) or television audience attached to the television set within an identified demography. In response to the rising influence of audience engagement on social media, the Nielsen company (the world's leading media measurement company) introduced the Nielsen Twitter TV Ratings in 2013 (Nielsen, 2013). This improvement integrates the engagement of television audience on Twitter by measuring the number of engaged Twitter accounts that a television program has attracted and a wider audience who viewed the tweets associated with it. While we acknowledge the importance of these Nielsen Twitter TV Ratings to the television landscape, especially to the effectiveness of targeted advertisements, we believe the fundamental flaw with this measurement practice of social television is the misconception that 'Twitter TV-related audience engagement', according to Nielsen (2013), equates to an engaged audience of social media-enabled television content. More precisely, the Nielsen Twitter TV Rating assumes that activities around an engaged audience on social media are sufficient to understand the inherent values of social media-enabled engagement of television audience.

Furthermore, the technological-driven shift in performance metrics of television audience from traditional rating charts, such as the Nielsen's ratings has been put under "tremendous strain" due to increased access to television channels per household (Kosterich & Napoli, 2016, p. 260). The data retrieval process from this audience-centric approach to audience measurement reveals little of the inherent behavioural pattern of a television audience, the social influence of television enthusiasts and how they respond to television content. Recently, the introduction of Nielsen's Social Content Ratings (SCR) is another improvement of the industry's leading media measurement company. According to Nielsen (2020), the measurement process of the SCR integrates real-time data of audience activities from "over-the-top streaming providers" of linear television episodes and with their "geo-bound" audience activities on Facebook, Twitter and Instagram. However, the main challenge with this improvement to social television measurement practice is its limitation to certain television markets, primarily Australia, Mexico, Italy and the United States. More so, the accuracy of the 'geo-bound' features of this audience measurement practice is limited as the user-defined geolocation functions on social media are relatively low due to privacy concerns. A study by Leetaru, Wang, Cao, Padmanabhan (2013) reveals that less than 3% of tweets have geolocations metadata.

Crucial to the objectives of this study, it becomes imperative to ask how does the social television analytical approach differ from other existing technological-driven audience measurement practices? Simply put, as previously mentioned, it integrates data from audience ratings measured from the television internal mechanism with big data measured from the audience social interactions on social media. However, the shift to this analytical alternative prompted a heavily contested understanding of audience measurement within the television industry. The changes in the medium by which audience consume television content and the methods by which such consumption are measured transformed audience values in the marketplace (Kosterich & Napoli, 2016). In the campaign to gain competitive advantage, Moor and Lury (2011, p. 440) acknowledged the complex approach to understanding the "relational activities" that determine the performance and valuation of aired campaigns among brand owners and advertising agencies. Equally, in the context of multiplatform measurement services, Hayes (2014) acknowledged "a distinct lack of consensus around how all of this data will shake out" in determining the existing correlation between Twitter audience activities and television audience ratings.

Inherent in this shifting dynamic of television audience measurement, the integration of social media data with the measured performance of television content pre-empts a complex process of understanding the behavioural pattern of a television audience. To tackle this challenge with the analysis of social television, we propose an analytical model comprising of four main components. While there are existing studies on the framework for social media analytics (e.g Bekmamedova & Shanks, 2014; Oh, Sasser, & Almahmoud, 2015; Stieglitz & Dang-Xuan, 2013), very few studies present a framework for social television analytics or understand the behavioural pattern of television audience beyond exposure to the television set. As a result, the next section of the study presents a framework that integrates existing social media analytics with the analytical approach of television audience research. There are two motivations to this analytical framework. Firstly, since the shift to multi-channel television, there have been significant interests across the television landscape in understanding the inherent values of social media-enabled interactions and engagement of television audience. Secondly, we believe an understanding of the behavioural pattern of television audience is a huge benefit to the entire value chain of digital television services, comprising advertisers, content producers, content aggregators, signal transmission and distribution companies etc.

Framework for Social Television Analytics

To examine the significance of recent development in television audience performance and its connection with various communicative interactions on social media, the study acknowledges that understanding audience behaviour in the digital television era involves a complex process and fragmented along varying demographic lines. In so doing, the study presents an intensive process of analysis of television audience measurement data from selected digital terrestrial television services in Nigeria and the corresponding social interactions of television audience on the official Twitter accounts of the selected television channels. This comparative analysis is based on the analytical practice that data from social television behaviour, according to Hill (2014), when combined with big data increases predictive accuracy of audience behavioural patterns.

To this end, we propose a model of social television analytics for television audience research by integrating some existing framework of social media analytics (e.g Batrinca & Treleaven, 2015; Fan & Gordon, 2014; Guo & Saxton, 2014; Kenix & Abikanlu, 2019; Stieglitz & Dang-Xuan, 2013; Zeng et al., 2010) and analysis of television viewership performance trends (e.g Buschow et al., 2014; Gallego, 2013; Hu et al., 2014; Hu et al., 2015; Kosterich & Napoli, 2016; Larsen et al., 2016; Oh, Yergeau, et al., 2015). It is important to note that this proposed model is not a one-size-fits-all for social television analytics, but an applicable analytical approach primarily based on a deep understanding of the central research questions and objectives of the study in question. As a result, it is highly recommended that before data collection and mining processes of any TV audience research, the primary questions and objectives of the study must be clarified by the entity conducting the study.

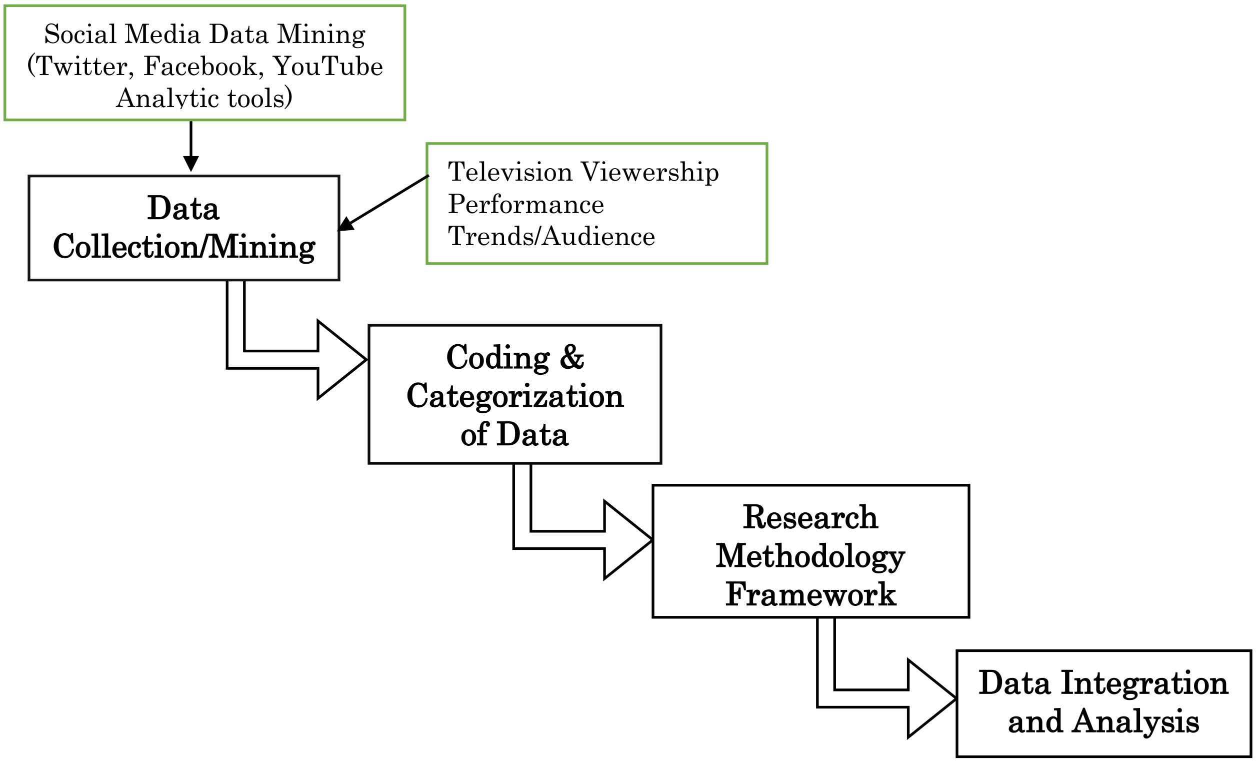

Figure 1 Research Framework of Social Television Analytics. To make an analytical summary, the proposed model consists of four main components.

The components of the framework for social television analytics set the path to an integrated analysis of datasets collected from social media and performance trends of television viewership collected from a metering system usually attached to a television set. The details of each of the components are briefly described below.

Data Collection and Mining. The first component involves a process of identifying, monitoring and extracting the main sources of datasets involving viewership performance from a digital television measurement system and data mining of audience engagement on the selected social media platforms using applicable programming tools. The accuracy of these data mining and collection is dependent on various factors and inclusive of the tools adopted for these processes. Before the commencement of these processes, the entity conducting the study must identify the content, formats and the correct sources of the data to be collected. The process and limits of data collection from the available data analytics of social media platforms will depend on the primary objectives of the study in question.

Furthermore, the coverage area of the dataset may either be limited to the official pages and accounts of the selected television channel or program or extended to extract specific keywords from the newsfeeds or APIs (using # or @ signs) and across a broad spectrum of social media platforms. As Fan and Gordon (2014, p. 5) noted, in order to understand a dataset, "various pre-processing steps may be performed, including data modelling, data/record linking of data from different sources, stemming, part of speech tagging, feature extraction, and other syntactic and semantic operations that support analysis." The archival data of social media platforms could be sourced from relevant sources, particularly from their newsfeeds or APIs.

Coding and Categorization of Data. The second component of the model involves a process of identifying and selecting the required data. The criteria for data selection depend on the objectives and questions of the study as not all archival data are necessary or useful. Equally, the selected data will need to be coded and categorized into the required analytical format using relevant data processing worksheets such as Excel or SPSS spreadsheets. Finally, the coded and categorized data will need to be stored in a structured format for easy and convenient analysis.

Research Methodology Framework. The third component of the model involves the process of sensemaking and determination of the relevant research methods, either quantitative or qualitative, that apply to the study in question. Also, this component clarifies the intention of the researcher and the research methods used to interpret or manipulate the collected data. It also helps to revise the data collected, ascertain if the data are representative of the problem and detect any possible gaps in the data collection process. Subsequently, the necessary strategy to address the gaps in data are implemented before moving to the subsequent component.

Data Integration and Analysis. This final component of the proposed model involves an intensive and overlapping process of data analysis, interpretation and integration into engaging and interactive visual analytics consistent with the objectives of the study in question. The collected data from all sources will need to be integrated to eliminate redundant data from the collection process.

In the subsequent section of the study, we adopt this model in the attempt to investigate the interdependent relationships between audience ratings of the selected television network and the corresponding social interactions of television audience on Twitter.

METHODS

Television Audience Ratings Measurement Method

In the context of this study, the measurement of audience ratings (AR) on digital television channels integrates various studies of television measurement systems and audience behavioural patterns (e.g Aina et al., 2014; Ghashghai & Barton, 2015; Lu et al., 2002). The analysis of the audience measurement systems primarily integrates audience rating of 98 channels from StarTimes digital terrestrial television network in Nigeria. The Audience Ratings (AR) is conceived as a percentage measurement of the number of subscribers watching a specific channel or program per the total number of television subscribers at any given minute. It is also a fraction of the number of subscribers watching a television channel per the total number of subscribers across the entire network.

The criteria of sample selection of households for measuring Audience Ratings include television subscribers that fall within the lower-class bouquet and with a minimum of ten months uninterrupted subscriptions. The criteria were also extended to television channels with high followership rates, frequent engagement by followers and regular updates on their official Twitter accounts. Also, we focused on television channels with countrywide viewership rates and available on all major television platforms. The other criteria of measurement based on the Twitter accounts are highlighted in the next theme of this section. Based on this selection and measuring criteria, three television channels were selected and include Channels Television, TV Continental and state-owned Nigeria Television Authority (NTA). The selected television channels are all national news channels.

The data collection process involves the AR values of the three selected television channels collected at a 30-minutes interval measured every 24 hours and for 30 days period, between April 1, 2020, and April 30, 2020. This period also falls within the global travel lockdown due to the Covid-19 pandemic. As a result, the study assumes an increased viewership rate per household compared to any other times. In total, 4, 320 AR values were collected and analysed in this study. The components of the retrieved dataset include the Percentage Audience Ratings (%AR), AR ranking, Percentage AR Month-on-Month comparison (%ARMoM), Percentage AR Year-on-Year (%ARYoY) comparison, Percentage Market Share, Percentage Average Reach Rate, Average viewing time or Daily Viewing Hours per Capita (minutes) and Percentage Average Audience Loyalty. Equally, these channels are categorized into Local, International and Self-produced channels. The audience ratings from the StarTimes Television Platform conform to the International Industrial Standard Global Guidelines for Television Audience Measurement (GGTAM). However, as a result of our research question, which asks what are the relationships between television audience experience and audience engagement of social media-enabled communication by television services, the study focussed only on the AR values of the viewership performance.

Due to limitations in data accessibility and the absence of data from connected television viewing experiences such as the Electronic Programming Guide (EPG) of some television channels, our analysis of the retrieved AR data is limited to the city of Lagos, Nigeria. Lagos is the commercial capital of Nigeria and the most populous city in Africa with a population of more than 20 million people. The AR values of the selected demography make up a significant proportion of the subscriber base of StarTimes DTT services in Nigeria. These datasets were retrieved with permission from the StarTimes Audience Research Centre. In total, the intensive data collection process consists of 292 sample households in the city of Lagos, Nigeria.

Twitter Data Collection Process

Primarily, some sets of data collected from Twitter API were identified to understand the social interactions of the television audience and its effect on television audience ratings. The data collection for social interactions of television audience on Twitter reflects a high degree of engagement. In specific cases, beyond the official pages and accounts of the selected television channels, the data collection process also extended to engagements and citation mechanisms of personal social media platforms. These extended communicative engagements were formally identified by hashtags (#) and identification code (@) preceding the names of the selected television channels.

The selection criteria of the Twitter accounts of the television channels are based on the number of engaged audience and frequency of use. First, using the dataset from the audience ratings, we selected the 'most-watched television channels' across different cities in Nigeria. However, the result reveals a wide variation in the level of audience engagement based on underlying factors that are beyond the scope of this study. For instance, some of the social media pages of the local television channels with the highest audience ratings have limited presence and engagement on Twitter. Equally, in some cases where a foreign television channel has high audience ratings and a highly engaged audience on social media (such as Nickelodeon, StarPlus, ST Novela E and ST Novela E Plus), we assumed that this high level of engagement cannot be attributed to audience engagement of the selected demography alone. Due to the technical limitations of geo-tracking data from the Twitter Application Programming Interface (API), all foreign television channels from the resulting data were excluded from our selection process. Following an intensive process of revision and elimination, we narrowed our selection criteria to local television channels with relatively high presence and engagement on social media. The result of the selected samples involves three local television channels: The Channels Television (@channelstv), TV Continental (@TVCconnect) and NTA News Channel(@NTANewsNow). As previously mentioned, the three selected television channels are all news channels with a nationwide coverage.

The data collection process of audience social interactions from Twitter API adopts the analytical path of some recent studies on social television analytics (Baym, 2013; Hill, 2014; Kelly, 2019; Kosterich & Napoli, 2016; Murschetz & Schlütz, 2018; Nelson & Webster, 2016), which involves monitoring of big data and behavioural patterns of a television audience. The data collection process of audience engagement on Twitter integrates intensive data categorization and coding techniques using Python programming tool and Twitter API. Due to the complex nature of accessing past tweets on Twitter API, the data collection and analysis of tweets were restricted to a period of 30 days. The categorization of the datasets, based on the typical actions of Twitter users, include:

i. Total number of daily Tweets (*Tweets*)
ii. Total number of daily Likes (*Likes*)
iii. Total number of daily Retweets (*Retweets*)

iv. Total number of daily Hashtags (*Hashtags*)

Our approach to the computed data metrics from Twitter API forms the basis of our comparative analysis with the audience ratings and was analysed through a computational method that requires a combination of Excel spreadsheets and integrated Python/SQL programming scripts. The significance and predictive abilities of this computational approach has been widely adopted, validated, and found to be very accurate by various analytical studies using Facebook and Twitter-based datasets. In total, a combined total of 1,120 tweets retrieved in the same period as the audience ratings were analysed in this study. These tweets were mined from the official Twitter pages of the three selected television channels for a period between April 1, 2020, and April 30, 2020.

Data Analysis

Primarily, the process data analysis involves Audience Ratings (AR) and Twitter metrics (T_M). As highlighted in Tables 1, 2 and 4, the datasets contain Twitter metrics which were taken as the independent variables and categorized as *Likes*, *Retweets*, *Tweets* and *Hashtags*. Equally, the Audience Ratings (%) were taken as the dependent variable. To understand the significant relationships between viewership trends of the selected audience sample and the corresponding social interactions on Twitter, we conducted a simple linear correlation and regression analysis on the two sets of variables. In the context of this study, we conceived a correlation analysis as a measure of the interdependent relationship between a dependent and an independent variable. Simple linear regression analysis is widely used to determine the variance or effect of a possible change in the value of the dependent variable on the value of the independent variable.

Table 1

Datasets of TV Continental (@TVCconnect) of the first 10 observations

Date	Likes	Retweets	Tweets	Hashtags	AR (%)
1/04/2020	989	156	40	86	0.295
2/04/2020	932	133	22	16	0.308
3/04/2020	1145	178	22	12	0.420
4/04/2020	58	8	3	1	0.180
5/04/2020	1571	228	27	11	0.257
6/04/2020	694	95	14	7	0.295
7/04/2020	772	123	37	19	0.325
8/04/2020	752	109	21	62	0.300
9/04/2020	869	121	20	24	0.351
10/04/2020	1226	245	35	18	0.491

Summation of Twitter metrics = β_o X (summation of Audience Ratings) + α (Intercept)

$$\Sigma\ ^{TM} = \beta_o\ (AR_X) + \alpha \qquad (1.0)$$

β_o is the slope and the Twitter metrics include the number of Likes, Tweets, Hashtags & Retweets.

By adding a random error, e_i, the statistical model accounts for deviation in the total number of observations recorded for the twitter metrics (i= 1,2,3,4,5,...n).

$$\Sigma\ ^{TM} = \beta_o\ (AR_X) + \alpha + e_i \qquad (2.0)$$

Table 2

Datasets of Channels Television(@channelstv) of the first 10 observations

Date	Likes	Retweets	Tweets	Hashtags	AR (%)
1/04/2020	14253	5802	19	5	0.891
2/04/2020	13242	3363	6	2	0.950
3/04/2020	18219	4578	22	12	0.687
4/04/2020	12481	3047	1	0	0.690
5/04/2020	16235	5254	4	3	0.834
6/04/2020	20261	5539	16	5	0.815
7/04/2020	12767	3084	9	0	0.938
8/04/2020	21614	6024	4	6	0.645
9/04/2020	19044	4809	7	2	0.719
10/04/2020	14649	3670	12	2	0.858

Summary of Statistical Data of Key Variables of Each Television Channel

Correlation Analysis of Television Audience Ratings (%) with Tweet Metrics. Broadly, correlation analysis is widely used to determine the extent to which an independent variable can change with a dependent or predictor variable. The value of the correlation coefficient (r) ranges between +1 and -1. A positive value of r means there is a linear relationship between the two variables in comparison. On the other hand, a negative value of r may mean there is a nonlinear relationship between the two variables in comparison. A value of r=0 may mean there is no interdependent relationship between the two variables in comparison.

To determine the significance of the model and the strength of the relationship between the viewership trends and extended engagement on social media, the study computes a linear correlation analysis between the dependent variable, Audience Ratings (AR) and the four independent variables of the selected twitter metrics. The sample data contained 30 observed data points which correspond to each day of the selected month. The result of the linear correlation reveals a scatter plot with a linear trend and readings of the correlation coefficients were taken and documented in a tabular format as shown in Table 3.

Table 3
Pearson Correlation Coefficients, r of Television Tweet Metrics with Audience Ratings (%)

Variables	@NTANewsNow	@TVCconnect	@channelstv
Likes	0.387939	0.254103	0.075733
Retweets	0.247401	0.327442	0.268264
Tweets	0.125026	0.238557	-0.24233
Hashtags	-0.09956	0.12686	-0.1604

Simple Linear Regression of Television Audience Ratings (%) with Tweet Metrics. Similar to the correlation coefficient, the R-squared value (R^2), is used to determine the strength of the relationship between two variables and ranges from a scale between 0 and100%. A value of $R^2=0$ may denote there is no variance between the two variables in comparison. On the other hand, a value of $R^2=100\%$ may mean a strong variance between the two variables in comparison. A larger R^2 value may mean the more the scatter points fit into the regression lines and the more a change in the value of the dependent variable will affect the value of the independent variable. However, in some exceptional cases, a low root-squared value may not necessarily mean a weak variance between the two variables in comparison largely due to external factors.

Table 4
Datasets of NTA News (@NTANewsNow) of the first 10 observations

Date	Likes	Retweets	Tweets	Hashtags	AR(%)
1/04/2020	1218	269	4	0	0.0933
2/04/2020	511	91	3	0	0.069
3/04/2020	225	53	2	0	0.0654
4/04/2020	631	134	3	0	0.0148
5/04/2020	654	144	8	0	0.0532
6/04/2020	655	110	3	3	0.0602
7/04/2020	1268	279	3	2	0.0721
8/04/2020	3352	1266	3	5	0.0775
9/04/2020	1436	232	0	2	0.1073
10/04/2020	1725	1241	5	3	0.0592

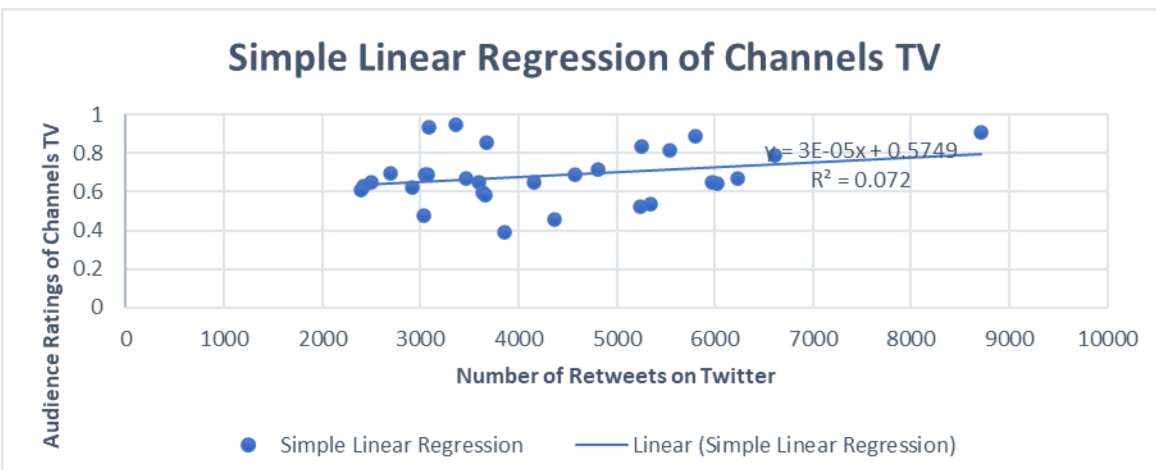

Figure 2 Scatter graph showing Simple Linear Regression for Channels Television

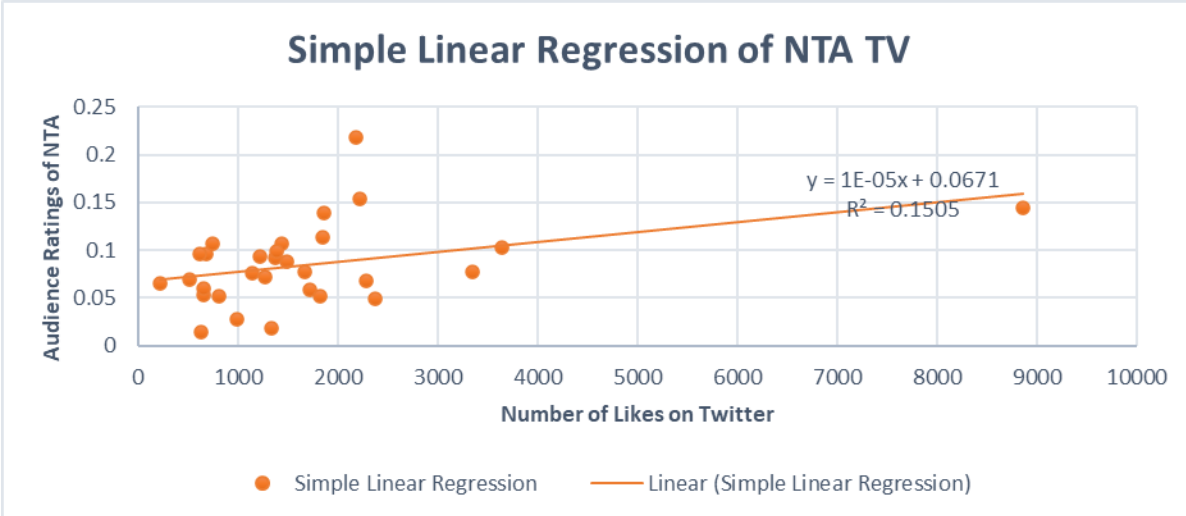

Figure 3 Scatter plot showing Simple Linear Regression for NTA Television

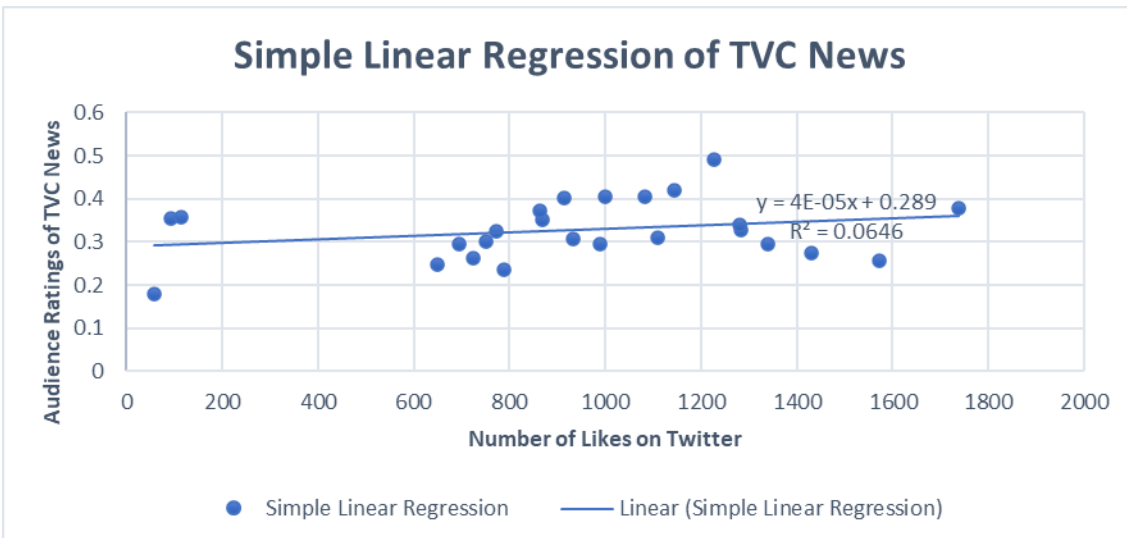

Figure 4 Scatter plot showing Simple Linear Regression for TVC News

To determine the significance of the model and variance of the relationship between the viewership performance and extended engagement on social media, the study computes a simple linear regression analysis between the independent or predictor variables, the four selected tweet metrics and the dependent variable, Audience Ratings (AR). The sample data contained 30 observed data points and their scatters fit around the regression lines. The scatter plots of the Audience Ratings and selected Twitter metrics from each of the selected television channels are revealed in Figures 2, 3 and 4. Also, the root-squared values of all the datasets were evaluated and documented in a tabular format as shown in Table 5.

Table 5
R-squared values, R^2 of Television Tweet Metrics with Audience Ratings (%)

Variables	@NTANews	@TVCconnect	@channelstv
Likes	0.1505	0.0646	0.0057
Retweets	0.0612	0.1072	0.072
Tweets	0.0156	0.0669	0.0587
Hashtags	0.0099	0.0161	0.0257

RESULTS

In the context of this study, the positive values of the Pearson correlation coefficients are indicative of an entangled relationship between audience ratings and social interactions of the television audience on Twitter. However, from the results of the simple linear regression analysis, the R-squared values appear to be statistically insignificant across the three selected news channels. In the context of the selected demography, the low R-squared values may imply that a change in the value of Audience Ratings may not necessarily impact audience engagement or the pattern of content consumption on social media. This invariance also suggests that engagement and communicative attempts on social media may not necessarily be influenced by television viewers alone. Likewise, the results suggest there is a new form of audience engagement on social media platforms that may be completely separate from the television audience.

Results suggest the value of the audience ratings may not be a crucial factor in any forecast of communication and engagements of television audience on social media. Several external and complex factors influence audience engagement and consumption of television audience on social media. In the context of television audience experience on social media, some of the factors that influence television audience engagement on social media include the character of national media culture and the technical strategy of social media utilization by television broadcasters (Moe et al., 2016). Equally, a study to determine the reasons behind the consumption of television content on social media highlights three main factors that involve the 'television program-related perceptions, social media characteristics and audience attributes' (Guo & Chan-Olmsted, 2015).

Based on the findings of the study, it is apparent that extended audience interactions on social media are a crucial part of audience experience. Also, the use of social media-enabled communication by television services creates a new audience base and accompanied by an alternative revenue stream through targeted advertisements. As a result, it is important for broadcast television services to explore the enormous opportunities of social media-enabled and interactive communication. An inclusive part of this investment may be to engage the services of social media managers for regular engagement, create content regularly, analyse performance data and create advertisement content that may generate additional revenues.

CONCLUSION

The study adds to the scholarship of television audience research in the era of digital convergence. Also, the study presents an intensive data analysis of the audience behavioural patterns based on television audience ratings and social interactions of the television audience on Twitter. The study also proposes an analytical model of social television analytics which consists of four main components that set the path to an integrated analysis of datasets collected from social media and performance trends of television viewership. This comparative analysis is based on the analytical practice that data from social television behaviour and social media-enabled communication of television audience increases the predictive accuracy of audience behavioural pattern. The results of the correlation analysis are indicative of an entangled relationship between the audience ratings and social interactions of the television audience on Twitter. Also, the regression analysis implies that a change in the value of audience ratings may not necessarily affect social interactions of television audience or the pattern of content consumption on social media.

Finally, the case study of social television analytics involves datasets of TV audience in the city of Lagos, Nigeria, and limited to a selected sample of television viewers obtained from StarTimes Television Network. Equally, the social media dataset is limited to Twitter and does not include extended audience communication on other social media networking platforms such as Facebook, Instagram, YouTube, Snapchat, etc. As a result, this study is not indicative of the behavioural pattern of all online experience of television audience and the findings are limited to a measured sample within the selected television demography. For a more accurate audience measurement of extended communications based on technology, beyond the present status-quo of social television measurement, we call on future studies to integrate the performance of television content across multi-platform networks such as direct-to-home (DTH), cable television, on-demand video streaming services, live stream internet television usually accessible on the website of the respective television channel and other existing digital television networks. This is required to better make sense of the behavioural pattern of television audience across the multi-channel, multi-platform and diverse landscape of digital television services. Due to evolving technologies and the fluid nature of digital television services, we acknowledge the complexity of integrating performance data of multi-platform television networks across a diverse and fragmented demographic concentration.

REFERENCES

Aina, T., Ye, Z., Dai, Z., & Jianghui, C. (2014). *Field tests of two-way television audience measurement system.* Paper presented at the 2014 IEEE international symposium on broadband multimedia systems and broadcasting.

Batrinca, B., & Treleaven, P. C. (2015). Social media analytics: a survey of techniques, tools and platforms. *Ai & Society, 30*(1), 89-116.

Baym, N. K. (2013). Data not seen: The uses and shortcomings of social media metrics. *First Monday, 18*(10).

Bekmamedova, N., & Shanks, G. (2014). *Social media analytics and business value: a theoretical framework and case study.* Paper presented at the 2014 47th Hawaii international conference on system sciences.

Buschow, C., Schneider, B., & Ueberheide, S. (2014). Tweeting television: Exploring communication activities on Twitter while watching TV. *Communications, 39*(2), 129-149.

Fan, W., & Gordon, M. D. (2014). The power of social media analytics. *Communications of the ACM, 57*(6), 74-81.

Gallego, F. (2013). Social TV Analytics: Nuevas métricas para una nueva forma de ver televisión. *Index. Comunicación: Revista científica en el ámbito de la Comunicación Aplicada, 3*(1), 13-39.

Ghashghai, J., & Barton, J. M. (2015). Audience measurement system. In: Google Patents.

Guo, C., & Saxton, G. D. (2014). Tweeting social change: How social media are changing nonprofit advocacy. *Nonprofit and Voluntary Sector Quarterly, 43*(1), 57-79.

Guo, M., & Chan-Olmsted, S. M. (2015). Predictors of social television viewing: How perceived program, media, and audience characteristics affect social engagement with television programming. *Journal of Broadcasting & Electronic Media, 59*(2), 240-258.

Hayes, D. (2014). Don't Confuse a TV Show's Twitter Impact with Its Ratings Power. *Forbes, November, 30*.

Hill, S. (2014). TV audience measurement with big data. *Big Data, 2*(2), 76-86.

Hu, H., Huang, J., Zhao, H., Wen, Y., Chen, C. W., & Chua, T.-S. (2014). *Social tv analytics: a novel paradigm to transform tv watching experience.* Paper presented at the Proceedings of the 5th ACM Multimedia Systems Conference.

Hu, H., Wen, Y., Gao, Y., Chua, T.-S., & Li, X. (2015). Toward an SDN-enabled big data platform for social TV analytics. *IEEE network, 29*(5), 43-49.

Kelly, J. (2019). Television by the numbers: the challenges of audience measurement in the age of Big Data. *Convergence, 25*(1), 113-132.

Kenix, L. J., & Abikanlu, F. (2019). A comparative analysis of social media messaging by African-centred LGBT refugee NGOs. *Journal of African Media Studies, 11*(3), 313-329.

Kosterich, A., & Napoli, P. M. (2016). Reconfiguring the audience commodity: The institutionalization of social TV analytics as market information regime. *Television & New Media, 17*(3), 254-271.

Larsen, H. H., Forsberg, J. M., Hemstad, S. V., Mukkamala, R. R., Hussain, A., & Vatrapu, R. (2016). *Tv ratings vs. social media engagement: Big social data analytics of the scandinavian tv talk show skavlan.* Paper presented at the 2016 IEEE International Conference on Big Data (Big Data).

Leetaru, K., Wang, S., Cao, G., Padmanabhan, A., & Shook, E. (2013). Mapping the global Twitter heartbeat: The geography of Twitter. *First Monday*.

Lu, D., Kempter, P., & Feininger, W. (2002). Audience measurement system for digital television. In: Google Patents.

Méadel, C. (2015). Moving to the peoplemetered audience: A sociotechnical approach. *European Journal of Communication, 30*(1), 36-49.

Moe, H., Poell, T., & van Dijck, J. (2016). Rearticulating audience engagement: Social media and television. *Television & New Media, 17*(2), 99-107.

Moor, L., & Lury, C. (2011). Making and measuring value: comparison, singularity and agency in brand valuation practice. *Journal of Cultural Economy, 4*(4), 439-454.

Murschetz, P.-C., & Schlütz, D. (2018). Big Data and Television Broadcasting: a Critical Reflection on Big Data's Surge to Become a New Techno-Economic Paradigm and its Impacts on the Concept of the Addressable Audience. *Big Data and Television Broadcasting: a Critical Reflection on Big Data's Surge to Become a New Techno-Economic Paradigm and its Impacts on the Concept of the Addressable Audience*, 23-38.

Nelson, J. L., & Webster, J. G. (2016). Audience currencies in the age of big data. *International Journal on Media Management, 18*(1), 9-24.

Nielsen. (2013). NIELSEN LAUNCHES 'NIELSEN TWITTER TV RATINGS'. Retrieved from https://www.nielsen.com/us/en/press-releases/2013/nielsen-launches-nielsen-twitter-tv-ratings/

Nielsen. (2020). ABOUT NIELSEN SOCIAL. Retrieved from https://www.nielsensocial.com/about/

Oh, C., Sasser, S., & Almahmoud, S. (2015). Social media analytics framework: the case of Twitter and Super Bowl ads. *Journal of Information Technology Management, 26*(1), 1-18.

Oh, C., Yergeau, S., Woo, Y., Wurtsmith, B., & Vaughn, S. (2015). *Is Twitter psychic? Social media analytics and television ratings.* Paper presented at the 2015 Second International Conference on Computing Technology and Information Management (ICCTIM).

Oyeyemi, T. (2020). Minister Appoints Team To Design Framework For Audience Measurement System. Retrieved from https://fmic.gov.ng/minister-appoints-team-to-design-framework-for-audience-measurement-system/

Pensa, R. G., Sapino, M. L., Schifanella, C., & Vignaroli, L. (2016). Leveraging cross-domain social media analytics to understand TV topics popularity. *11*(3), 10-21.

Pynta, P., Seixas, S. A., Nield, G. E., Hier, J., Millward, E., & Silberstein, R. (2014). The Power of Social Television: Can Social Media Build Viewer Engagement?: A New Approach to Brain Imaging of Viewer Immersion. *54*(1), 71-80.

Stieglitz, S., & Dang-Xuan, L. (2013). Social media and political communication: A social media analytics framework. *Social Network Analysis and Mining, 3*(4), 1277-1291.

Zeng, D., Chen, H., Lusch, R., & Li, S.-H. (2010). Social media analytics and intelligence. *IEEE Intelligent Systems, 25*(6), 13-16.

Funding and Acknowledgements

The authors declare no funding sources or conflicts of interest.