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Investigating Types of Second Screeners and Their Social Media Behaviors

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Abstract

Using survey data on second screening activities while watching eight types of television programs among 570 Twitter users, we identified four types of second screeners: Specifically, Second Screeners for Politics and News mainly second screens for political events and news; Second Screeners for Sporting Events and Commercials mostly second screens for sporting events and commercials; High Second Screeners second screens all eight types of television programming, with particularly high levels while watching scripted dramas, situation comedies, and live television programming; Low Second Screeners do not exhibit salient second screening behaviors. Matching survey data with a year's worth of Twitter activities from survey respondents, this paper extends the previous research on second screening as purposive hybrid media practice by examining how fine-grained Twitter behaviors are associated with four types second screeners. We discuss the implications of how different types of television programs can better engage with different types of second screeners.

Keywords: second screen, hybrid media practice, Twitter behavior

Introduction

Screens are now ubiquitous in modern society, with more than two thirds of the world's population carrying a connected screen in the form of a mobile device (The mobile economy 2019, n.d.). With the rapid development of the global economy and information technology, more and more people have the technological access and literacy necessary to engage in second screening, which refers to audiences using a companion device, such as a smartphone, tablet, laptop, or computer while watching television (Lee & Andrejevic, 2014). In 2011, nearly 70% of smartphone owners in the U.S. used their device while watching TV (Nielsen, 2011), and by 2017, almost 90% of the U.S. respondents claimed that they used their smartphone while viewing TV (Statista, 2021). This exponential rise in second screening makes the passive single-screen television watching experience a thing of the past. Accordingly, the topic of second screening has become a bourgeoning research field.

Previous research on second screening generally falls into two categories. The first line of research uses experimental and survey research to study second screening as a non-purposive cognitive act relating to multitasking (Jeong & Hwang, 2016).

Scholars working in this research stream believe that second screening habits are often not related to the first screen content (Nizam, 2020) and have focused on studying the negative effects of second screening on processing TV programs related to news and politics on the cognitive level (e.g., Cauwenberge et al., 2014; Schaap et al., 2018). The second line of research theorizes second screening as a communicative mediating process whereby second screening is a purposive hybrid media practice (Barnidge et al., 2017; Chadwick, 2013; Chen, 2019) comprised of information seeking and discussion. This line of research explored how second screening practices have redefined the nature of audiences, equipping them greater ability and power to shape public narratives alongside journalistic organizations and political elites (Gillespie, M., & O'Loughlin, B., 2015). In particular, the existing literature in this area has focused on the domain of political communication. Scholars mainly employed survey methods or social media analytics to examine second screening around political content and news and the resulting effects on political engagement, both online and offline.

Our research enriches the above two lines of research by linking survey and social media data to supplement and improve both, with the purpose of revealing more fine-grained digital behavioral patterns that are associated not only with second screening around political content and news but also with a broad range of second screening activities for better understanding the social scientific distinctions between various types of second screening. Compared to many social media data sources, Twitter is the most accessible for data collection through Twitter Application Programming Interfaces (APIs). According to surveys conducted by the Pew Research Center, 22 percent of U.S. adults use Twitter (Perrin & Anderson, 2019), and 71 percent of those actively seek news on Twitter (Shearer & Matsa, 2018). Twitter also remains a mostly public source of social expressions (Remy, 2019). Our study matches survey data on second screening with a year's worth of actual posts on Twitter to examine the relationship between various types of second screeners and their Twitter behaviors, expanding the literature and providing strategies to reach and engage with second screening audiences efficiently.

Literature Review

Second Screening as Non-purposive Cognitive Behaviors

A rich body of previous literature has defined second screening as one type of media multitasking that has negative influences on cognitive outcomes such as attention, recall, recognition, and task performance (Jeong & Hwang, 2016). For example, in an experiment, Cauwenberge et al. (2014) and Schaap et al. (2018) found that second screening, while watching news, negatively impacts factual recognition, comprehension of news content and program enjoyment. Likewise, Gottfried and colleagues (2016) used a survey to find that resulting knowledge of presidential debate viewing is lessened when participants simultaneously engage in social media multitasking.

Kazakova et al. (2015) expanded the analysis of the detrimental effects of second screening to investigate the impact of media multitasking on information processing style and argued that media multitasking leads to a less global and more local and concrete perceptual processing style that prevents the critical and abstract evaluation of messages. However, Ran and Yamamoto (2019) divided second screening into the categories of task-irrelevant and -relevant and argued that while task-irrelevant second screening during election news consumption on TV is negatively related to factual political knowledge, task-relevant second screening has positive effects on knowledge. Studies of task-relevant second screening represent another important line of second screening research, in which second screening is identified as a purposive communicative mediating process.

Second Screening as Purposive Communicative Mediating Process

Scholars working in this tradition have used the lens of uses and gratifications theory to identify information seeking and discussion as two distinct but related motivations for second screening (Barnidge et al., 2017; Gil de Zúñiga et al., 2015). Therefore, second screening has been defined as "a process in which individuals watching television use an additional electronic device, or 'screen' to access the Internet or social networking sites to obtain more information about the program or event they are watching or to discuss it in real time" (Gil de Zúñiga et al., 2015, p. 795).

This line of research has its focus on the sphere of political communication. Several studies have shown that audiences second screen during breaking news, live coverage, political debates, and campaigns because a secondary device offers immediacy (Anderson, 2016; Giglietto & Selva, 2014; Pew Research Center, 2012; Wohn & Na, 2011) and gives audiences more power to interact with media industries in a complex way (Moe et al., 2016; Wilson, 2016). Therefore, second screening as hybrid media practice embodies the tension between new and old media logics (Chadwick, 2013). In particular, many studies describe second screening as a purposive act that incorporates self-reflection and information processing behaviors into the process of consuming news, possibly linking news use to political action. However, how second screening leads to online and offline political behavior is still open to question.

For example, in a two-wave panel survey, Gil de Zúñiga, et al., (2015) found that second screening for news is a significant predictor of online political participation. Based on a survey of audiences in 20 countries, Gil de Zúñiga and Liu (2017) found that more intensive second screeners tend to politically express themselves in social media and participate more often in offline political activities. McGregor and Mourão (2017) used a cross-lagged autoregressive panel survey to explore how second screening mediated political participation. They found that the mediating role of second screening was contingent upon second screeners' attitudes toward the former President Donald J. Trump. Specifically, for those who held negative attitudes toward Trump, second screening Trump-related content during news lead to both online and offline political disengagement rather than engagement.

Furthermore, in the digital age, second screeners are likely to use social media to discuss a wide range of television interests (Lotz, 2007). Even so, researchers have used social media analytics to mostly examine how second screening relates to political engagement. For example, Anstead and O'Loughlin (2011) analyzed the real-time Twitter commentary on a weekly British political debate show and found that Twitter users' live commentary challenges broadcasting and political institutions seeking to integrate more organic models of audience engagement. Iannelli and Giglietto

(2015) examined more than two million tweets that included the official hashtags of Italian political talk shows to understand hybrid practices of political communication and participation and found that only a narrow audience had access to these practices, and that the potential for media and politicians to interact with citizens for agenda setting has not been actualized.

Types of Second Screening

Whether studying second screening as non-purposive cognitive process or as purposive hybrid media practice, most researchers have not examined second screening outside of news and politics. A recent exception is from Williams and Golin's (2017) case study of second screening of an American drama television series "How to Get Away with Murder" on Twitter. These authors examined how African American viewers used second screening on Twitter to enable techno-cultural discourse on a shared cultural history of Black womanhood.

There is an increasing call for studying second screening on television programs beyond news and politics. After all, tweets about politics make up less than 2% of the total, even in presidential election years (Jiang et al., 2018.) McGregor et al. (2017) divided second screening into categories of interpersonal and extrapersonal based on different information processing channels. Specifically, interpersonal second screening involves discussing media programs through private text messaging, email, and messaging applications such as WhatsApp with people one already knows. They found that this type of second screening can reinforce existing interpersonal relationships. In contrast, extrapersonal second screening refers to using social media sites (e.g., Facebook, Twitter) and online forums to discuss media programs with people users do not necessarily know and outside one's personal network. McGregor and her co-authors suggested that understanding what type of programs people are watching when they second screen is important for differentiating different types of second screening.

This paper extends previous research on second screening by taking a broader look at second screening as purposive hybrid media practice. We first use survey research to examine how participants use an additional electronic device to get more information or talk about the program or event they are viewing while watching eight types of television programs, including news and politics, commercials, sporting events, live television programming, scripted dramas, and situation comedies to explore the following research question:

RQ1: What are the different types of second screeners?

To make better social scientific distinctions between different types of second screeners, this paper explores not only self-reported patterns of second screening but also respondents' online behaviors expressed on social media to examine the relationships between various types of second screeners and their online digital behaviors, as well as how demographics play a role in these relationships.

Linking Survey with Social Media Analytics for Second Screening Research

While survey research has played an important role for social science for decades, social scientific research using digital trace data, especially social media analytics has grown rapidly over the last few years. These two research paradigms have their own limitations that might be overcome by combining them (Al Baghal et al., 2020; Stier et al., 2020). For example, behavioral measures from surveys are highly abstract and vary depending on participants for more fine-grained behaviors. Also, the validity and reliability of self-reports suffers since respondents often have difficulties in assessing their behaviors, especially in digital media environments (Henderson et al., 2019; Stier et al., 2020).

In contrast, data collection methods from computational social science (e.g., social media analytics) can gather detailed, reliable, and objective data on human behaviors (Lazer et al., 2009), and can reveal more fine-grained behavioral patterns, such as the quantity and contents of social media posts by a person over time.

On the other hand, digital trace data alone also encounters issues of data representativeness, validity, and reliability since it usually provides incomplete or no information about the identity and relevant attitudes of the individuals whose data are collected (Stier et al., 2020). Moreover, digital trace data is most often based on biased samples, making it difficult to normalize observed online behaviors to inform microlevel theories from the social science (Jungherr, 2018).

Recently, scholars, such as Al Baghal et al. (2020), have suggested that linking survey and social media data is useful for both substantive and methodological research. Integrating survey and digital trace data provide many advantages compared to using a single data source (Stier et al., 2020), including supplementing additional measurements of interest, explaining fine-grained human behaviors at a large scale, and creating novel ways to improve casual inference in experimental settings. Among different types of data linking strategies, "linking data at the individual level currently is the fastest expanding area since it allows scholars to study individual-level digital behaviors in an ecologically valid way while giving them control over all steps of the research process (Stier et al., 2020, p. 508)."

Despite the above-mentioned advantages, few studies have combined survey research with social media analytics, and scholars have mainly focused on linking survey with Twitter data within the realm of political communication. For example, Vaccari and colleagues (2015) devised a unique research design combining a large-scale Twitter dataset and a custom-build panel survey to examine how audiences on Twitter engaged with political debates on TV during the 2014 European Parliament Elections in the United Kingdom. They found that commenting live on Twitter and engaging with conversations via Twitter hashtags have strong positive associations with political engagement.

To bridge this gap, our work enriches the few studies combining survey and social media analytics to study the more fine-grained behavioral patterns of second screening. Specifically, after receiving informed consent of survey participants, we used a Python script and the Twitter API to collect their Twitter data produced in 2016. Then, we linked Twitter and survey data at the individual level to provide supplementary measurements of Twitter behaviors, distinguishing different types of second screeners and used the data-driven insights to develop efficient strategies for engaging with various types of second screeners. Specifically, we asked the following research:

RQ2: How do Twitter behaviors of various types of second screeners differ from each other?

Recently, scholars also explored the relationships between socioeconomic status (SES) and second screening for news. Based on a random sample of face-to-face interviews, Barnidge et al. (2019) examined how SES related to the adoption of second screening practices in Colombia and found that the positive relationship between SES and second screening for news is mediated through technological access and engagement with public affairs content online and via social media. This indicates that hybrid media practices such as second screening may exacerbate the digital divide, leading to information inequalities in developing countries.

By linking survey research and social media analytics, our work delves further into the relationship between SES and the Twitter behavior patterns of various types of second screeners, expanding the work of Barnidge et al. (2019) to the United States and beyond the realm of news consumption. Linking survey and social media data also allows us to take more demographic variables, such as SES, age, gender, ethnicity into account to reveal more nuanced Twitter patterns of various types of second screeners. The related research question is:

RQ3: How do demographics influence the Twitter behaviors of different types of second screeners?

Methods

As part of a larger inductive study on digital participation, we built a unique social media panel of 3,811 survey respondents who indicated they had Twitter accounts identified by Qualtrics Online Panels. We fielded an online survey between June 10 and July 28, 2016, for compensation. Of our total sample, 904 opted in for additional compensation and provided us with a verified Twitter account name, among which 570 respondents' tweets were public. Using a Python script, we collected the 570 public twitter users' 165,912 English tweets from 2016.

For the survey, we adapted questions from McGregor and her colleagues (2015; 2017) and asked participants to identify how often they use an additional electronic device to get more information or talk about the program or event they are viewing (i.e., second screening) while watching eight types of television programs: political speeches or debates, news, election coverage, commercials, sporting events, live television programming, scripted dramas, and situation comedies. They reported their second screening behavior frequency on a five-point Likert scale: "Never (1)," "Rarely (2)," "Sometimes (3)," "Very often (4)," and "Always (5)."

To answer the question regarding the types of second screeners (RQ1), we conducted a K-means cluster analysis to identify homogenous groups based on selected characteristics (K-means cluster analysis, n.d.). K-means cluster analysis is a distance-based algorithm with the objective of minimizing the sum of distances between data points and their respective cluster centroid (Sharma, 2019). To decide the number of cluster K, we assigned the K value from 3 to 10 for the K-means cluster analysis and calculated the respective inertias that reflect how well a dataset was clustered by K-means by measuring the sum of squares of all dataset points to their closet centroid. Although the value of inertia decreases as the number of cluster increase, the good model for K-means is the one with low inertia and a low number of clusters (Amelia, 2018). We eventually assigned the K value as 4 since the change in the value of inertia was not significant when K was greater than 4. The K-means cluster analysis in this research is based on the analysis of the normalized values (i.e., Z-scores) of the frequencies of participants second screening while watching the eight types of television program.

To answer RQ2 (How do Twitter behaviors of various types of second screeners differ from each other?), we used the merge function (RDocumentation, n.d.) in R programming to create a database matching the types of second screeners identified in RQ1 with the 570 public Twitter users' behavioral data by using common Twitter usernames. We coded the different second screener groups as categorical variables. We ran ANOVA to compare Twitter behaviors of various types of second screeners. Specifically, we traced Twitter behaviors by examining the salient Twitter conversation topics that emerged, the amount of Twitter content produced, the individual influence of Twitter users, and the sentiment expressed in Twitter discourses.

We conducted a topic modeling analysis of the content of English-language tweets produced by these 570 public Twitter users to determine the salient Twitter conversation topics using ConText software (Diesner et al., 2013). Specifically, we used Latent Dirichlet Allocation (LDA, Blei et al., 2003), which is one of the most widely used topic modeling algorithms. Prior to topic modeling, we preprocessed the texts by removing stop words and stemming. The number of the topics (k) was decided based on qualitative review by the expert opinion of four Ph.D. researchers from mass communication and political science. We examined a range of k from 3 to 20 topics, extracting corresponding top 100-word lists for each. Then, we reviewed each group of topics against the following criteria: cohesive meaning within topics and mutually exclusive meaning between topics. LDA also models each tweet as a mixture of topics. It examines the per-tweet-per-topic probabilities, called γ, ranging from 0 to 1. The value 0 indicates no words in the tweet were generated from the topic, and the value 1 means all words in the tweet were corresponding to the topic. Using ConText software, we calculated the γ of each topic for each tweet posted in 2016, and then aggregated the weight of each topic for each participant using the mean value of γ. We also multiplied the weight for each topic by number of tweets produced in 2016 to estimate the quantity of tweets related to each topic created by each participant.

We measured the number of tweets, retweets, direct messages, photos, videos, and tweets related to each topic posted in 2016 as the indicators of the amount of Twitter content produced. We also measured the number of followers, the number of times users were listed as members in social groupings by other users, and the number of times users' tweets were retweeted and favorited in 2016 as indicators of user influence.

We used subjectivity and polarity as two indicators to measure sentiment expressed on Twitter. The polarity and subjectivity classifiers are the two most common lexicon-based strategies for

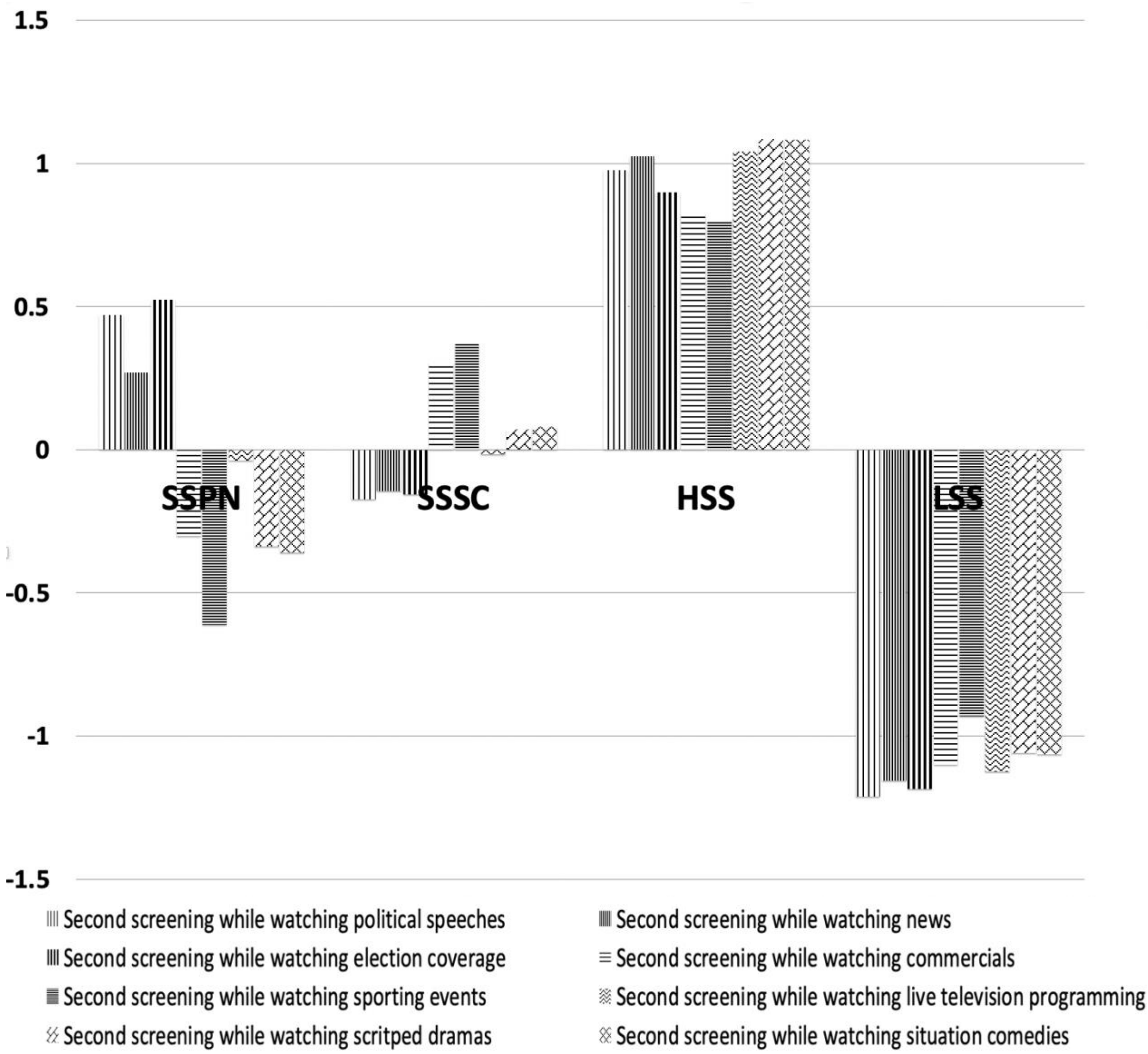
Twitter sentiment analysis (Kharde & Sonawane, 2016; Yaqub et al., 2018). Subjectivity refers to the classification of sentences as subjective opinions or objective facts through using a dictionary to quantify the opinion words (e.g., adjectives, adverbs, group of verbs and nouns) (Kharde & Sonawane, 2016). The value of subjectivity ranges from 0 to 1. A value close to 0 indicates an objective tweet while a value close to 1 indicates a highly subjective tweet. Polarity refers to whether the expressed opinion in a tweet is positive, negative, or neutral through using a sentiment dictionary to assign sentiment scores to the opinion words identified by the analysis of subjectivity (Kharde & Sonawane, 2016). The polarity scores range from -1 to 1, with -1 being most negative and 1 most positive. A polarity score of 0 indicates a neutral sentiment. Specifically, we used the TextBlob Sentiment library and Natural Language ToolKit (Shah, 2020) in Python to compute the value of polarity and subjectivity for each tweet. Then, we calculated the mean values of polarity and subjectivity for each participant.

To answer RQ3 (How do demographics influence the Twitter behaviors of different types of second screeners?), we used the merge function (RDocumentation, n.d.) in R programming to create a database matching the types of second screeners identified in RQ1 and their Twitter behavioral data used in RQ2 with the demographic information collected in the survey by using common Twitter usernames. Specifically, we asked participants a series of demographic questions including their family income, education, age (in years), ethnicity (dummy coded variables for African American, Latinx and Other Non-white participants, with Whites as the baseline category), and gender. We weighted all of our analyses to be consistent with the estimated population profile of U.S. Twitter users as reported by the Pew Research Center in 2016. Consequently, we computed sampling weights as a function of gender, age, family income, education, and race/ethnicity. These weights helped correct for biases in our sample of Twitter users.

Results

To answer RQ1, what are the types of second screeners, Figure 1 illustrates the results of a K-mean cluster analysis of the z-scores of how often participants use an additional electronic device to get more information or talk about the program or event they are viewing while watching eight types of television programs. We found four types of second screeners. The first type of second screeners (Second Screening Politics News [SSPN], n = 99) tend to use an additional electronic device to get more information or talk about the program or event they are viewing during watching election coverage, political speeches or debates and news. The second type of second screeners (Second Screening Sports Commercials (SSSC), n = 175) mostly second screens while watching sporting events and during commercials, with a smaller amount of second screening while watching scripted dramas and situation comedies. The third type second screens while watching all eight types of television programs, with particularly high levels while watching scripted dramas, situation comedies, and live television programming (High Second Screening [HSS], n = 153). The fourth type of user does not exhibit salient second screening behaviors in terms of using second screens for information seeking and discussion of the watched programs. (Low Second Screening [LSS], n = 143).

Figure 1. Types of Second Screeners



Note. The values of y-axis indicate the mean Z-scores of the frequency of second screening while watching the eight types of television programs. On the y-axis, the value 0 indicates that the value of the data point is identical to the mean score. The value 1 indicates a value that is one standard deviation above the mean. The value -1 indicates a value that is one standard deviation below the mean. On the x-axis, the clustered columns represent the four types of second screening identified by the K-Means cluster analysis.

To answer RQ2, how Twitter behaviors of various types of second screeners differ from each other, Table 1 lists the results of comparing the weights and quantity of the four salient topics, amount of Twitter content produced, user influence, and sentiment between the four types of second screeners. Specifically, through the topic modeling of the content of English-language tweets produced by these 570 public Twitter users, four salient topics emerged: “lifecasting,” “promotion,” “politics,” and “entertainment”. “Lifecasting” refers to people tweeting about their personal lives, such as their work, family, children, and friends. A lifecasting example is “Thank you all for your kind 37th birthday wishes. It's a nice to be remembered by my family and friends.” In the “promotion” field, people tweeted to share coupons or information related to promotional contests. For example, one user tweeted “Enter for a chance to #win a Clover Amour Steel Crochet Hook Set @OombawkaDesign.” Under the “politics” field, people tweeted about issues related to the president and political events, such as the presidential election. For example, a user tweeted “most Americans are not impressed with @realDonaldTrump's transition, but his popularity is rising.” Under the “entertainment” field, people tweeted about games, reality shows, movies, sporting events, and music. One user tweeted “The first episode of this new reality show called ‘America’ was kind of boring!” Table 2 lists the five most frequent words used in the four fields.

Table 1

Comparing Twitter Behaviors between Four Types of Second Screeners

		SSPN (n =99)	SSSC (n = 175)	HSS (n =153)	LSS (n =143)	Sig.
Weight of Salient Topics	Lifecasting	0.30	0.23	0.29	0.25	.027
	Promotion	0.32^{a}	0.41^{ab}	0.35^{ab}	0.45^{b}	.011
	Politics	0.06^{a}	0.04^{ab}	0.03^{ab}	0.02^{b}	.053
	Entertainment	0.09	0.10	0.14	0.11	.135
Quantify of tweets related to Salient Topics	Lifecasting	55.40	69.10	113.88	57.30	
	Promotion	78.89	140.25	86.26	95.36	
	Politics	26.45	10.15	16.50	5.13	
	Entertainment	44.93	50.03	102.10	44.87	
Amount of Twitter Content Produced	*Tweets_T	2470.19	3168.32	6708.00	2844.94	
	*Tweets_2016	208.21	290.50	337.21	212.64	
	*Retweets_2016	56.25	83.85	90.53	40.64	
	*Messages_2016	31.66	34.53	56.58	27.07	
	*Photos_2016	34.72	52.26	54.00	46.07	
	*Videos_2016	3.52	6.46	13.50	2.10	
User Influence	*Retweeted_2016	823.35	504.89	1113.72	387.88	
	*Favorited_2016	0.35	0.26	0.72	0.26	
	*Followers	300.79	202.23	1047.23	264.01	
	*Listed	5.99	8.86	19.42	11.12	

Sentiment	**Subjectivity**	0.33	0.33	0.34	0.35	.612
	Polarity	0.17	0.20	0.16	0.21	.075

Note. *Tweets_T: Mean of total number of tweets created by the end of 2016; Tweets_2016: Mean of number of tweets created in 2016; Retweets_2016: Mean of number of retweets shared in 2016; Messages_2016: Mean of number of messages sent in 2016; Photos_2016: Mean of number of tweets created with photo URLs in 2016; Videos_2016: Mean of number of tweets created with video URLs in 2016; Retweeted_2016: Mean of number of times one's tweets created in 2016 being retweeted by other users; Favorited_2016: Mean of number of times one's tweets created in 2016 being favorited by other users; Followers: Mean of number of followers; Listed: Mean of number of times one being listed by other Twitter users in a social group.

Table 2

Top Five Most Frequent Words Used in the Four Salient Topics

Lifecasting	**Day** 3314	**Think** 2546	**Friend** 1535	**Life** 1436	**Work** 1391
Promotion	**Win** 14386	**Earn** 8229	**Mplusreward** 7217	**Free** 5388	**Giveaway** 3917
Politics	**Trump** 1597	**Clinton** 354	**Obama** 337	**Syria** 26	**Romney** 9
Entertainment	**Play** 3457	**Video** 2183	**Game** 1888	**Watch** 1489	**Music** 1380

Among the four types of second screeners identified in RQ1, we found statistically significant differences for the weight of lifecasting, $F(3, 566) = 3.077$, $p = .027$, promotion, $F(3, 566) = 3.777$, $p = .011$, and marginally significant differences for the weight of politics, $F(3, 566) = 2.582$, $p = .05$. Specifically, post-hoc comparisons using Tukey HSD showed that SSSC put less emphasis on tweeting their personal lives ($M = .23$, $SD = .23$) than both SSPN ($M = .30$, $SD = .24$, $p = .08$) and HSS ($M = .29$, $SD = .24$, $p = .06$). LSS ($M = .45$, $SD = .36$) emphasized more promotion content compared to both SSPN ($M = .32$, $SD = .32$, $p = .02$) and HSS ($M = .35$, $SD = .35$, $p = .07$). In addition, SSPN ($M = .06$, $SD = .14$) put more emphasis on politics than LSS ($M = .02$, $SD = .16$, $p = .03$). There are no significant differences for subjectivity and polarity among the four types of second screeners.

Given that the variables we used to measure Twitter productivity (e.g., number of tweets related to four salient topics, number of tweets) and Twitter user influence (e.g., number of followers) are count data, a series of Poisson Regression was conducted to examine whether the four different types of second screeners exhibited different levels of influence and productivity. We used the high second screening category (HSS) as the reference group in all the analyses.

Results showed that the type of second screeners served as a significant predictor of the quantity of tweets created related to all four salient topics: lifecasting (Wald χ^2 = 4082.13, *df* = 3, *p* = .000), promotion (Wald χ^2 = 3315.203, *df* = 3, *p* = .000), politics (Wald χ^2 = 1974.445, *df* = 3, *p* = .000), entertainment (Wald χ^2 = 5257.215, *df* = 3, *p* = .000).

Specifically, for lifecasting-related tweets, HSS created 49.7%, 51.3%, and 39.3% more tweets on lifecasting than LSS [exp(B) = .503, (95% CI, .49, .517), *p* = .000], SSPN [exp(B) = .487, (95% CI, .472, .501), *p* = .000], and SSSC [exp(B) = .607, (95% CI, .593, .621), *p* = .000], respectively.

For promotion, SSSC created 1.626 times more tweets about promotion than HSS, exp(B) = 1.626, (95% CI, 1.592, 1.661), *p* = .000, LSS created 1.106 times promotional tweets than HSS, exp(B) = 1.106, (95% CI, 1.079, 1.132), *p* < .001. But HSS created 9.5% more tweets on promotion than SSPN, exp(B) = .915, (95% CI, .889, .940), *p* < .001.

For politics, SSPN created 1.603 times tweets on politics as HSS, exp(B) = 1.603, (95% CI, 1.518, 1.693), *p* = .000. But HSS created 38.5% and 69.9% more tweets on promotion than SSSC, exp(B) = .615, (95% CI, .579, .653), *p* = .000, and LSS, exp(B) = .311, (95% CI, .286, .337), *p* = .000, respectively.

For entertainment, HSS created 57.1%, 56%, and 51% more tweets on entertainment than LSS, exp(B) = .439, (95% CI, .427, .452), *p* = .000, SSPN, exp(B) = .440, (95% CI, .426, .455), *p* = .000, and SSSC, exp(B) = .490, (95% CI, .477, .503), *p* = .000, respectively.

Results also showed that the type of second screener significantly predicted the number of tweets (Wald χ^2 = 609.705, *df* = 3, *p* = .000), retweets (Wald χ^2 = 593.258, *df* = 3, *p* = .000s), messages created (Wald χ^2 = 28.409, *df* = 3, *p* < .001), as well as photos (Wald χ^2 = 123.947, *df* = 3, *p* = .000) and video links (Wald χ^2 = 344.061, *df* = 3, *p* = .000) embedded in them.

Specifically, HSS created 32.6%, 48.4%, and 27.5% more tweets in 2016 than LSS, exp(B) = .684, (95% CI, .654, .716), *p* = .000, SSPN, exp(B) = .526, (95% CI, .497, .556), *p* = .000, and SSSC, exp(B) = .725, (95% CI, .695, .756), *p* = .000, respectively. HSS also created 72.9%, 53.9%, and 26.1% more retweets in 2016 than LSS, exp(B) = .271, (95% CI, .242, .304), *p* = .000, SSPN, exp(B) = .461, (95% CI, .414, .513), *p* = .000, and SSSC, exp(B) = .739, (95% CI, .685, .798), *p* = .000, respectively. Moreover, HSS sent 29.1%, 27.8%, and 17.4% more messages in 2016 than LSS, exp(B) = .709, (95% CI, .614, .818), *p* < .001, SSPN, exp(B) = .722, (95% CI, .615, .847), *p*

$< .001$, and SSSC, exp(B) = .826, (95% CI, .726, .940), $p = .004$, respectively.

Furthermore, HSS embedded 11.4%, and 58% more photo links in tweets posted in 2016 than LSS, exp(B) = .886, (95% CI, .796, .987), $p = .027$, and SSPN, exp(B) = .420, (95% CI, .359, .491), $p = .000$, respectively. HSS also embedded 92.5%, 92.0%, and 79.3% more video links in tweets posted in 2016 than LSS, exp(B) = .075, (95% CI, .049, .114), $p = .000$, SSPN, exp(B) = .080, (95% CI, .049, .130), $p = .000$, and SSSC, exp(B) = .207, (95% CI, .161, .264), $p = .000$, respectively.

Results also showed that the type of second screeners served as a significant predictor of four indicators of user influence: number of times tweets being retweeted (Wald $\chi^2 = 4240.169$, $df = 3$, $p = .000$), being favorited (Wald $\chi^2 = 78.635$, $df = 3$, $p < .001$), number of followers (Wald $\chi^2 = 113275.876$, $df = 3$, $p = .000$), and number of times participants being listed as members of social groups by other users (Wald $\chi^2 = 1104.543$, $df = 3$, $p = .000$).

Specifically, SSPN's tweets were retweeted 1.475 times as HSS's, exp(B) = 1.475, (95% CI, 1.419, 1.534), $p = .000$. But HSS's tweets having been retweeted 98.4% and 62.2% more than LSS's, exp(B) = .016, (95% CI, .012, .02), $p = .000$ and SSSC's, exp(B) = .378, (95% CI, .360, .396), $p = .000$, respectively. Also, HSS's tweets have been favorited 95%, 91.7%, and 89.1% more than LSS's, exp(B) = .050, (95% CI, .016, .159), $p < .001$, SSPN's, exp(B) = .083, (95% CI, .030, .228), $p < .001$, and SSSC's, exp(B) = .109, (95% CI, .055, .218), $p < .001$, respectively.

Furthermore, HSS had 73%, 68.7%, and 79.7% more followers than LSS, exp(B) = .270, (95% CI, .267, .273), $p = .000$, SSPN's, exp(B) = .313, (95% CI, .309, .317), $p = .000$, and SSSC's, exp(B) = .203, (95% CI, .200, .205), $p = .000$, respectively. Also, HSS was 42.9%, 69.6%, and 42.9% more likely to be listed as members of social groups than LSS, exp(B) = .571, (95% CI, .537, .607), $p = .000$, SSPN, exp(B) = .304, (95% CI, .278, .332), $p = .000$, and SSSC, exp(B) = .571, (95% CI, .537, .607), $p = .000$ respectively.

To answer RQ3, how demographics influence the Twitter behavior of different types of second screeners, we first listed the demographic breakdown of four types of second screeners (Table 3) and then examined the interaction effects of demographic variables (i.e. Gender, Family Income, Education, Age, and Race and Ethnicity) and types of second screeners on Twitter behaviors (i.e. weight of salient topics, quantity of tweets related to salient topics).

Table 3

Demographics of the Four Types of Second Screeners

Demographics		**SSPN (n =99)**	**SSSC (n = 175)**	**HSS (n = 153)**	**LSS (n =143)**
Gender	Male (n = 182)	23.2%	32.5%	35.3%	33.6%
	Female (n = 388)	76.8%	67.5%	64.7%	66.4%
Ethnicity & Race	Hispanic (n = 154)	27.3%	28.0%	33.3%	18.9%
	Black (n = 149)	23.2%	21.7%	34.0%	25.2%
Age	20-29 (n = 127)	26.3%	27.4%	24.8%	10.5%
	30-39 (n = 205)	32.3%	34.9%	**49.7%**	25.2%
	40-49 (n = 116)	17.2%	25.1%	15.0%	22.4%
	50-59 (n = 75)	12.1%	7.4%	7.8%	26.6%
	60 and elder (n =44)	12.1%	4.0%	2.6%	14.7%
Education	<= high school (n = 122)	18.2%	24.6%	11.1%	21.7%
	some college (n =160)	**26.3%**	25.7%	26.8%	33.6%
	two year associate degree (n = 90)	19.2%	16.0%	16.3%	12.6%
	BS, BA, AB (n = 133)	23.2%	22.3%	29.4%	18.2%
	some postgraduate no degree (n =14)	3.0%	2.9%	3.3%	0.7%
	MA, MS, PHD, MD, JD (n = 51)	7.1%	6.3%	12.4%	9.8%
Income	less than $14,999 (n =58)	7.1%	9.1%	3.9%	20.3%
	$15,000 to $ 24,999 (n =57)	11.1%	10.9%	7.8%	10.5%
	$25,000 to $34,999 (n = 84)	19.2%	13.7%	11.8%	16.1%
	$35,000 to $ 49,999 (n =100)	20.2%	15.4%	22.9%	12.6%
	$50,000 to $ 74,999 (n =132)	**26.3%**	25.1%	23.5%	18.2%
	$75,000 to $ 99,999 (n =62)	7.1%	12.6%	13.1%	9.1%
	$100,000 to $149,000 (n =50)	7.1%	7.4%	11.1%	9.1%
	$150,000 to $199,999 (n =11)	1.0%	2.3%	2.6%	1.4%
	$200,000 or more (n =7)	0.0%	0.6%	2.6%	1.4%

For the weight of lifecasting, we found a significant interaction effect between types of second screeners and gender, $F(3, 562) = 2.738$, $p = .043$, as well as types of second screeners and ethnicity, $F(3, 562) = 3.137$, $p = .025$. Specifically, as illustrated in Figure 2a, Post-hoc pairwise comparisons showed that for female Twitter users, SSSC ($M = .21$, $SD = .02$) put less emphasis on tweeting about lifecasting than both SSPN ($M = .34$, $SD = .03$, $p = .001$) and HSS ($M = .29$, $SD = .02$, $p = .05$); meanwhile, LSS ($M = .22$, $SD = .03$) emphasized less lifecasting content than SSPN ($M = .34$, $SD = .03$, $p = .009$) as well. However, these differences were not found among male users. Moreover, Latinx SSPN ($M = .38$, $SD = .05$) put more emphasis on tweeting about lifecasting than SSSC ($M = .21$, $SD = .03$, $p = .035$), while such difference was not found among non-Latinx (Figure 2b). In terms of the quantity of lifecasting tweets, the post-hoc pairwise comparisons showed that among HSS, African American users ($M = 197.86$, $SD = 23.21$) tweeted more about lifecasting than HSS Non-African Americans ($M = 70.64$, $SD = 16.65$, $p < 0.001$).

Figure 2a. Interaction Effect of Types of Second Screening and Gender on Weight of Lifecasting

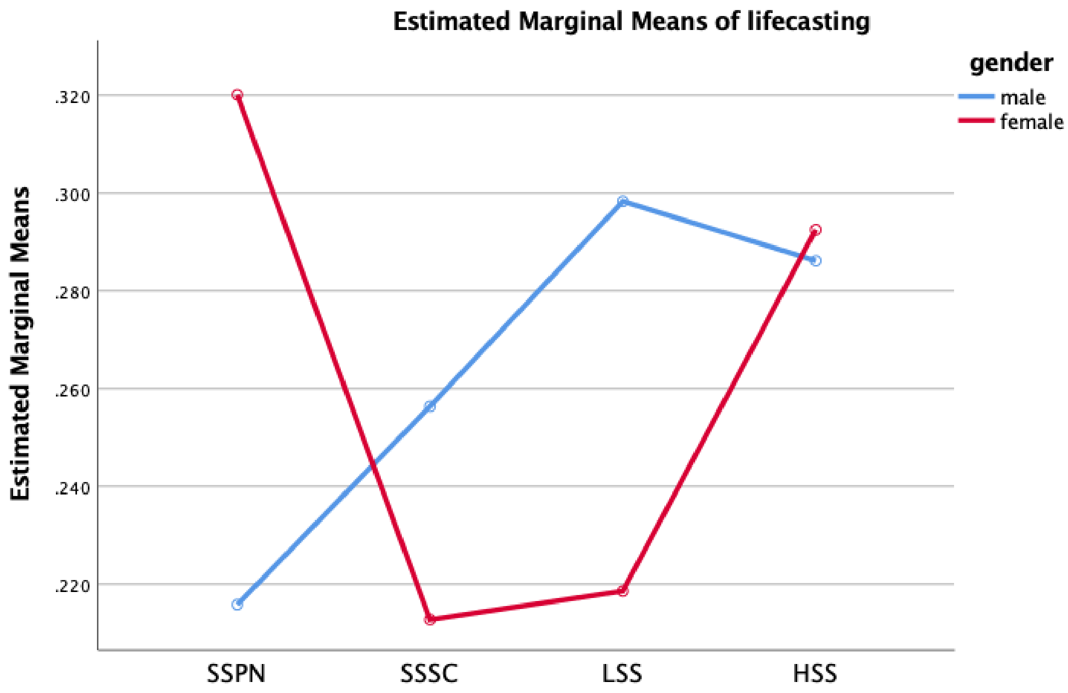
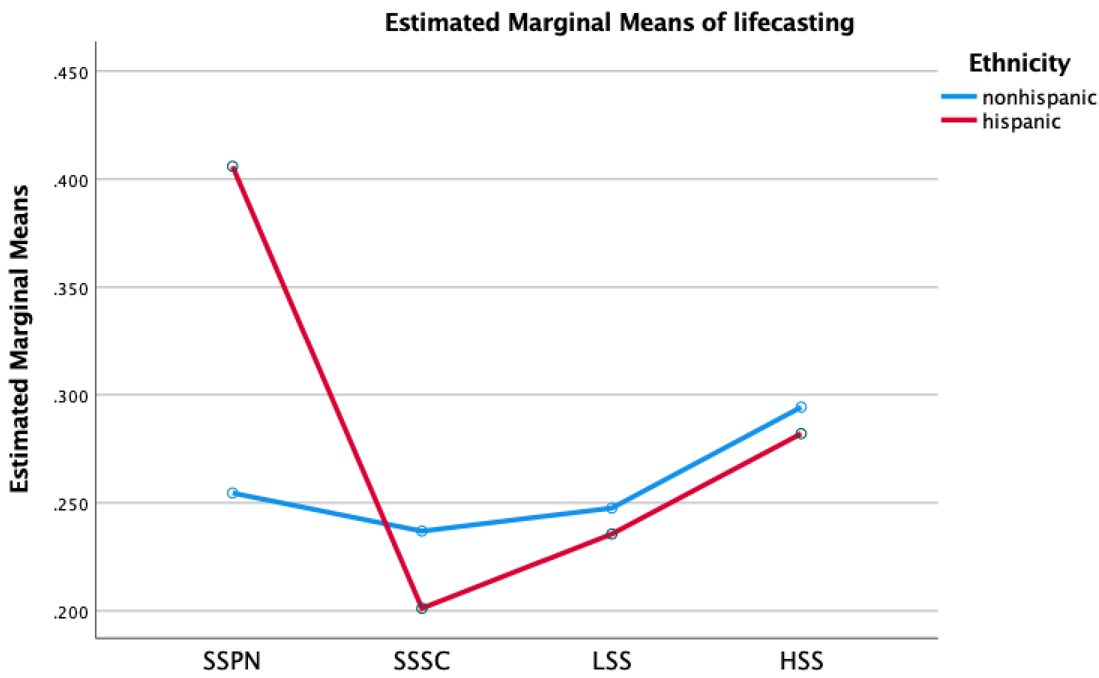
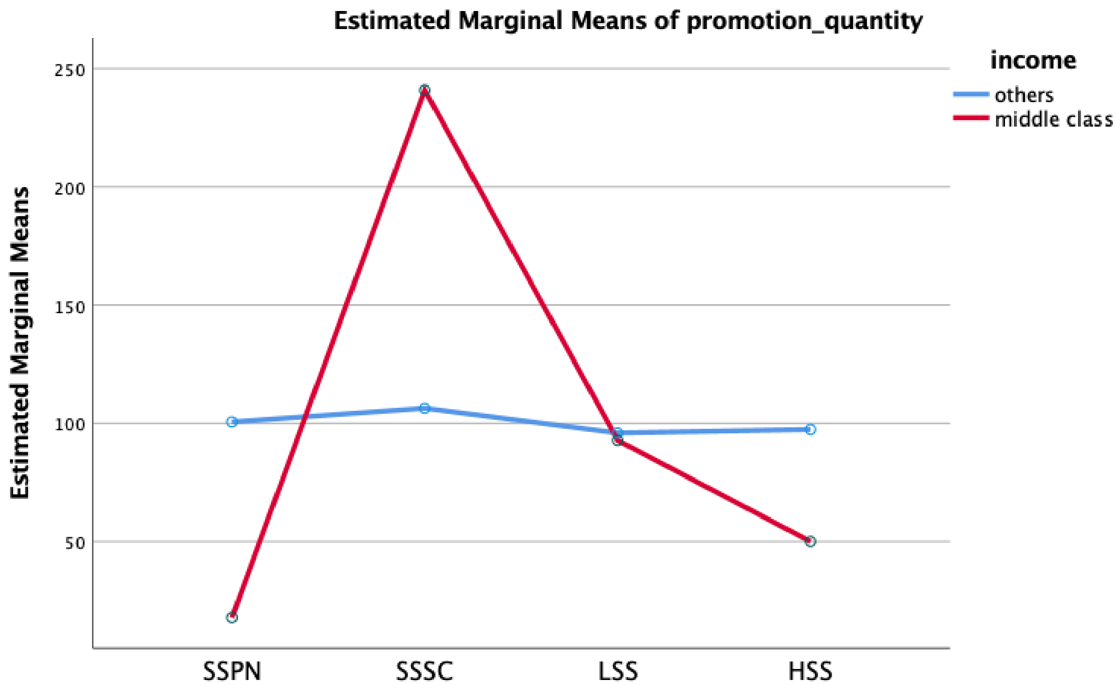


Figure 2b. Interaction Effect of Types of Second Screening and Ethnicity on Weight of Lifecasting



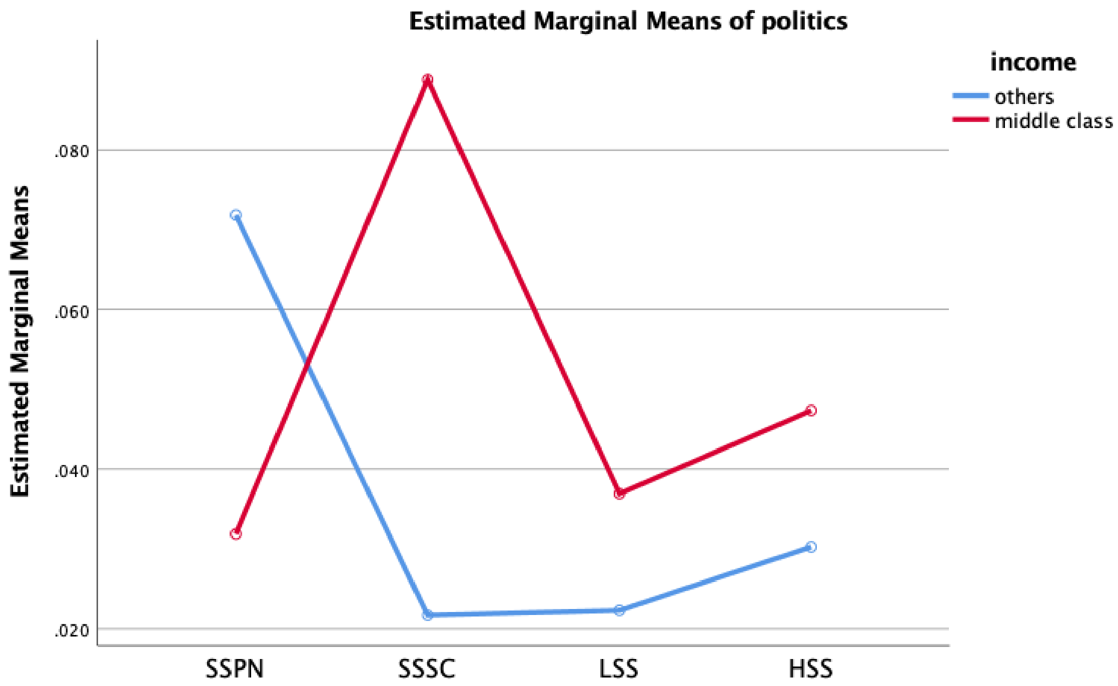
For the weight of promotion, post-hoc pairwise comparisons showed that among LSS, females (*M* = .49, *SD* = .35) put more emphasis on tweeting about promotion than males (*M* = .31, *SD* = .34, *p* = 0.043). For the quantity of promotional tweets, we found a significant interaction effect between types of second screeners and income, *F*(3, 562) = 4.245, *p* = .0006. Specifically, as illustrated in Figure 2c, post-hoc pairwise comparisons showed that among SSSC, Twitter users whose annual income are on the middle level (i.e., income ranging from $50,000 to $ 74,999) tweeted more about promotion (*M* = 240, *SD* = 466) than users whose annual income did not lie on the middle level (i.e., less than $50,000 or more than $74,999) (*M* = 106, *SD* = 265, *p* = 0.002). However, among other types of second screeners, Twitter users with middle level income tweeted relatively less about promotion. Moreover, post-hoc pairwise comparisons showed that among SSSC, female (*M* = 167.04, *SD* = 22.69) tweeted more about promotion than males (*M* = 84.77, *SD* = 32.64, *p* = .039), and users without bachelor's degrees (*M* = 180.00, *SD* = 21.82) tweeted more about promotion than users with bachelor's degrees or above (*M* = 40.86, *SD* = 34.66, *p* <0.001).

Figure 2c. Interaction Effect of Types of Second Screening and Income on Quantity of Promotional Tweets



For the weight of politics, we found significant interaction effects between the types of second screeners and income, *F* (3, 562) = 4.694, *p* = .003. For the participants whose incomes are not in the middle level (i.e. income not ranging from $50,000 to $ 74,999), SSPN (*M* = .08, *SD* = .02) put significantly more emphasis on tweeting about politics than SSSC (*M* = .02, *SD* = .01, p = .008), HSS (*M* = .03, *SD* = .01, *p* = .036), and LSS (*M* = .03, *SD* = .01, *p* = .022). However, these differences were not found among participants whose incomes were in the middle level. In particular, among SSSC, participants with middle level income (*M* = .08, *SD* = .17) put significant more emphasis on politics than participants not having middle level income (M = .02, SD = .06, p < .001) (Figure 2d). For the quantity of tweets related to politics, post-hoc pairwise comparisons showed that among SSPN, males (M = 67.39, SD = 198.35) tweeted more about politics than females (M = 14.06, SD = 63.11, p = .002); users with bachelor's degrees (M = 57.30, SD = 184.11) tweeted more on politics than users without bachelor's degrees or above (M = 13.04, SD = 52.93, p = 0.006). These differences also can be applied to HSS. Among HSS, males (M = 33.50, SD = 156.04) tweeted more about politics than females (M = 7.23, SD = 19.523, p = .035); users with bachelor's degrees (M = 31.78, SD = 143.72) tweeted more on politics than users without bachelor's degrees or above (M = 5.52, SD = 16.83, p = 0.029).

Figure 2d. Interaction Effect of Types of Second Screening and Income on Weight of Politics



For the quantity of tweets related to entertainment, we found a significant interaction effect of types between second screeners and ethnicity, $F(3, 562) = 3.335$, p = .019, as well as types of second screeners and race, $F(3, 562) = 2.991$, p = .031. Specifically, as illustrated in Figure 2e, post-hoc pairwise comparisons showed that among HSS, Hispanic users (M = 177.84, SD = 476.32) tweeted more about entertainment than non-Hispanic users (M = 64.23, SD = 193.00, p = 0.002). However, Hispanic users tend to produce relatively fewer tweets about entertainment among other types of second screeners. As illustrated in Figure 2f, post-hoc pairwise comparisons also showed that among HSS, African American users (M = 176.51, SD = 29.46) tweeted more about entertainment than non-African American users (M = 63.78, SD = 21.14, p = 0.002).

However, this difference does not exist among other types of second screeners. Furthermore, post-hoc pairwise comparisons showed that among HSS, users with middle level income (M = 166.81, SD = 505.35) tweeted more about entertainment than users noting having middle level income (M = 82.19, SD = 235.07, p = 0.038).

Figure 2e. Interaction Effect of Types of Second Screening and Ethnicity on Quantity of Tweets related to Entertainment

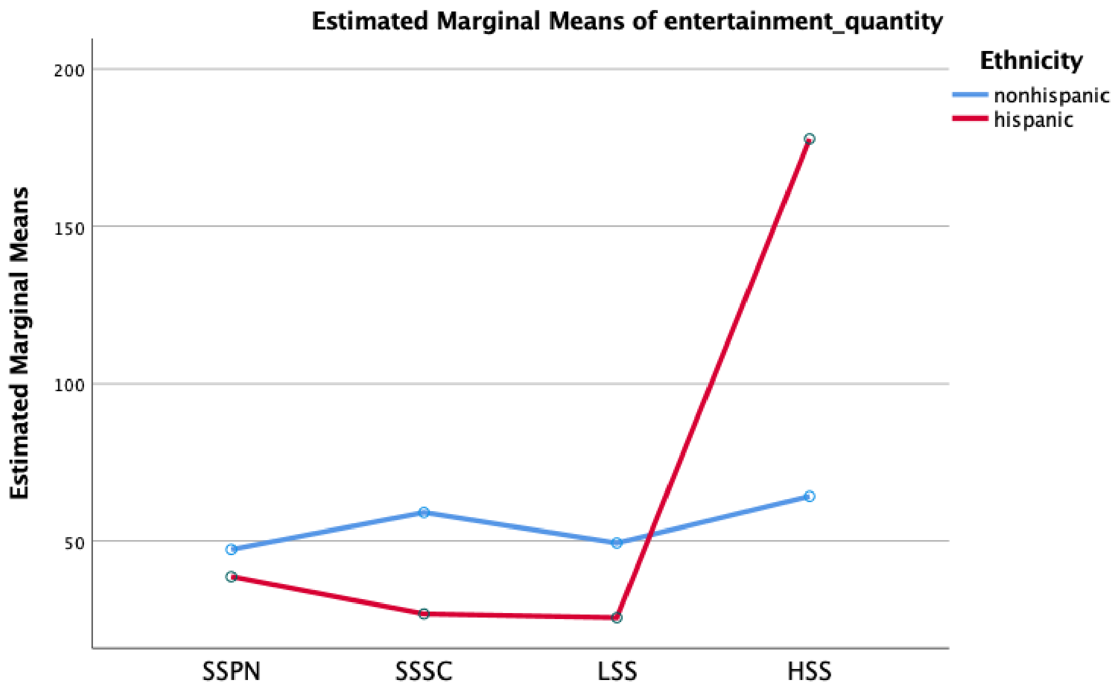
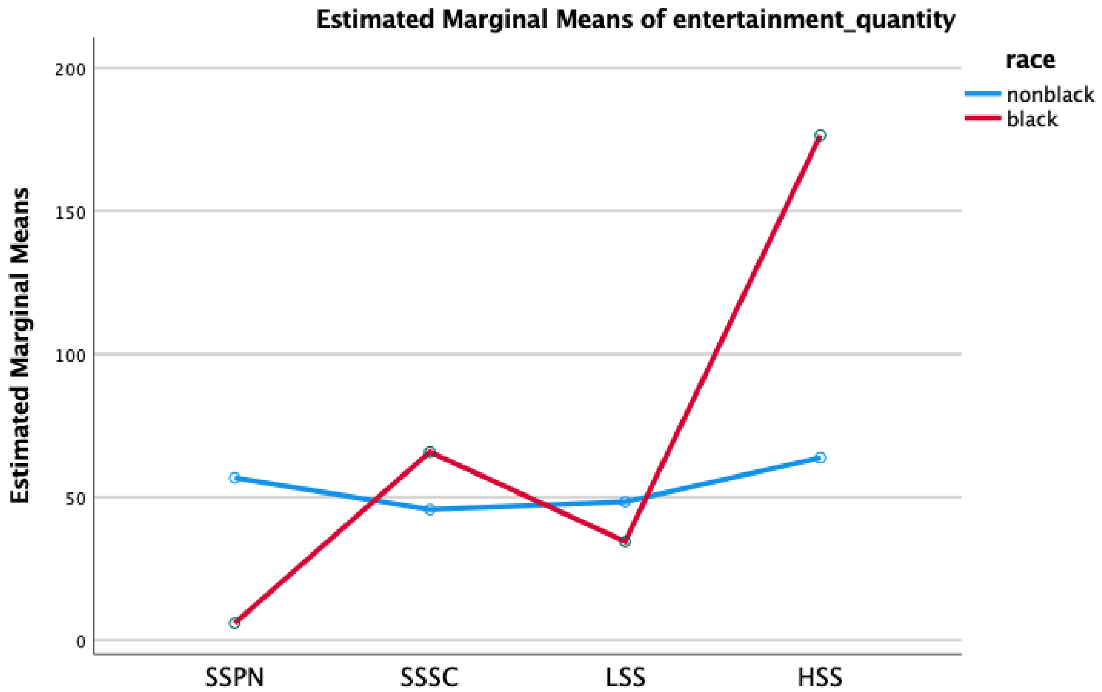


Figure 2f. Interaction Effect of Types of Second Screening and Race on Quantity of Tweets related to Entertainment



Discussion

Despite of the abundant literature on second screening of political content and news, a broader range of second screening activities on other types of television programs has been a less-explored territory of research. There is scant literature focusing on exploring second screening outside of politics. This study extends the previous research on second screening as purposive hybrid media practices by exploring how different types of second screeners use an additional electronic device to seek information or talk about the programs they are viewing while watching a variety of television programs (i.e., news and politics, commercials, sporting events, live television programming, scripted dramas, and situation comedies). Since tweeting about politics only makes up a small proportion of total Twitter conversations, our examination of diverse second screening activities sheds new light on how the hybrid media practices are associated with information seeking beyond the scope of politics.

Methodologically, this paper linked survey data with social media data at the individual level to reveal more fine-grained Twitter behavioral patterns that are associated with various types of second screeners in a more ecologically valid way. On the one hand, the Twitter data demonstrated more detailed, reliable, and objective behaviors of second screeners; on the other hand, the self-reported survey data illustrated second screeners' SES, age, gender, and ethnicity to better reveal second screeners' nuanced hybrid media practices.

Furthermore, our typology of second screeners provides practical implications for how different types of television programs can better engage with different types of second screeners. Specifically, High Second Screeners (HSS) were the most productive group on Twitter, producing the greatest number of tweets, retweets, and messages. In particular, HSS created the greatest number of tweets about lifecasting and entertainment. This group of participants also embedded the largest number of video links in their tweets. These findings provide evidence that HSS use Twitter to join in the discussion of entertainment television programs, such as the scripted dramas, situation comedies, and live television programming. In particular, Hispanic and African American HSS and HSS with middle level income created the greatest number of tweets related to the entertainment topic, indicating that ethnic and racial minorities with middle level income were more actively engaging in the second screening of entertainment television programs than other audiences.

Furthermore, the productivity of HSS on Twitter pays off by helping these groups of people gain digital capital. We found HSS were also the most influential group on Twitter. HSS had the greatest number of followers and were listed as members of social groups by others the most. Their tweets were favorited the most and retweeted second most. We attribute this finding to HSS creating the greatest number of posts related to lifecasting, which was shown to be positively associated with Twitter users' influence in previous research (Jiang et al., 2018). These findings also indicate that those who second screen at high levels are key audiences on Twitter. With their higher levels of content and influence, HSS obviously enrich digital conversations for TV programs. Furthermore, HSS can use their digital influence to increase the awareness, authority and credibility of TV programs in digital spaces. Therefore, live-tweeting (Nizam, 2020) about entertainment television shows can be an effective way to engage with HSS and let HSS play an important role in the process of building brands for TV programs.

Tweets about promotional content are at high levels across all four types of second screeners, indicating that Twitter serves as a significant platform for sharing transactional content (e.g., coupons, gift cards, free samples). While SSSC produced the greatest number of promotional tweets, LSS had the heaviest weight on promotions in their tweets. In particular, among SSSC and LSS, females and people without bachelor's degrees tweeted more about promotional content. The difference between SSSC and LSS lies in that while SSSC actively seek information and discuss the commercials they are viewing, LSS do not exhibit behaviors of information seeking through second screening. Also, it is interesting to find that the mediating role of second screening for commercials is contingent upon second screeners' income level. Twitter users with middle level income in SSSC tended to create more promotional tweets. However, users with middle level income among other types' second screeners tended to create less tweets about promotion. This finding indicates the attractiveness of promotional information for middle-level income Twitter users who second screened during commercials. To better engage with SSSC, television advertisements can enable a live tweeting function to spread more promotional information for the related brands.

On the other hand, although SSSC was the second most productive group in terms of the number of tweets, retweets, and direct messages they produced, SSSC is the least influential group with a relatively small number of followers, number of times being listed as members of social groups by other users, and number of times their tweets were retweeted and favorited. This might be due to the fact that SSSC tend to tweet less about their personal life (Lifecasting) than HSS and SSPN. According to recent research on the digital production gap (Jiang et al., 2018), lifecasting on Twitter has a significant positive impact on users' influence in terms of the number of times users' tweets are retweeted and favorited by other Twitter users. This indicates that the potential influence of promotional tweets shared by SSSC were limited. Marketers need to create more live tweeting opportunities during commercials that not only ask participants to share promotional information but also encourage them to lifecast in a creative way, such as conducting a photo contest to show off the brand via user generated content. This strategy also can be applied to engaging with LSS, who also produced less tweets about lifecasting and who are not influential and not productive compared to HSS and SSPN. Since LSS do not exhibit the hybrid practice of second screening activities, media and marketing agents need to create more digital campaigns encouraging LSS to talk more about how the promoted brand is related to their personal lives to make LSS as more influential ambassadors for their brand.

SSPN created the greatest number of tweets related to politics, and HSS produced the second largest number of political tweets. These findings are consistent with previous research (Gil de Zúñiga et al., 2015), which showed that users who second screened on politics were more likely to engage in online political participation. However, the weight of SSPN across the four types of second screeners remained low, around 5% on average, indicating second screening does not have strong associations with behaviors of online political engagement. Our findings also provide a better understanding of how socio-economic status moderates the influence of second screening on online political discussion. We found, among SSPN and HSS, males and users with bachelor's degrees or above created more political tweets. We also found that the mediating role of second screening for politics and news on online political participation was also contingent upon the second screeners' income level. According to Statista's report in 2021, the largest proportion of citizens, at 16.5 percent, earn an annual household income between $50,000 to $74,999 in the U.S. in 2019. Interestingly among the users whose incomes were below $50,000 or above $74,999, SSPN tweeted significantly more about politics than the other three groups. This finding may reflect a split whereby wealthy people and people with lower income levels actively engage in online political conversations while watching TV programs of politics and news. Future research may explore if this split may contribute to the increasing polarization of public opinion on politics emerging from social media discussions (Gruzd & Roy, 2014).

Furthermore, SSPN produced the least amount of content among the four groups. In particular, SSPN created the least number of tweets related to promotion. However, they are still influential since their tweets were retweeted the most by other users. This finding is probably due to SSPN users' mentions or replies to political and media agents, which may have placed them more centrally in the political discussion network (D'heer & Verdegem, 2014). Future research can use network analysis methods to understand how SSPN interact with politicians and media professionals to increase their influence on Twitter. From this perspective, enabling live commentary during the television political shows and encouraging direct messages between politicians, media professionals and SSPN can be efficient ways to better engage with SSPN and build more organic models of audience engagement (Anstead & O'Loughlin, 2011).

Limitation and Future Studies

Linking survey and social media data, this paper defined four types of second screeners mainly associated with tweets about lifecasting, entertainment, politics, and promotions. However, future studies can link automated social media analytics with machine learning assisted by manually coding to match the social media and survey data in a more precise way to explore how tweets were related to specific screen media.

Furthermore, this paper matched the four types of second screeners and their Twitter behaviors with demographic information collected in a survey to explore how the mediating role of second screening is contingent upon Twitter users' social economic statuses (e.g., income, education). Future research can benefit by matching second screeners' Twitter behaviors with a broader range of survey variables to reveal the linkage between Twitter behaviors and perceptive and attitudinal changes of second screeners related to specific types of programming. Also, the findings of this research need to be tested in future studies using longitudinal data with a larger sample size.

This paper found no significant differences for sentiment expressed (i.e. polarity & subjectivity) in tweets among the four types of second screeners. This was probably due to the use of the lexicon-based sentiment classifiers. Future research can use supervised learning to build a machine learning model to classify and predict words into different categories for more accurate sentiment analysis (Abhinandan, n.d.).

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