Journal of Retailing and Consumer Services 58 (2021) 102301

Contents lists available at ScienceDirect

Journal of Retailing and Consumer Services

journal homepage: http://www.elsevier.com/locate/jretconser

# Social network analysis and domestic and international retailers: An investigation of social media networks of cosmetic brands

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ARTICLE INFO

*Keywords:*
Social network analysis
Social media marketing
Customer service
Twitter
Brands

ABSTRACT

As brands' use of social media to connect with customers becomes increasingly important, there is a need to continually monitor social network activities. Although numerous studies have examined consumer behaviors on social media, only a handful of studies have adopted a social network analysis approach. Considering this gap, the current study analyzed Twitter networks of two multi-brand retailers to investigate network activities. The findings from analyzing network patterns reveal that while brands are able to deliver messages through digital platforms, they may only have limited control over the communications within networks, and thus cannot govern the spread of information.

## 1. Introduction

Social media offers tremendous potential for companies to get closer to customers and, as a result, increase revenue, cost reduction, and efficiencies. In the past decade, social networking sites (SNS) have become important media for Business-to-Business (B2B), Business-to-Consumer (B2C), and Consumer-to-Consumer (C2C) communications. Messages on SNS platforms are often open to the public and diffused rapidly and widely through interconnection amongst users. In the consumer-empowered environment, building and managing good relationships with consumers on SNS are increasingly critical to a business's marketing efforts and sustainability (Hennig-Thurau et al., 2010; Trusov et al., 2010). Additionally, these types of communications have become more dynamic than before due to the real-time mobile accessibility to SNS. Through social media platforms, companies are able to be a part of conversations that their potential and current customers are engaged in (Mills and Plangger, 2015). In this way, brands are presented with the opportunity to interact with customers on the platforms they actively tune into for information, as well as curate content and messages to influence such conversations (Ki et al., 2020; Kilgour et al., 2015).

In approaching consumer behavior from the social network paradigm, researchers have highlighted the importance of understanding how users connect to each other in the digital realm, and how this can affect relationships (Borgatti et al., 2009; Sokolova and Kefi, 2020). For example, in examining digital user behavior, it was found that individuals often display a high intention to engage in direct communications with a brand's official social media account (Felix et al., 2017). Such connections were not limited to seeking information, but also entailed customer service requests, as well as building a relationship with a brand, and thus becoming a part of the brand's social network (Felix et al., 2017). As such, the brand-customer relationships formed in social networks are interactive, multi-directional, and socially driven. Consequently, strengthening the brand's connection with its customers through social media analysis is vital to increase customer interactions and loyalty. Therefore, it is important for companies to understand how communications are facilitated throughout social networks.

Despite the importance of social networks in marketing, however, studies on structural characteristics of a social network that facilitate diffusion of information and customer engagement on social media are scarce in the current retailing literature. To fill this important void in the existing literature, this study attempts to analyze two brands' social network characteristics using actual network data from Twitter. Notably, Twitter is one of the most popular platforms for social networking, enabling registered users to read and post short messages - Tweets, which can be posted to a publicly available profile or can be sent as direct messages to other users. Twitter has an average of 330 million monthly active users worldwide with 67.54 million monthly active users in the United States (statista.com, 2018). Unlike other SNS, Twitter is unique in its dynamics and users can follow any other user with a public profile, enabling them to interact with one another leading to the process of creating influencers (Arova, Bansal, Kandpal, Aswani and

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https://doi.org/10.1016/j.jretconser.2020.102301
Received 19 March 2020; Received in revised form 31 August 2020; Accepted 1 September 2020
Available online 16 September 2020

Dwivedi, 2019). An important aspect of social network communications is its unique ways of concentrating and dispersing information among participants (actors) – density and centrality of the network. Density refers to the degree of connectivity among all actors in the network, while centrality focuses on the extent to which an individual interacts with other individuals in the network (Laat et al., 2007). By examining density and centrality, the relationships among actors and their ability to influence others can be revealed, allowing a deeper understanding of networked behaviors.

The vast majority of the research regarding social media communications have focused mainly on consumers' perceptions, attitudes, and intentions based on their evaluations and reviews, WOM, and repurchase intentions (e.g., Shareef et al., 2018; Felix et al., 2017; Katona et al., 2011). Although recent social media marketing research has utilized data analytics, most studies have been limited to focusing on descriptive analytics (e.g., Twitter use, counts, mentions/replies, worlds cloud, etc.). Furthermore, a number of business studies have incorporated the use of content analytics (e.g., polarity analysis, emotion analysis, topic modeling, etc.) into their examinations (Joseph et al., 2017; Awani et al., 2018). However, network analytics has not received significant attention in research focused on social media marketing and retailing. Although the use of descriptive statistics and content analysis in social media has provided important understanding of consumer behaviors on social media, such an approach often overlooks another important aspect of SNS communications, which is the ability of brands to influence others and exert control over the network connections with current and potential consumers in their intended social environment.

Considering this gap, the current study examines the graphical patterns of the Twitter network of brand-consumer and consumer-consumer communications in both Ego-networks (brand-centered) and Hashtag networks (whole network). Through analyzing communications on social media by examining the network pattern based on centrality (control) and betweenness (connectivity), this research provides new insight into who is in control of the network communications and who has the power to spread the information. Therefore, the methods used in this study enables researchers and managers alike to further understand the complex relationships that exist in digital networks, and thus consider new ways to unleash the power of social media in terms of spreading messages to a wide range of connected customers in an effective and efficient manner.

This study utilizes network statistics to examine the ego-networks and whole networks of two multi-brand cosmetic retailers, Sephora (an international brand) and Ulta Beauty (a domestic brand based in the U.S.). We have chosen Sephora and Ulta Beauty because both retailers offer products from numerous independent brands, which minimizes the effects of brand-specific factors (e.g., brand reputations, their own SNS activities, brand-influencers, etc.) that can potentially bias the interpretation of the results. That is, they carry a similar variety of brands yet Sephora operates internationally and Ulta Beauty domestically. In addition, the cosmetics and beauty industry has become largely dependent on social media marketing, which makes the selection of these two brands appropriate considering the focus of the research questions in this study. Undoubtedly, both have been actively involved in social media (e.g., Facebook, Twitter, Instagram, and YouTube) to connect with their customers for product and brand information, promotions and events, question and answer sessions, and feedback.

Methodologically, the use of network mapping and centrality scores allows this research to examine potential commonalities and differences in network patterns as well as the prominence of brands and individual actors. As such, the findings of this research provide significant insights in understanding how influencers form and how users connect and spread information within and across their ego- and whole networks. In turn, these results are able to provide a useful guide for managers to develop more sophisticated social media marketing strategies.

## 2. Theoretical framework and literature review

### 2.1. Social network approach

The social network approach represents a combination of theory and analytical methods of networked relationships. Rooted in sociology (Granovetter, 1983), the social network approach attempts to account for individual's behaviors/characteristics by contemplating the social structure and the nature of social interactions among actors in a network, rather than their individual attributes (e.g., education, income, etc.). The focus of this approach is the configuration of relationships as a determinant of social outcomes and identifying each actor's characteristics based on their position in the network (Borgatti et al., 2009). As such, the social network approach accounts for the behaviors and social processes within a group through connectivity and the nature of social ties among its members such as the density and the strength of the ties (Emirbayer and Goodwin, 1994).

In this approach, a network consists of actors (members of the network) and relational ties/links that connect the actors. Any entity including individuals, companies/brands, etc. can be an actor in a network. Studies with this approach often attempt to understand structural properties of a network using network mapping and statistical measures that assess density and centrality. The density of a network indicates network cohesion, which is often captured by the ratio of ties observed in a network to all possible ties in the network. A network with a high density facilitates collaboration among actors (Webster and Morrison, 2004). A highly centralized network refers to a network in which interactions among the network members are mediated by one or relatively few actors, which means those few have an important role of the information being dispersed throughout the network. Generally, strong, dense, and relatively isolated social networks are more conducive to the development of cohesive groups (Emirbayer and Goodwin, 1994). Social network analysis is also useful in identifying network members who are most influential in the diffusion of innovation and information. That is, individuals' connections in networks determine their ability to leverage resources embedded in the networks and their ability to influence other members (Granovetter, 1983). Those who are highly connected or in a bridging position have more opportunity to affect others because of their reach to broader audiences (Van den Bulte and Wuyts, 2007). Thus, the social network approach has proven to be instrumental in exploring social phenomena in many disciplines (Borgatti et al., 2009; Monaghan et al., 2017).

### 2.2. Literature review

With the increasing importance of social media in marketing and retailing, social network analysis has been used to examine and understand B2C and C2C communications on various social media platforms (Risselada et al., 2014; Sharma et al., 2018). Notably, the social network approach has been employed to understand word-of-mouth (WOM) and electronic word-of-mouth (eWOM) communications and diffusion of innovation (Katona et al., 2011; Risselada et al., 2014). Overall previous studies found evidence that network structure (e.g., size and density) can have a substantial effect on information sharing and diffusion of innovation (Vilpponen et al., 2006). For example, Katona et al. (2011) documented a positive relationship between an individual's likelihood to adopt a social media site and the size of already adopted friends in the same social network. They also found an effect of the interconnectedness of one's local network, confirming the significance of network structure on the adoption of new technology. Previous studies also emphasized the importance of strength of network ties. Consumers are more likely to share advertising messages from close friends than those from other sources (Levin and Cross, 2004); They also tend to maintain favorable attitude regardless of advertising formats when messages are from a close social tie (Shen et al., 2016) as they are believed to be more trustworthy and credible.

Social network analysis has also been employed to identify the social network characteristics of an individual who has potential to make a viral marketing successful. The number of followers in social media (i.e., network size) is one of the most commonly used indicators to identify influencers on social media (Zhang and Dong, 2008). Studies focused on those characteristics confirmed the relationship between an individual's connectivity and their significance as an influencer. Yoganarasimhan (2012), for example, found a positive relationship between the size of one's network and the diffusion of messages posted by the individual on YouTube. Furthermore, it was found that influencers with a large number of followers were more likable as they were perceived to be more popular (De Veirman, Cauberghe and Hudders, 2017). However, existing literature also reported a trade-off between the size of one's social connections and the individual's influence over the social network. Liu-Thompkins (2012), for example, reported a negative relationship between the number of connections people have in social networks and their influence over social networks in the context of diffusion of a viral message. Similarly, Katona et al. (2011) confirmed that the influential power of a network member over other network members decreases as their connections in the network increase. In a similar vein, it is important to look at one's ratio of followers vs. followees when assessing the influence of an individual as those with an overwhelmingly high number of followers to followees are often found to be less likable (De Veirman et al., 2017). Due to the cost of maintaining a large number of connections, those with many connections tend to have weak ties, which results in less impact on other members in the network (Smith et al., 2007). Overall, previous studies suggest that not only is the size of a network important in determining influence and connectivity on social media, but also that the strength of connections matters as well.

While previous studies provided extensive knowledge to enhance the effectiveness of social media marketing, studies analyzing how an actual social network of a brand looks like in light of the established knowledge in the current literature is still in its nascent stage. For marketers and social media managers, it is critical to monitor the social networks of various social media accounts to establish proper social media strategies. Considering this, in order to help marketers create and implement an effective social media marketing strategy, it is important to examine social media network structure, network activities, and the role of the brand in the network in propagating information to others. Given that increasingly more brands use various SNS as a major marketing platform, they are an integral part of networks, and their goals, and thus behaviors, are different from other network actors. Therefore, it is important to analyze a brand's positions and roles in the network and investigate whether there exist noticeable differences in social networks in terms of their structural patterns. As such, this research utilizes ego-centered network analysis and whole network analysis in examining the Twitter network activities of two retailers. Along these lines, the following research question is formulated:

> **Research Question 1**: Is there a difference between the ego-networks and whole networks for retail brands in terms of the number of actors, type of connectivity, or the prominence of the brands?

### *2.3. Analytical concepts in social network analysis*

Two approaches utilized in trying to conceptualize and investigate the various dimensions and patterns of relationships between social network actors are ego-centered analysis and whole network analysis (Emirbayer and Goodwin, 1994). The ego-centered analysis is when the focus is placed on examining the behavioral patterns by placing a single actor (as the main focus) in the center of a network (Wellman and Berkowitz, 1988). In this, ego-centered analysis tends to concentrate on the networked relationships for a specific actor (ego - in this study, a retail brand), and then to consider how this actor and their relative position to others (alters – other participants in the network) may impact behavioral patterns and relationships within the rest of the network. On the other hand, the whole network analysis examines the entire network, including the density, strength of relationships, connectedness, and so forth (Emirbayer and Goodwin, 1994).

To examine whole networks and actors in those networks, statistical measures are used to analyze the connections between actors and to identify those important actors hold who influence and prominence (Brass et al., 2004). Specifically, this study utilizes the two most common types of measures utilized in social network analysis research: density and centrality (Borgatti et al., 2013). The choice of these metrics is driven not only by their popularity within research, but also their ability to highlight specific dimensions of the connective relationships that exist within networks (Borgatti et al., 2009). Although the ego-centered and whole network analyses are different methods in which to consider social networks, the statistical measures used to determine the importance and the connectivity in the network are the same. The density of a network is calculated through tabulating the number of actual ties in a network and then dividing it by the maximum number of connections, which could theoretically exist (Borgatti et al., 2009). In this manner, the density measure does not provide information about any single node or edge but instead signifies the overall connectivity between individuals in a network (Brass et al., 2004).Whereas density focuses on the entire network, the analysis for centrality focuses on the importance of each actor within a network (Borgatti et al., 2009). Eigenvector and betweenness centrality are two measures of network centrality used most often in social network analysis (Brass et al., 2004). First, eigenvector signifies the importance of a node in the construction of a network and is calculated by assigning relative scores to each node in a network, and then weighting them based on the importance of all other nodes they are connected to (Borgatti et al., 2013). A higher eigenvector centrality means a node is of greater prominence within a network and thus indicates having more ability to influence and spread information to others. The second centrality measure is that of betweenness centrality, which tells how important a node is in bridging together other actors in the network (Brandes et al., 2016). Specifically, betweenness centrality is calculated by analyzing the shortest paths between nodes, and then to add up the number of these paths which pass through each specific node. In this manner, a node with a higher betweenness centrality score serves as a more important node in terms of connecting individuals to one another and thus helps to extend conversations and messages to more actors in the network.

## 3. Method

In order to explore the research question, we have examined the Twitter networks of two multi-brand retailers in the cosmetics and beauty product category (e.g., makeup, skincare, fragrance, hair care, and tools). Based in France, Sephora is an international retailer that has approximately 2300 stores in 33 countries and offers more than 17,000 listed products from over 300 brands that are moderate to high-end in price and quality. Ulta Beauty, the largest U.S. beauty retailer, offers approximately 20,000 products from over 500 brands, ranging from affordable to high-end. Ulta operates 974 stores in the U.S. Focusing on the social media accounts of these brands on Twitter, in particular, Sephora has 2.37 Million Followers, 6826 Likes and 97.4 K Tweets whereas Ulta Beauty has 630 K Followers, 7124 Likes and 59.6 K Tweets.

### *3.1. Data collection and analysis*

In order to examine the Twitter network activities for Sephora and Ulta Beauty, the NodeXL software developed by the Social Media

Research Foundation[1] was used to scrape daily Twitter data for both ego-networks (@Sephora and @UltaBeauty) and the whole networks (#Sephora and #UltaBeauty). Specifically, the scraping was conducted over an eight-day time period to observe normal and unusual network activities. The data from the timeframe of November 20th till November 27th was selected for data analysis because this period includes both weekdays and a weekend during one of the most important holiday shopping seasons. Notably, Black Friday (11/24) and Cyber Monday (11/27) are considered the biggest shopping days of the year in the U.S. and thus should be a time of high volume of consumer interest in various brands. As such, the choice of this timeframe allows for us to examine the potential growth and development of networks during this key point of the holiday shopping season.

NodeXL is well suited for collecting daily data, as it functions by stipulating a specific social media platform (e.g., Twitter, Facebook, YouTube, etc.) and keywords or users, and then begins scraping data starting at the point in time when the search is executed and then moving backwards in time (Yan et al., 2019). As such, NodeXL has been widely utilized in examining the interaction between consumers and brands on social media in a number of contexts including sporting events, natural disasters, education, marketing, and so forth (Kim and Hastak, 2018). In this manner, daily data collection was carried out gathering as much user-generated social media content and interactions as possible. Following this collection procedure, due to the fact that NodeXL can often collect historical data dating back many days or even months depending on the volume and velocity of data generated for each search, the data was cleaned to only include observations for the 24-h time period of each calendar day included in the chosen eight-day time period.

With this cleaned daily data, a social network analysis was conducted by first mapping out the daily network for the brand official account networks and hashtag networks of each brand. Typically, networks are mapped out to determine which nodes are important using the Fruchterman-Reingold algorithm (Fruchterman and Reingold, 1991), a mathematical equation which considers the forces of attraction and repulsion between objects to determine the ideal distance between each node (actor), as well as the optimal length of each edge (connection) between two nodes (Jacomy et al., 2014). From this, the current study utilizes the Forces Atlas method, which utilizes the Fructherman-Reingold equation, but changes the attraction and repulsion slightly in order to develop a network map that spaces out the clustered groups within the network (Jacomy et al., 2014). Following the creation of these network maps, the aforementioned statistics of density, eigenvector centrality, and betweenness centrality were calculated for all networks.

## 4. Results

To begin with, turning focus to the ego-networks of the official Sephora (@Sephora) and Ulta Beauty (@UltaBeauty) Twitter accounts, the results from Table 1 highlight the relative size and number of users interacting with the brands on social media in a 24-h time period. Notably, both accounts had over 6000 different accounts connected to them on Twitter each day that data was collected. Because these networks were large in size, they also all had low density scores of under 0.0001, suggesting a low level of overall connectivity within the network. In examining ego-network activities (see Table 1), one can see that both Sephora and Ulta Beauty were the most important node in each network as measured by their eigenvector centrality. Indeed, in examining Fig. 1, the most prominent node in the center of the network is the official account for each brand. Indeed, all ego-networks that were plotted for the brands were identical to the one shown for Ulta Beauty in Fig. 1, with brands sitting at the center of the network engaging in numerous conversations with other actors who all hold very little influence in these ego-networks.

However, while both brands were the most prominent nodes within their ego-network, the actual eigenvector scores were rather low, with Sephora never having a value of about 0.008, and UltaBeauty mostly below 0.01. This alongside the high betweenness centrality for both official accounts (ego) and the extremely low betweenness centrality values for all other accounts suggests that the communication in these networks does not branch out and spread among users. Rather, the findings indicate that when either Sephora or Ulta Beauty engages in communications with individuals through their official accounts, the messages often reach only one individual or small groups, and does not have the ability to span across wider audiences on digital platforms.

To further consider this point, an additional level of analysis was conducted by examining the content of the Twitter communications between these two brands and the customers in their ego-networks. Generally, it appears that most of the discussions are for handling customer-service issues, complaints about products, or answering product or promotion related questions. For example, numerous users posted on 11/22 with inquiries directed at @Sephora and @UltaBeauty accounts asking why their shipments had not arrived, issues in regards to products that had been damaged during shipping, customer service issues from stores or phone lines, and so forth. From this, the @Sephora and @UltaBeauty accounts often responded to these inquires/issues by messaging the consumers back directly apologizing, and asking the consumers to please follow up through email or direct message so the brands could get more information about the issue. As such, it is evident that the communications in the ego-networks of these two brands mostly are two-way interactions between the brand and a single individual. Although brands are able to hold a lot of power and influence in these types of communications, such interactions are not able to expand beyond these forms and are highly unlikely to become “viral” content that is propagated widely among social media users. In this sense, while the official Twitter accounts for these brands are used as a platform for their digital marketing efforts and customer service, the network analysis reveals that such efforts have been mostly limited to customer-based interactions that are not of interest to wider audiences.

Moving along to the whole network analysis by examining the hashtag networks of both brands (#Sephora and #UltaBeauty), the results reveal a markedly different picture than those from the ego-networks. In examining Table 2, and Fig. 2, it is evident that there are a smaller number of actors who are involved in the hashtag network for Sephora and Ulta Beauty, and this was the case across the entire sample of data collected for this study. Perhaps the most evident difference between the ego-networks and hashtag networks is that while Ulta Beauty managed to remain the most prominent member in both ego and hashtag networks, Sephora often was not the most prominent member of their own hashtag network. For example, in analyzing Table 2, it is clear that while Sephora was the most important account in the hashtag network on Thanksgiving Day (the 23rd of November), they were not even in the top-25 of most important accounts on the day before (the 22nd) and on the day after (Black Friday). This is further evident in Fig. 2, where the central node in the image for the Sephora hashtag network on November 22nd is not the official Sephora account, but rather is another account that is not associated with the retailer.

In further examining the network maps for brands, it is evident that there is a significant difference between the whole networks and ego-networks for the brands. While the ego-networks were rather homogeneous across both brands in all time periods due to the use of these networks for one-on-one communications with consumers, the hashtag networks shown in Fig. 2 displays markedly different communicative patterns. In the ego-networks, there are clearly a lot of strong ties, but that these ties are formed between the brand and only one individual. Counter to this, the whole networks has numerous weaker ties, which have been noted as being important in the formation of strong communities (Granovetter, 1983; Hansen and Villadsen, 2017). Specifically,

[1] Social Media Research Foundation - https://www.smrfoundation.org/.

**Table 1**
Ego-network statistics.

| 11/22/2017 | | | 11/23/2017 | | | 11/24/2017 | | |
|---|---|---|---|---|---|---|---|---|
| Vertex | Eigenvector | Betweenness | Vertex | Eigenvector | Betweenness | Vertex | Eigenvector | Betweenness |
| **sephora** | 0.007022 | 40864056 | **sephora** | 0.007003 | 41107332 | **sephora** | 0.006992 | 41261352 |
| ambypamby4290 | 0.000155 | <0.0001 | nad88dosh | 0.000155 | <0.0001 | 2cchi_mua | 0.000155 | <0.0001 |
| itsnixky | 0.000155 | <0.0001 | imjosss | 0.000155 | <0.0001 | xoskat | 0.000155 | <0.0001 |
| graciealice13xx | 0.000155 | <0.0001 | daniecali4nia | 0.000155 | <0.0001 | nikkism46491872 | 0.000155 | <0.0001 |
| hjoykec | 0.000155 | <0.0001 | misscourtney_99 | 0.000155 | <0.0001 | vondourden | 0.000155 | <0.0001 |
| pigenemma | 0.000155 | <0.0001 | ferespi23 | 0.000155 | <0.0001 | reagan_garcia9 | 0.000155 | <0.0001 |
| yybeauty2 | 0.000155 | <0.0001 | beautyaddict_12 | 0.000155 | <0.0001 | surinashah | 0.000155 | <0.0001 |
| duana_jennings | 0.000155 | <0.0001 | iliana_magana | 0.000155 | <0.0001 | miranda_mallery | 0.000155 | <0.0001 |
| timotthea | 0.000155 | <0.0001 | mary_juana06 | 0.000155 | <0.0001 | kenziec44625574 | 0.000155 | <0.0001 |
| wifithefeeling | 0.000155 | <0.0001 | karyquintanilla | 0.000155 | <0.0001 | daldesign | 0.000155 | <0.0001 |
| **11/22/2017** | **11/23/2017** | **11/24/2017** | **11/22/2017** | **11/23/2017** | **11/24/2017** | **11/22/2017** | **11/23/2017** | **11/24/2017** |
| **Vertex** | **Eigenvector** | **Betweenness** | **Vertex** | **Eigenvector** | **Betweenness** | **Vertex** | **Eigenvector** | **Betweenness** |
| **ultabeauty** | 0.000249 | 16116210 | **ultabeauty** | 0.000249 | 16116210 | **ultabeauty** | 0.000249 | 16116210 |
| lexiluwho | 0.000249 | <0.0001 | lexiluwho | 0.000249 | <0.0001 | lexiluwho | 0.000249 | <0.0001 |
| maddie_hammitt | 0.000249 | <0.0001 | maddie_hammitt | 0.000249 | <0.0001 | maddie_hammitt | 0.000249 | <0.0001 |
| lucifiol | 0.000249 | <0.0001 | lucifiol | 0.000249 | <0.0001 | lucifiol | 0.000249 | <0.0001 |
| mayra_vazquez_s | 0.000249 | <0.0001 | mayra_vazquez_s | 0.000249 | <0.0001 | mayra_vazquez_s | 0.000249 | <0.0001 |
| skittlez_33 | 0.000249 | <0.0001 | skittlez_33 | 0.000249 | <0.0001 | skittlez_33 | 0.000249 | <0.0001 |
| janders32 | 0.000249 | <0.0001 | janders32 | 0.000249 | <0.0001 | janders32 | 0.000249 | <0.0001 |
| gaalalga | 0.000249 | <0.0001 | gaalalga | 0.000249 | <0.0001 | gaalalga | 0.000249 | <0.0001 |
| tamera7x | 0.000249 | <0.0001 | tamera7x | 0.000249 | <0.0001 | tamera7x | 0.000249 | <0.0001 |
| shelly87757396 | 0.000249 | <0.0001 | shelly87757396 | 0.000249 | <0.0001 | shelly87757396 | 0.000249 | <0.0001 |

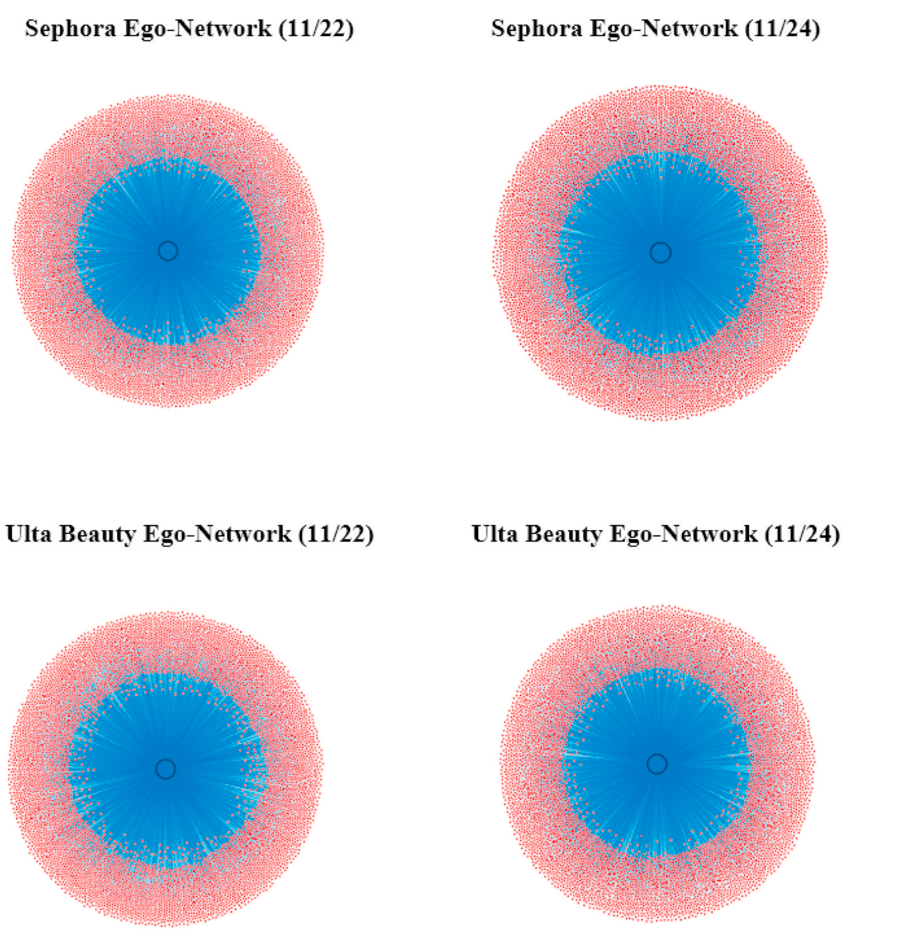


**Fig. 1.** Social media ego networks.

in examining the network for the Sephora hashtag on 11/24, it is evident that while there is a lack of strong connections between all of the actors in the network, there are several clusters in which multiple individuals are connected and interacting with one another. Focusing on the two blue nodes, the larger darker node in the lower half of the network map belongs to an online reviewer in Thailand who has a large following

**Table 2**
Hashtag network statistics.

| 11/22/2017 | | | 11/23/2017 | | | 11/24/2017 | | |
|---|---|---|---|---|---|---|---|---|
| Vertex | Eigenvector | Betweenness | Vertex | Eigenvector | Betweenness | Vertex | Eigenvector | Betweenness |
| giftcard1703 | 0.035714 | 702 | **sephora** | 0.07807 | 3663 | jebansundae | <0.0001 | 2 |
| kushage_og | 0.035714 | <0.0001 | toofaced | 0.075945 | 1952 | giftcard1703 | <0.0001 | 552 |
| jojoboboi | 0.035714 | <0.0001 | palette_tech | 0.013218 | 152 | bysamanthamarch | <0.0001 | 208 |
| youtjet | 0.035714 | <0.0001 | jaskaiya | 0.013122 | 0 | thisisinsider | <0.0001 | 6 |
| intanipk | 0.035714 | <0.0001 | olivia_osterloh | 0.013122 | 0 | projpina | <0.0001 | 0 |
| kgebag | 0.035714 | <0.0001 | amandamarie1116 | 0.013122 | 0 | spotthedealusa | <0.0001 | 30 |
| dalenaclaveria | 0.035714 | <0.0001 | palomalomalita | 0.013122 | 0 | misswonderp | <0.0001 | 2 |
| andromedas13 | 0.035714 | <0.0001 | raynnbozek | 0.013122 | 0 | kirarista | <0.0001 | 2 |
| folocfollo | 0.035714 | <0.0001 | ajeanruggiero | 0.013122 | 0 | rihrobyn | <0.0001 | 0 |
| dorelantica | 0.035714 | <0.0001 | pnchrat | 0.013122 | 0 | deibouraaay | <0.0001 | 0 |
| **11/22/2017** | **11/23/2017** | **11/24/2017** | **11/22/2017** | **11/23/2017** | **11/24/2017** | **11/22/2017** | **11/23/2017** | **11/24/2017** |
| **Vertex** | **Eigenvector** | **Betweenness** | **Vertex** | **Eigenvector** | **Betweenness** | **Vertex** | **Eigenvector** | **Betweenness** |
| **ultabeauty** | 0.141272 | 297 | **ultabeauty** | 0.141272 | 297 | **ultabeauty** | 0.141272 | 297 |
| thebeachwaver | 0.127053 | 91 | thebeachwaver | 0.127053 | 91 | thebeachwaver | 0.127053 | 91 |
| thomas04113229 | 0.044559 | <0.0001 | thomas04113229 | 0.044559 | <0.0001 | thomas04113229 | 0.044559 | <0.0001 |
| meshell_kayla | 0.044559 | <0.0001 | meshell_kayla | 0.044559 | <0.0001 | meshell_kayla | 0.044559 | <0.0001 |
| babydollkirk | 0.044559 | <0.0001 | babydollkirk | 0.044559 | <0.0001 | babydollkirk | 0.044559 | <0.0001 |
| palitpp9 | 0.044559 | <0.0001 | palitpp9 | 0.044559 | <0.0001 | palitpp9 | 0.044559 | <0.0001 |
| bnadyn | 0.044559 | <0.0001 | bnadyn | 0.044559 | <0.0001 | bnadyn | 0.044559 | <0.0001 |
| maskeith_ | 0.044559 | <0.0001 | maskeith_ | 0.044559 | <0.0001 | maskeith_ | 0.044559 | <0.0001 |
| captain_smores | 0.044559 | <0.0001 | captain_smores | 0.044559 | <0.0001 | captain_smores | 0.044559 | <0.0001 |
| itsgabvespi_ | 0.044559 | <0.0001 | itsgabvespi_ | 0.044559 | <0.0001 | itsgabvespi_ | 0.044559 | <0.0001 |

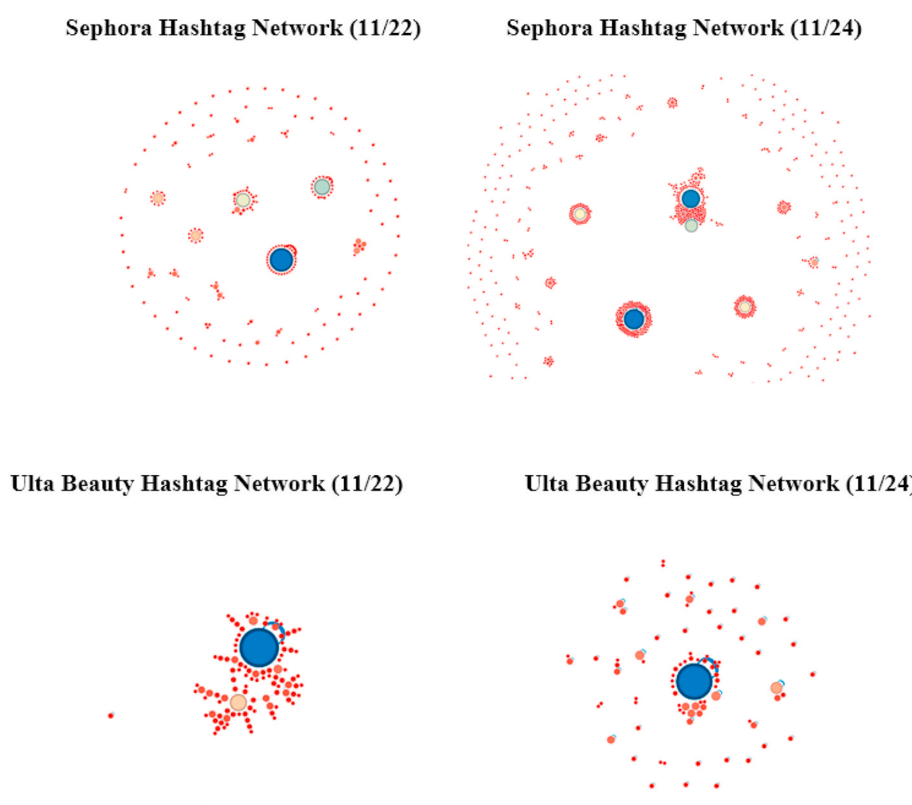


**Fig. 2.** Hashtag networks.

based on her review of cosmetics. The other blue node in the upper half of the network belong to an online retailer devoted to the resale of products through the Internet. While neither of these actors represents Sephora in an official capacity, both play an important role in discussing and communicating about the brand in the hashtag network.

In contrast to the Sephora hashtag networks, the Ulta Beauty hashtag networks are smaller in terms of the number of actors, the overall size of the networks, as well as the number of connections and interactions occurring. While on first glance, the presence of a larger number of actors in a network would seem to be more beneficial for a brand, it is important to note that Ulta Beauty's official account holds the greatest prominence in their hashtag networks, and thus are the key influencer of communications and engagement. That is, in looking at both the network statistics, it is evident that Sephora often is not a top influencer within their own network, while Ulta Beauty remains the most important in all of their hashtag networks. From this, it can be said that while

Ulta Beauty is able to curate and help control the messages and conversations in their network, Sephora is often reliant on the messages and actions from other entities such as online retailers or popular social media figures. Indeed, in examining the content from the Ulta Beauty network, the content often links back to Twitter posts created by the brand, such as individuals retweeting the post from @UltaBeauty on 11/24: "You've noticed them noticing these. Come in store and find the fragrance they will fall in love with #UltaBeauty." Counter to this, the posts using #Sephora were typically controlled by prominent online retailers promoting their own deals, such as the message on 11/24 stating: "I Got Free #Sephora Gift #Code with #Free #Sephora #Gift #Card Generator." Overall, the post from the online retailer promoting Sephora received 135 retweets over a several day period, and received numerous likes and other interactions. Thus, while Sephora is able to enjoy a larger volume of online discussion and interactions from consumers, the brand itself is not able to interject itself into these conversations. In this manner, though Sephora has a larger network with more engagement, they do not have any real control over the conversations, especially in comparison to Ulta Beauty who has stronger reign over the communicative patterns in the digital realm.

## 5. Discussion and conclusion

### 5.1. Discussion

To answer the research question, this study used social network analysis to examine Twitter data for the ego-networks (@Sephora and @UltaBeauty) and whole network of brand hashtags (#Sephora and #UltaBeauty). Overall, the results suggest that while these two brands may share many similarities in regards to how they operate their social media accounts, they experience markedly different relevance and presence on social media. Specifically, in this particular study, the sizes of ego-networks for both brands are large but the connections between the brands and network members and among the members are relatively sparse. Although such network structure has the potential to reach a large audience (Zhang and Dong, 2008), it is less likely that communications spread out enough to contribute to the development of a cohesive community (Emirbayer and Goodwin, 1994). Besides, while the ego-networks for the brands were quite similar to one another, there was a big difference between the ego-networks and whole networks in regards to the number of actors, type of connectivity, as well as the prominence of brands.

Specifically, the results from these networks show that, unlike its ego-networks, the global brand, Sephora, was often not an important part of its hashtag network, and thus was not able to maintain strong control over communications and messages in these networks. This indicates that while it is certainly possible that Sephora was not able to exhibit as much control because they had a higher number of followers (2.3 million compared to Ulta Beauty's 624,000), it may also be the case that Sephora's international reach presented difficulties. That is, while Ulta Beauty mainly has to only operate in one language (English) in relatively small time-frame each day, Sephora faces the difficult task of having to deal with users speaking dozens of languages discussing their brand from all around the world. Because of the challenges to engage users in multiple languages they were often ousted from a central position, exerting marginal influence in the networks (Katona et al., 2011; Liu-Thompkins, 2012). In this sense, the very nature of being an international brand may hamper Sephora's ability to effectively use social media as a communication tool to engage with and capture the attention of a wide array of audiences worldwide.

As seen in images of the networks from the data gathered on the different days of the investigation, real-time changes occur in terms of centrality and density in the network. First, brands have considerably tight control over the ego-network connecting with their customers, remaining as the center of the network connectivity. However, the content appears to be mostly customer service-related issues, such as product/promotion questions and complaints. From this, it is suggested that brands may use various social media platforms for different purposes. For example, Twitter, in particular, may be used for immediate product purchase-related customer service due to its dynamics and instant reach. Second, the contents of the brand-customer communications in their ego network, in particular, suggest that most brand communications via Twitter tend to be very limited to answering individual customers' inquiries, resulting in the relatively narrow reach. This finding is not limited to just Twitter, or these two retail brands. Rather it is a phenomenon observed in other retail brands such as JCrew and Gap on social media platforms such as Facebook. For retailers and the service industry, in particular, social media has served as an easier way for consumers to inquire and complain, and thus has turned into another customer service line.

As such, connecting with current and prospective customers on social media requires an understanding of the media characteristics, as well as the user behaviors on a particular platform. Consumers will follow brands and engage with their marketing messages only when they find the content and information valuable to them. Because of the easy and quick ways of connecting on SNS, consumers have the same expectations when communicating with the brands present in a network. As such, social media can serve an important role as a vehicle for brands to make close connections with the customers rather than just delivering marketing messages to them, such as through delivering content that avoids conventional corporate images (Kim and Ko, 2012).

### 5.2. Contributions and implications

In considering the overall impact of this study, the current research advances the use of social network analysis as a means to better understand the communicative relationships and that exist within the digital environment (Borgatti et al., 2009). That is, through examining how the spread of information is related to the power and relational dynamics of networks on social media, this study contributes to the theoretical and empirical understanding of the role that user connectivity plays in governing the spread of marketing messages to consumers. Furthermore, this study also contributes to the examination of social media marketing by utilizing two different approaches to social network analysis to examine ego networks and whole networks. Such method is beneficial as it provides insights into the network that is centered on the brand itself as well as the entire network, thus allowing for a multidimensional investigation of brand presence on digital platforms. In this manner, the findings from the ego-centered analysis and whole network analysis using the same statistical measures in investigating social networks help us understand the "scene" of actors on social media platforms. Along these lines, when looking at the scene for these two brands, it is evident that there are a lot fewer people and control over the hashtag network. Thus, there would seem to be a lack of critical mass, suggesting an absence of audience attention and effectiveness in being able to communicate and market to individuals and groups through the hashtag networks. While Sephora and UltaBeauty are both quite popular on social media, UltaBeauty has more importance within their networks, while Sephora does not.

At the same time, for social media marketers of retail brands, it is critical to constantly monitor the networks of their various social media accounts and establish proper strategies based on how messages are spread and promoted within their networks (Jacobson et al., 2020). In this sense, this research provides unique, practical insights that allow marketers to diagnose the effectiveness of leveraging social networks of their social media accounts. For example, the analysis of the ego-networks of the two brands revealed that the communications are mostly between the brand and a single individual. This phenomenon may indicate the lack of "viral" content that appeal to larger social media users in the brands' social media strategy. When such a pattern is observed in a brand's social networks over an extended time period, social media marketers should review the content of their social media interactions and take corrective actions to best leverage the potential of their ego-networks.

Nowadays, more brands are turning to artificial intelligence (AI) as part of their customer service platforms, rather than having employees work through all of the posts. Customer inquires must be addressed in a timely manner by identifying the problem and resolving the issues. While the use of bots and AI to start conversations can be useful in reducing the pressure to deal with customer service issues, such a reactive approach does not warrant the brands to fully realize the potential of their ego-network where they can exert a strong control. In order to take advantage of the power of social media in terms of spreading messages to a wide network of customers in an effective and efficient manner, the brands should consider developing more interest-provoking content to engage broader audiences. For example, organizing an event that encourages customers to post and share user-generated content and flash sales to generate traffic on online platforms may help brands to create and maintain positive sentiments in their social media conversations.

Using social media as a tool to engage customers and enhance their brand experience is vital for brand success. However, as evidenced in the results, it is possible for brands to lose control of networks, and thus potentially not be able to connect to consumers and emphasize their targeted messages. In this sense, the role of marketers has evolved in the social media landscape where they no longer should just be focused on the creation and delivery of information, but also the constant cultivation of communicative relationships to facilitate a collaborative social experience that customers value (Shareef et al., 2018). In this, the use of network analysis is beneficial to brands as it can provide an effective way to improve both their social media customer service, as well as one-to-one marketing that can deliver a more authentic experience to consumers. Furthermore, in establishing and developing such relationships with customers, social media provides a new opportunity to enhance brand-customer intimacy leading to long-term relationships and brand loyalty (De Veirman et al., 2017).

### 5.3. Limitations and suggestions for future research

There are limitations that need to be acknowledged in this study. Though our analysis finds that some brands are using their social media accounts as a way to deal with customer service issues, it is certainly the case that not all brands will use social media in the exact same manner. Therefore, while the recommendations provided within this study discuss certain strategies, it is important that the implementation of social media strategies should consider the individual characteristics and context of each brand. Based on this, there is certainly room for future studies to expand the use of social network analysis to examine the communication and behaviors of brands in both ego and whole networks. In regards to the data collection and analysis provided within this study, the time period examined was only one week in the year. Considering the dynamic nature of social media, it is certainly possible that brands may alter their social media strategies and behaviors based on certain events. As such, future studies of brand behavior using social network analysis should contemplate analyzing longer periods of time, as well as how special events such as a crisis could impact networked behavior on SNS.

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