Socialization on Sustainable Networks: The Case of eBay Green's Facebook

HaeJung Maria Kim [1], Kyung Wha Oh [2] and Hye Jung Jung [3],*

[1] College of Merchandising, Hospitality and Tourism, University of North Texas, Denton, TX 76203-5017, USA; haejung.kim@unt.edu
[2] Department of Fashion, Chung-Ang University, Seoul 06974, Korea; kwhaoh@cau.ac.kr
[3] Research Institute of Human Ecology, Seoul National University, Seoul 08826, Korea
* Correspondence: jayski@snu.ac.kr

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Abstract: Given that novel merchandising informatics is seen as a better approach to studying eco-friendly markets, this study aimed to explore consumer socialization of sustainable networks based on the theory of consumer socialization. By employing social network analysis using the NodeXL program, we examined the social class hierarchy, investigated the structure of social agent–learner relationships, and explored the social learning properties of the eBay Green Team Facebook network. The results indicated that the network has been structured as a 'tight-crowd network' through 76,482 interactions among 1612 actors from 19 clusters. Specifically, the centrality measure revealed the top influentials and their interactions with other eBay Green participants. The semantic analysis discerned the salient words, which implies that consumers gain utility from this network. We concluded that sustainable networks in social media can provide an account of the socialization of consumer attitudes and the role of top influentials in sustaining the relational network.

Keywords: big data; consumer socialization theory; eco-friendly market; social network analysis

1. Introduction

The fashion and textiles (F & T) industry faces the challenge of moving toward sustainable consumption and building an ecologically friendly (eco-friendly) market [1] (Kim, Kim, Oh, & Jung, 2016). Consumers might be reluctant to join this movement due to institutional barriers, inequalities in access to information, and restricted product choice [2] (Jackson, 2005), in addition to conflicting values, norms, and habits in terms of individual, social, and cultural expectations and regulations [3] (Lee & Hwang, 2019). Firms often encounter difficulty and complexity associated with developing and maintaining sustainable consumers and eco-friendly markets [4] (Jung, Kim, & Oh, 2016). While building a sustainable and pro-environmental market is a complicated task for a single firm or for consumers, social media platforms such as Facebook, Pinterest, and Twitter may enable such entities to initiate and shape a network for sustainability by taking advantage of the medium's connectivity and mobility [5] (McFarland & Polyhart, 2015). Several recent social campaigns demonstrate the factors through which eco-friendly and sustainable campaigns impact their brands' public perception. In the wake of the U.S. administration's decision to back out of the Paris environmental agreement, the "Earth–Shot on iPhone" project by Apple aimed to capture how beautiful our planet is through the lenses of everyday iPhone users [6] (Rogers, 2018). This is because social communication promotes awareness, motivates trial behaviors, reinforces purchase decisions, and sustains product loyalty, all of which may eventually lead to large-scale social movements whose members have shared beliefs and attitudes [7] (Kahle & Gurel-Atay, 2013).

In our current social zeitgeist, we have witnessed several F & T brands that have taken social or environmental stands, publicly stating their brand values, and details on how this has impacted their brand's public perception are now available. However, simultaneously, many brands' sustainable and eco-friendly campaigns have become obsolete in their social media accounts, without fully exploiting their publicity potential. For example, the initiative of the eBay Green Team (eBGT) exemplified a social community movement that promoted smart ways to shop green and encouraged more sustainable buying choices that could save consumers money and help save the planet [8] (Chain Store Age, 2009). They created a concerted strategy of ensuring incentive structures and institutional rules for sustainable behavior, enabling access to eco-friendly choices, engaging people in initiatives to help themselves, and exemplifying the desired changes within the firm's own policies and practices [8] (Chain Store Age, 2009). The eBGT's movement followed a top-down process led by the inspiration and creativity of eBay participants, which the firm attempted to harness for the benefit of the public. Nonetheless, this pioneering sustainable network has vanished from social media now. The ongoing dialogue has been insufficient, and shortcomings in research into the program have been uncovered. It is unclear whether consumers were aware of or learned sustainable attitudes and behaviors from the eBay Green Facebook network, and research exploring consumers' socialization of this network could provide practical contributions and have substantial implications for the F & T industry and academia.

Conventionally, a comprehensive process of consumer decision making occurs over several consecutive levels. This process includes all the parameters a consumer may encounter while buying products for the first time when they are experiencing a high level of buying commitment [9] (Solomon et al. 2006, p. 258). While the F & T field has been interested in the cognitive approach to beliefs, attitudes, intention and behavior in conjunction with consumer internal and external factors, consumers are no longer merely classical buyers or product consumers. They are becoming active participants in their engaged networks, and are aggressively seeking relationships and sharing knowledge with other entities. Recently, a few fashion informatic approaches have been initiated to identify this type of consumer social dynamic by employing big data and advanced analytic skills [10] (Zhao & Min, 2019). Aligning data informatics efforts with marketing, design, store operations, and merchandising could enable the F & T field to understand and connect to customers in more meaningful ways than ever before. Merchandising informatics, an information management perspective on merchandising practices for retail, can compensate for a lack of research following conventional quantitative and qualitative approaches by integrating computational, cognitive, and social aspects [11] (Kim, 2018). For the current study, we employed Social Network Analysis (SNA) to carry out merchandising informatics research.

Social Network Analysis (SNA) can provide a means of identifying social structures and relationships by giving precise definitions to aspects of the social structural environment [12] (Wasserman & Faust, 2009), including social support [13] (Wellman & Wortley, 1990), diffusion and adoption of innovation [14] (Chong & Kim, 2020), belief systems [15] (Boutyline & Vaisey, 2017), and consensus and social influence [16] (Edmonds, 2020). SNA-based merchandising informatics can look at interactions among consumers and brand entities, and accordingly reveal the influences of key opinion leaders, topics, and clusters on consumers' networks of sustainability and pro-environmentalism. Consumer socialization (CS) theory is relevant in exploring consumers' social engagement, alongside information sharing and learning behavior, in social networks. The theory explains the social learning process in terms of the interaction between learners and various agents according to their social class hierarchy [17] (Okazaki, 2009). The logic is that a consumer is socialized by learning information from opinion leaders (i.e., influentials); thus, the consumer can develop his or her attitude, leading eventually to intention to purchase a product. This socialization of learning through network class hierarchy centers on the interactive relationships between opinion leaders and learners, which results in a sense of engagement, leading to participation in social interactions with others [18] (Hollebeek, 2014).

Given SNA-based merchandising informatics is seen as a better approach for sustainable networks, this study is grounded upon CS theory to understand the positions and the attributes of influentials' class hierarchy, to recognize the structural patterns of relationships among social entities, and to explore the learning properties of information on their socialization. Focusing on the eBGT Facebook network, the purposes of the study are: (1) to extricate the class hierarchy by probing the centrality measurements of top influentials; (2) to understand the structure of social agent–learner relationships by examining the pattern of directional ties for seeking information; and (3) to explore the learning property of authentic message contents by searching for salient keywords shared by clusters.

Based on our understanding of consumer socialization and sustainable networks, this study will advance the methodology of SNA-based merchandising informatics and extend the conceptual ground of consumer socialization theory to the social media context. Upon retrieving the obsoleted eBGT network, the findings will be of value in increasing our understanding, both socially and psychologically, of how potential eco-friendly and sustainable networks can be accessed as a profitable target segment, providing benefits to all stakeholders in the F & T industry. This SNA approach to big data construal in relation to social media could aid F & T scholars to grasp relevant big data concepts more quickly and fully, connect theory and application more adeptly, and facilitate the sharing of knowledge with other scholars [11] (Kim, 2018).

2. Literature Review

2.1. Eco-Friendly and Sustainable Networks in Social Media

Eco-friendly consumers adopt sustainable behaviors through changing their practices [19] (Harcar & Kaynak, 2007), paying additional costs for eco-friendly choices [20] (Dobson, 2003), and proactively and collectively responding to eco-friendly conversations [21] (Fraj & Martinez, 2006). Although eco-friendly consumers have become a significant segment in society [22] (Young, Hwang, McDonal, & Oates, 2010), access to and understanding of this consumer network is still elusive in the F & T field. To access this community, 'Nike's Making App' avows the particular eco-friendly goal of being a leader in sustainable design by sharing knowledge and inspiring a new generation of designers. This eco-friendly campaign provides free, detailed in-house sustainability impact information on 22 different product materials, so producers can create their own sustainable products [23] (Pritchard, 2013). 'Patagonia' planned to donate 100% of its Black Friday sales to organizations that benefit the environment. Social media caught word of this offer and it spread quickly, with this tweet receiving a nearly 1000% greater engagement rate than others of the same profile. While projecting $2 million in sales, the company discovered that, in fact, it sold more than $10 million worth of merchandise [6] (Rogers, 2018).

Proactive communications employed by social campaigns in an eco-friendly network can yield economic value for consumers and firms [24] (Lee & Lee, 2009). Theoretically, this is because sharing and seeking information about a product or service means consumers perceive lower risk [25] (Yolanda & Ngai, 2011) and spend less time on a purchase decision [26] (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004). It also helps them ease their dissonance after purchase [27] (Khammash & Griffiths, 2011) and enables them to solve product-related problems after purchase [28] (Andreassen & Streukens, 2009). Companies further achieve enhancement of the marketing effectiveness of advertising, media, and public relations because of spontaneous conversations among countless consumers [29] (Goyette, Ricard, Bergeron, & Marticotte, 2010). The development of social media has contributed significantly to changes in the forms of satisfying the needs and the participation of individuals in social life [30] (Wróblewski et al., 2018). This is reflected by the development of the information society and a society based on knowledge. This situation creates new opportunities for the diffusion of sustainability concepts. To empirically examine these premises, much research in the F & T field has centered on predetermined survey methods, traditional sampling, and inferential

statistics. However, it has been limited to measuring real-time responses and tracking fluid networks and spontaneous structural transformations on social media [31] (Salganik, 2017).

2.2. Consumer Socialization in Social Networks

Many social–psychological theories suggest that consumers cultivate their behaviors, attitudes, and concepts of self by observing what others think, say, and do in the social context [2] (Jackson, 2005). Explicitly, the social identity perspective argues consumer behavior is motivated by a tendency towards intra-group cohesion and inter-group competition [32] (Turner & Reynolds, 2001). Consumer social identity attributes intra-group favoritism to a psychological need for positive distinctiveness and describes situations where intra-group favoritism is likely to occur as a function of perceived group status, legitimacy, stability, and permeability [33] (Ellemers, & Barreto, 2001). From the F & T perspective, intra-group cohesion and inter-group competition on social media can become a marketing asset to facilitate conversations with and within the eco-friendly and sustainable community. TOMS' annual "One Day Without Shoes" campaign asks consumers to go barefoot to raise global awareness for children's health and education. The company consistently presents User-Generated Content (UGC) on its website, along with their social media. They host Instagram meet-ups in several cities, offer a toolkit for those who want to participate, and make available a Pinterest board full of shareable fact photos and participant photos. Furthermore, eco-friendly brands not only raise awareness for causes on multiple networks, but also tailor their campaigns to leverage the visual web and UGC by allowing consumers to submit selected content, give feedback, and gain exclusive information [34] (Harrison, 2014). UGC is usually comprised of customer reviews regarding brands, services, and products, ratings, product images, testimonials, how-to guides, and more [35] (NRF, 2012). The UGC on social networks offers opportunities for repeated interactions among all involved entities.

Consumers become socialized based on who is attractive to them or influential to them, or on the basis of people being simply 'like us' [2] (Jackson, 2005). Consumer socialization theory explains that a consumer's acceptance attitude is developed through the interaction between the learner and various agents in the context of various social surroundings [17] (Okazaki, 2009). Consumer socialization involves a learning process that is not only a cognitive-psychological process of adjustment to one's surroundings but also a social process that incorporates the individual's response to other social institutions [36] (Ward, 1974). The consumer socialization perspective characterizes the process in terms of social structure and the socialization process [37] (Moschis & Churchill, 1978), which lead to the development of consumer-related skills, knowledge, and attitudes [36] (Ward, 1974). We propose that the social network in social media is the core of a socialization process that incorporates both social structure (i.e., social class position) and the types of social agent–learner relationships (i.e., relations) that take place (Figure 1).
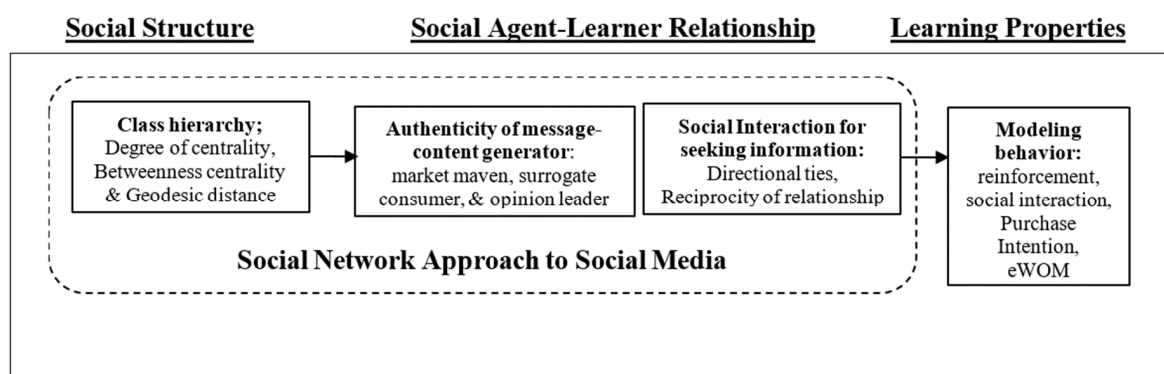

Figure 1. The proposed model of consumer socialization in social media.

The social structure is related to an individual's social class position according to his or her level of involvement in the community [37] (Moschis & Churchill, 1978). In the case of the eco-friendly

and sustainable network, 'market mavens' can spread information about all types of eco-friendly products and services that are available in the marketplace, and 'surrogate consumers' may provide input into a purchase decision [38] (Goldenberg, 2011). Consumers develop modeling behavior of information-seeking engagement through social networks, which is reinforced through either word of mouth or diffusion of information as consumers interact together to produce the outcome in their social networks [39] (Sashi, 2012). Influential or opinion leadership is important within groups in facilitating links between the two. Effective influentials may engage with key individuals in different sectors, facilitate links between social networks of different scales and interests, reconceptualize issues, and generate and integrate various ideas, perspectives and solutions [40] (Araujo et al., 2017). Influentials provide innovation, build trust, help improve understanding and develop knowledge, and motivate change for individuals or consumers.

The socialization process incorporates both the socialization agent and the type of learning actually occurring. The social network in social media is influenced by the authenticity of the message, which is determined by whether the content information is generated by consumers or by brands [41] (Chung & Shin, 2010). High authenticity of information results in significant changes in consumer responses (i.e., modeling behavior, reinforcement, and social interaction) [37] (Moschis & Churchill, 1978) toward social media. The notion of modeling behavior implies that consumers imitate the behavior of market mavens or surrogate consumers [39] (Sashi, 2012). In terms of reinforcement, social networks within social media allow for rapid dissemination and exchange of information [40,42] (Lovejoy, Waters, & Saxton, 2012; Araujo et al., 2017). Social interaction is the combination of modeling behavior and reinforcement as consumers' learning processes continue [37] (Moschis & Churchill, 1978). Social learning is considered crucial to achieving sustainability because the management of social–ecological systems represents a complex problem which requires participation and negotiation between different actors and interests to reach collective decisions [43] (Froome et al., 2010). Thus, consumer modeling behavior, reinforcement, and social interaction in the network are the foundations for developing an acceptance attitude toward eco-friendly and sustainable behaviors.

2.3. Social Network Analysis (SNA)-Based Merchandising Informatics

Using merchandising informatics, firms in the F & T industry can utilize big data from social media, gaining access to social networks in which they can participate and set targets for their market or community [11] (Kim, 2018). 'Chico's FAS' implemented the on-demand 'SAS Social Media Analytics' solution to understand what was being said about Chico's brands, and to apply this intelligence to decision making. Using the Conversation Center module, Chico's accessed tweets in real-time and identified significant networks or consumers based on sentiment and the influence of the Twitter author [44] (RIS, 2011).

Conventional social theories have often considered individual actors as independent choice makers who behave without thinking of others, a perspective which disregards the actor's place within the social context [45] (Bhowmick, Gueuning, Delvenne, Lambiotte, & Mitra, 2019). However, SNA not only prioritizes the relationships among actors within a social environment, but also emphasizes individual attributes in order to understand social events [46] (Eleni, Milaiou, Karyotis, & Papavassiliou, 2018). Indeed, SNA conceptualizes the social structure as a network with ties connecting members and channeling resources, focusing on the characteristics of these ties rather than on the individual members, and viewing communities as networks of individual relations that people foster, maintain, and use in their lives [47] (Wetherell et al., 1994. p. 645). The core of SNA is to collect a set of texts from critical connections in the life of a social movement for research [48] (Yoon & Chung, 2018). SNA identifies a new set or cluster of concepts, which enables researchers to explore meaningful information from the texts.

There are several key concepts fundamental to any discussion of SNA. The term 'actor' or 'node' refers to social entities, including individual consumers and corporate or collective social units. This study describes the key social agents in consumer socialization as influentials, a group that includes

market mavens, surrogate consumers, opinion leaders, and consumers. Relational ties establish linkages between pairs of actors, which may be 'followers, co-likers, or co-commenters' in the Facebook networks. A 'subgroup' of nodes can be defined as any subset of social agents in addition to all the ties among them. The current study uses the term 'cluster' instead of 'subgroup.' The term 'group' can be defined as referring to the collection of nodes among which ties are to be measured. 'Relation' refers to the collection of ties of a specific kind among nodes of a group. For example, the category of e-WOM among market mavens and opinion leaders in a cluster of eco-friendly markets is comprised of ties that define relations. A 'social network' consists of a finite set or sets of nodes and the relation or relations defined among them [12] (Wasserman & Faust, 2009, p. 17–21). SNA is a strategy for examining social structures [49] (Otte & Rousseau 2002). Recently, a few fashion informatics studies (e.g., [10,50,51] Brambilla, Ceri, Daniel, & Donetti, 2017; Lee, Han, Chambourova, & Kumar, 2017; Zhao & Min, 2019) have initiated diverse and practical dialogue relating to industry-specific informatics focusing on SNA.

CS theory [37] (Moschis & Churchill, 1978) can support consumer socialization on sustainable networks in social media. Logic can clarify social structures through class hierarchies, social agent–learner relationships, and learning properties of the eBGT Facebook network by applying SNA-based merchandising informatics. SNA validates the methodological competency by means of critical centrality measurements and semantic analysis on identifying the class hierarchy and the authenticity of message content generators of market mavens, surrogate consumers, and opinion leaders. In addition, network visualization algorithms recognize directional ties and modeling behaviors of social interaction and eWOM among social entities. Thus, focusing on the case of the eBGT Facebook network, we explored the following research questions:

RQ 1: To identify the social class hierarchy, who are the top influentials in the eBGT network?

RQ 2: To understand the social agent–learner relationship, who might serve as market mavens, surrogate consumers and opinion leaders, and what types of social interactions do the eBGT clusters have?

RQ 3: To explore the learning properties, what are the top keywords and word pairs that appear in postings shared by clusters?

3. METHODS

3.1. Selection of eBay Green Team Facebook Network

The preliminary phase of SNA involves building a list of conversations and clusters of conversations related to a potential eco-friendly and sustainable network. The initial step of crawling network data is iterated until it creates an automatic collection of posts containing eco-friendly keywords (e.g., green, ecologically, environmentally friendly, sustainability, and social responsibility) selected from a search using Google Trends. From among several eco-friendly communities, such as LOHAS [52] (Emerich, 2000) and retail brands (e.g., Amazon.com, Patagonia) on Twitter and Facebook, only the eBay Green Team (eBGT) Facebook provided measurable network data sets. With more than 86 million active buyers and sellers globally, eBay provides a space for not only buying and selling pre-owned, resource-saving, and sustainable products under several product categories, but also offering sustainability-related knowledge and information. Each community forum and product page links to social networks such as Facebook, Twitter, and Pinterest so that consumers can seek information and share their experiences with users. Thus, we decided to examine the eBGT Facebook network.

The eBGT initiative, which began as a proactive effort by 40 eBay employees in 2007, has grown into a full-blown company-wide initiative. The eBay Green Team boasts that it has over 1000 employees worldwide, and has continued to promote new ways of thinking about eco-friendly shopping. In fact, the eBGT initiative launched a social media campaign on Facebook in 2007. It is interesting to observe the way in which a public conversation was driven primarily by an open invitation for people to participate in an interactive discussion, called "Green Team Talks", about green shopping and the sharing of ideas with each other. Community members also were invited to take "eBay Green

Team Challenges" in order to learn how everyday changes could have a meaningful impact on the environment [8] (Chain Store Age, 2009).

3.2. Data Collection and Analysis

The NodeXL software allows for social network investigation through the importing of data from popular social media websites such as Facebook, Twitter, Wikis, and YouTube [53] (Hansen et al. 2011). NodeXL can display social network maps by visualizing participants and their connections in a network and can compute the influence of an individual node on others based on network metrics including density, centrality, and page rank [53] (Hansen et al. 2011). By means of the Application Programming Interface (API) tool in NodeXL, data were collected from the eBGT Facebook page from 2009 through to 2015. Using Facebook Group Page Importer, we downloaded posts, comments, and replies to create Post-Comment-Like network tree-maps. While the Facebook Pages Importer allows for exploring Page-Likes-Page networks up to a 3.0-degree network for one page [53] (Hansen et al., 2011), we limited it to a 1.5-degree network due to limits on measurability and accessibility of data.

The unit of analysis in NodeXL is the vertex (or node), a point in a network where ties cross or connect among eBGT Facebook accounts. This study considers vertices as social agents. An edge (or tie) is a connection between vertices from different eBGT Facebook account origins. A major indicator of structural properties is the overall network statistics, such as graph 'density,' which is the total number of ties divided by the total number of possible ties [54] (Borgatti, Everett, & Freeman, 2002). 'Centralization' (i.e., indegree, outdegree, eigenvector, betweenness, reciprocated ratios, and the geodesic distance) is a key metric for describing how densely ties are concentrated around a focal node in a given network. The social position and demographic characteristics of network participants are the social class hierarchy properties of vertices, such as the degree of centrality, betweenness centrality, and geodesic distance.

The clusters (sub-groups) were identified by cluster analysis. A pattern in the leading vertices' interactions within a cluster could be identified by analyzing the centrality indices of the vertices. The cluster analysis demonstrated the influence of the authenticity of the message-content generator, and that of the social interaction for seeking information shared within the eBGT Facebook network. Indeed, influential vertices lead the eco-friendly network by seeking out those who are leading each of the connected clusters.
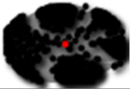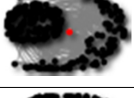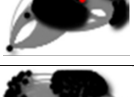
NodeXL provides the option of carrying out text semantic analysis by counting the words along with the pairs of words that occur next to each other. The salience is a measure of how 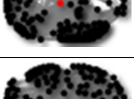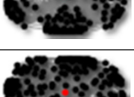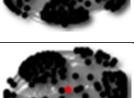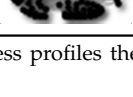important the word or word pair is within the entire text column [55] (Hu et al. 2013); such salience points to the learning properties resulting from socialization.

4. Results and Discussion

RQ1: Who Are the Top Influentials in the eBGT Network?

By conducting an analysis of vertex betweenness centrality (VBC) and vertex degree (VD), we recognized the top vertices as the influentials or social agents, reflecting the class hierarchy in socialization. Vertex profiles were discovered to be those of a technical writer, an environmentalist, homemakers, and merchandising managers who were in cluster G1 (Table 1). They represented online opinion leadership, which depended on their capability to influence information flow by expanding information and affecting other actors by dispersing information [56] (Weimann, Tustin, Vuuren, & Joubert, 2007). The entire eco-friendly network in the eBGT Facebook is tightly connected, with 76,482 edges among 1612 vertices (Table 2).

Table 1. The top 10 actors leading the eBay Green Team (eBGT) Facebook Network.

Vertex ID *	Actor (Vertex) Identification **	Betweenness Centrality	Vertex Degree	Subgraphs
1. Abbey	Technical writer for green sales and marketing	88662.53	535	
2. Dasey	Homemaker	61438.79	557	
3. Gabrian	Environmentalist and eBay Top Seller Account Manager	51501.34	230	
4. Manacco	Merchandising Manager for Sustainable Commerce at eBay Inc.	49468.76	204	
5. eBay Green Team	Business Organization	39801.66	166	
6. Michelle	Homemaker	34725.05	416	
7. Brian	Creator of Social Media Toolkit for Sellers at eBay Inc.	34471.90	190	
8. Sydney	Financial provider of working capital for small businesses	31816.66	150	
9. Anderson	Global Manager, Social Innovation Employee Engagement at eBay Inc.	30304.12	201	
10. Yip	Social Project Manager at eBay Inc.	28182.94	161	

* To protect the actors' privacy, the real names have been changed. ** Each actor's API address profiles the demographic information such as gender, location, time zone, favorites, etc.

Table 2. Descriptive statistics of clusters.

Group	Vertices	Unique Edges	Edges with Duplicates	Total Edges	Average Geodesic Distance
G1	905	14616	673	15289	2.546
G2	228	25643	18	25661	1.004
G3	131	6852	79	6931	1.182
G4	130	5989	107	6096	1.270
G5	86	2798	14	2812	1.443
G6	73	1564	8	1572	1.445
G7	-	-	-	-	-
G8	8	28	0	28	0.875
G9	7	21	0	21	0.857
G10	6	11	0	11	0.846
G11	6	0	0	30	0.833
G12	4	6	0	6	0.750
G13	3	3	0	3	0.667
G14	3	3	0	3	0.667
G15	2	1	0	1	0.500
G16	2	1	0	1	0.500
G17	2	1	0	1	0.500
G18	2	1	0	1	0.500
G19	2	1	0	1	0.500

RQ2: Who Serves as Market Mavens, Surrogate Consumers and Opinion Leaders, and What Types of Social Interactions do the eBGT Clusters Have?

Based on the integration of class authenticity with their personal profile information in Table 1, vertex #1 (Abbey, a technical writer) might be a market maven, vertex #7 (Brian, a creator of a social media toolkit for sellers on eBay) is a surrogate consumer, and vertices #2 (Daisey, a homemaker) and #6 (Michelle, a homemaker) might be opinion leaders. In addition, Abbey was connected to all six clusters with a VD of 535 and the highest VBC (Figures 2 and 3). There is competition for attention given that excessive information overflow remains unceasing; thus, the influentials in the eBGT network are those who not only grab the attention of other users, but also compel the redistribution of information [57] (Xu, Sang, Blasiola, & Park, 2014).
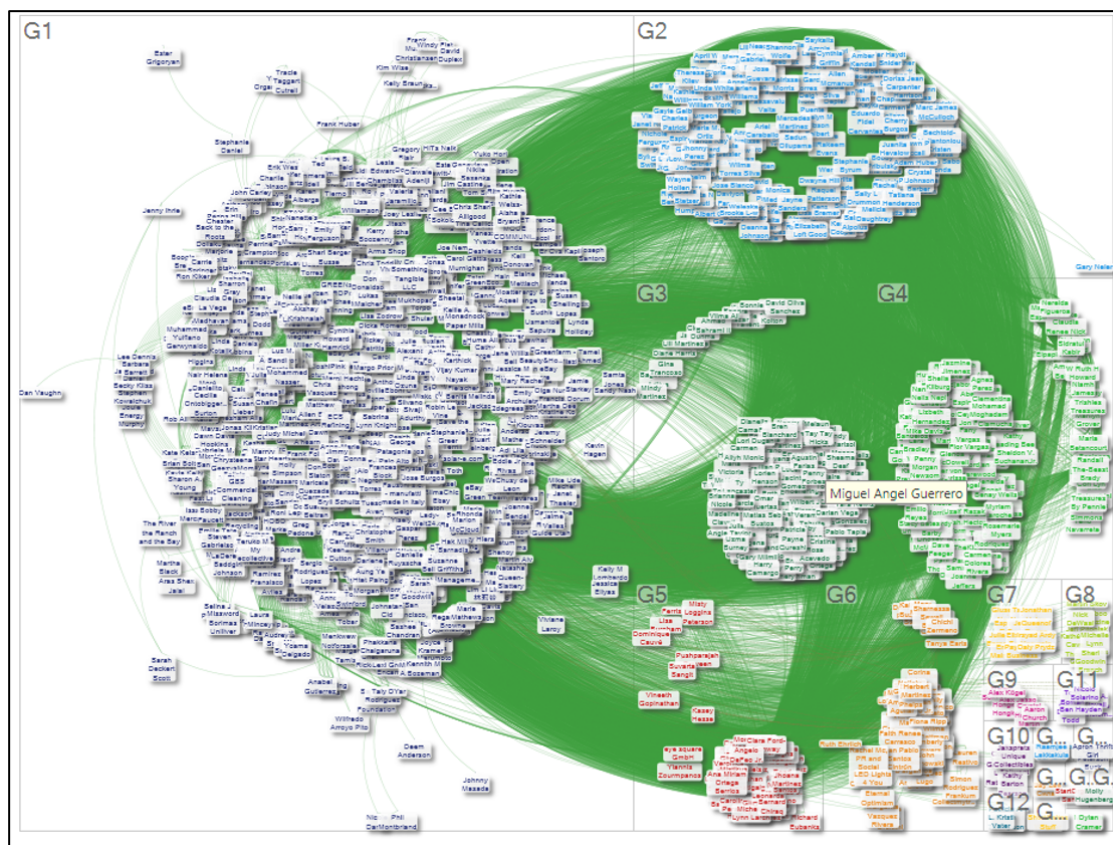

Figure 2. The entire network structure of eBay Green's Facebook network.

In order to identify the social agent–learner relationships of the entire group, cluster analysis was performed; this resulted in a total of 19 clusters. For categorization of the network structure among clusters, the data visualization was laid out using the group-in-a-box method with several iterations, especially those in clusters G1 through G19. Since the average geodesic distance of the six groups was over 1.00, and more than 97.1% of the total vertices and around 99.8% of the total edges were derived from the six groups (Table 2), we focused on these six clusters in our further analysis and interpretations.

As shown in Figure 2, the entire network is characterized by highly-interconnected consumers with few isolated participants. The entire network type is categorized as a 'Tight Crowd' network, according to Smith, Rainie, Shneiderman, and Himelboim's [58] (2014) typology. Consumers in a tight crowd network have strong connections to one another and significant connections that bridge between any clusters that follow, co-like, and co-comment on one another [58] (Smith et al., 2014). Cluster G1 is a salient sub-group composed of 905 vertices, including all top ten influentials (Table 1). Due to

the dominance of G1 and its top influentials on the entire network, we conclude that the eBGT has top-down communication with a social learning function, in which sharing and mutual support were facilitated by the eBay Green Team. Vertex #3, #4, #7, #9, and #10 from the eBGT formed an informal association of people who shared an interest in maintaining the network community. Comparing the intra-group metrics of the top six clusters (Table 2), we found that G2 was denser (total edges (TE) of 25,661 and average geodesic distance (AGD) of 1.004) than G1 (TE of 15,289 and AGD of 2.546). This implies that the eco-friendly market has been structured by the eBGT members and surrogate consumers from cluster G2, who had authenticity in the message content generator and built social interactions for seeking information.
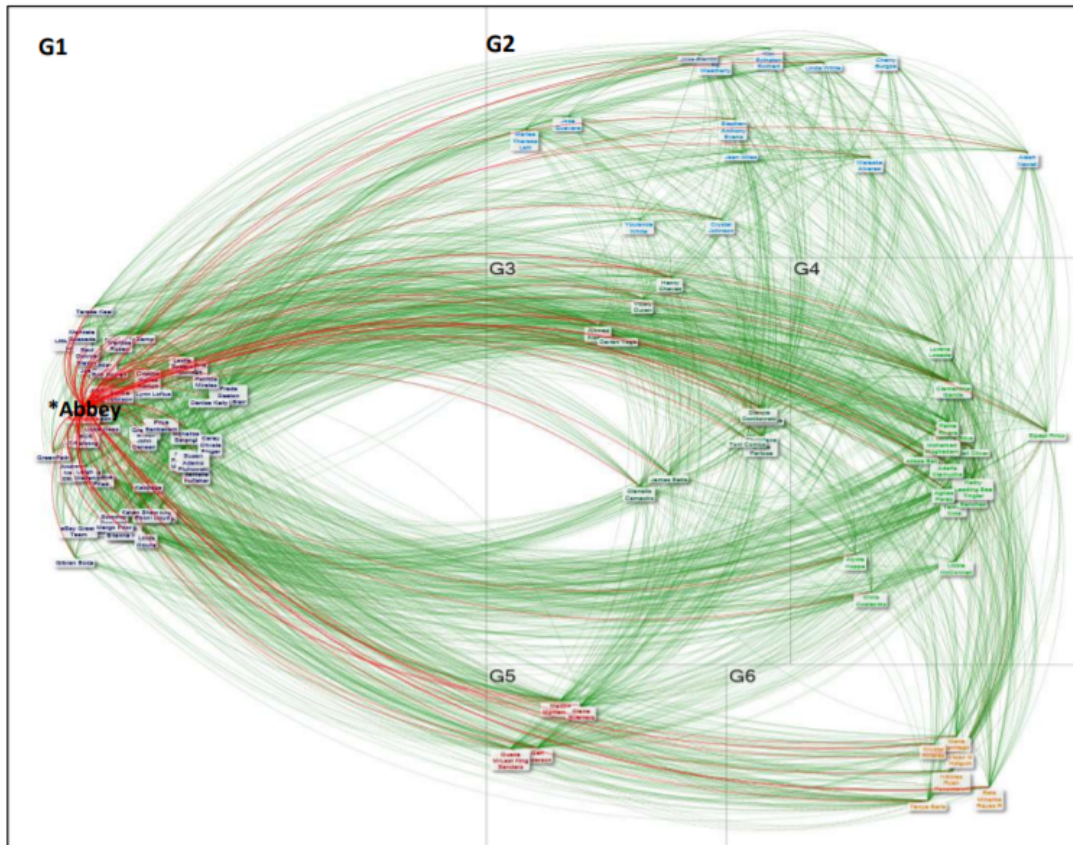

Figure 3. The filtered (by degree of 150 and betweenness centrality of 2251.75) visualization of eBay Green's Facebook network. * The red edges highlight the relations of the top influentials (Abbey) to the actors in other clusters.

To enhance the readability of the tight crowd network, we filtered out the data using a threshold of vertex degree (VD) of 150 and vertex edge betweenness centrality (VBC) of 2251.75. As shown in Figure 3, the tight crowd network was updated in a way similar to the 'Broadcast Network', according to the typology of Smith et al. [58] (2014). Often, social media commentary around breaking news stories and the output of well-known media outlets and analysts has a distinctive hub and spoke structure [58] (Smith at al., 2014). The top ten influentials, including 'Abbey' in G1, as powerful agenda setters and conversation starters, were most frequently connected with G4 (TE of 3201), followed by G2 (TE of 2786). Drawing on their profiles, we assumed G2 and G4 consisted of enterprises and personalities with loyal followers who had a large impact on the conversation. We noticed in Figure 3 that G1 had more than 40 dominant actors (the ID names are in each text box), and G2 and G4 were also composed of several opinion leaders and followers (N = 13 and N = 17, respectively) who might share a common interest, while conversations swirled around in other clusters.

RQ3: What are the Top Keywords and Word Pairs in the eBGT Network?

Consumer socialization in social media is a way to disseminate and learn about individuals' knowledge and opinions, which results in an accumulation of community knowledge [59] (Nonaka, 1994). The widespread use of Facebook provides opportunities for knowledge management and for making use of information intelligence that can be applied to merchandising informatics [11] (Kim, 2018). Semantic analysis can be conducted at different levels, such as the document, sentence, word, or feature levels. In this study, we conducted a semantic analysis at the word level to explore the contexts of posts and comments crafted by the actors of the eBGT network.

We systematically excluded common words such as "a," "about," "across," "after," "all," "almost," and "also." The count is case-insensitive so that "green" and "Green" are counted together. In the counting of word pairs, the word sequence is important: "give green" is counted separately from "green give." By counting words in a text column in addition to word pairs, while skipping the words and word pairs that occurred once, the NodeXL program calculated a "salience" which corresponded to the relative importance of interpretive semantics among all words appearing in the texts. This yielded the top ten words and word-pairs of the entire network and identified six clusters. While the top words from the six clusters carried only general messages, they might also have shared information with cognitive, affective, and behavioral engagement, as shown in a comment from 'Vertex # 1142.' His comment of *"REUSE is the PUREST form of recycling! Reselling your used electronics reduces the amount of resources extracted from the earth AND puts some cash in your pocket! Keep it up eBay!"* was shared in cluster G4 (VBC of 2855. 052) and was connected with 157 other consumers (VD of 157).

The top five words of G4 are 'green, ways, give, many, and physics' (Table 3), which might be characterized as a user-message matrix [55] (Hu et al., 2013). By examining the comments matrix, we can interpret whether they gained focus-related utility (i.e., concern for other consumers, aid to the company, social benefits, and the exertion of power), consumption utility (i.e., post-purchase advice-seeking), approval utility (i.e., self-enhancement and economic rewards), moderator-related utility (i.e., convenience and problem-solving support), and homeostasis utility (i.e., expressing positive emotions and venting negative feelings) [26] (Hennig-Thurau et al., 2004). Indeed, semantic analysis is an emerging research procedure due to its usefulness in terms of practical implications and providing research opportunities

Table 3. Semantic analysis: top word pairs.

Top 10 Word Pair of Entire group										
Rank	**Word 1**		**Word 2**		**Count**		**Salience**			
1	give		green		29898		0.0212			
2	ways		give		29296		0.0213			
3	many		ways		19770		0.0147			
4	ebay		green		9720		0.0079			
5	today's		pick		9697		0.0077			
6	green		know		9422		0.0076			
7	share		favorite		9347		0.0076			
8	now		until		9337		0.0076			
9	green		during		9316		0.0076			
10	during		holidays		9316		0.0076			
Top 5 Word Pairs by Groups										
Rank	**Group 1**		**Group 2**		**Group 3**		**Group 4**		**Group 5**		**Group 6**
1	give	green	ebay	green	Give	green	ways	give	ebay	green	gave	gave
2	ways	give	happy	Thanks giving	Ways	give	give	green	green	team	gave	taking
3	ebay	green	Thanks giving	ebay	Many	ways	many	ways	happy	new	taking	moment
4	many	ways	green	teamers	today's	pick	today's	pick	new	year	moment	honor
5	thoughts	prayers	give	green	Green	during	green	during	year	ebay	honor	brave

5. Conclusions and Implications

Sustainable networks often limit the accessibility to and measurability of prevailing consumers due to undistinguishable entities and the massive amount of information of this market segment [60] (Lee, Kim & Yang, 2015). Indeed, the study outcome provides an account of the development and

obsolescence of a sustainable network, the eBay Green Team Facebook community. We recognized that CS theory was pertinent to understanding the social class hierarchy, to recognizing the structural patterns of relationships among entities, and to exploring the learning properties of information on their socialization. Given the big data approach to social networks, SNA-based merchandising informatics was a better approach to explore who the top influentials were, what the type of the network was, and how information and relationships were shared among the entities. NodeXL, an analytic tool of SNA-based merchandising informatics, validated the method of identifying the influentials' hierarchy and the authenticity of the message content generators (i.e., market mavens, surrogate consumers and opinion leaders) by means of critical centrality measurements and semantic analysis. In addition, the network visualization algorithms of the NodeXL program exposed the directional ties and modeling behaviors of social interaction among the social entities.

We concluded that the eBGT initiative was a top-down, company-driven sustainable network which is now obsolete in the current eco-friendly network context. Three of our research questions can be resolved. Firstly, the entire eBGT Facebook network illustrated a 'Tight Crowd' structure pertaining to 76,482 relations among 1,612 vertices. The top ten influentials and the key social agents including the market mavens (vertex #1 Abbey, a technical writer), surrogate consumers (vertex #7 Brian, a creator for social media toolkit for sellers at eBay) and opinion leaders (vertex #2 Daisey, a homemaker; #6 Michelle, a homemaker) were identified in the Group 1 cluster. Secondly, the six meaningful clusters among the total number of 19 clusters illustrated that the vertices' social networking properties of homophily and heterophily between inter- and intra-clusters, such as vertex betweenness centrality and vertex degree, are key indicators [61] (Panagiotopoulos & Sams, 2012). G1 had more than 40 dominant actors (the ID names are in each text box in Figure 3), and G2 and G4 were also composed of several opinion leaders and followers (N = 13 and N = 17, respectively) who might share a common interest, while conversations swirled around in other clusters. The top ten influentials from G1 were most frequently connected with G4, followed by G2. Thirdly, the top keywords and word-pairs in a user-message matrix indicated multilateral information communication focusing on utility. The transitivity in the eBGT network demonstrated how information diffused through the authenticity of the message content generator, and the characteristics of the social agent–learner relationships revealed the patterns and structure of eco-friendly networks.

We suggest a theoretical application of consumer socialization to explore the development and obsolescence of the eBGT network. Two practical and academic contributions are as follow: firstly, the study improves our application of merchandising informatics to an eco-friendly community network through identifying the points of policy intervention or the marketing strategy; secondly, the consumer socialization model provides an empirical framework to test the strengths of different kinds of relationships in diverse clustering circumstances. This is important as the F & T discipline seeks to develop an empirical evidence base for particular assertions about eco-friendly behaviors, motivations, and behavioral changes in social and individual contexts [2] (Jackson, 2005).

Although this study has several implications, it also has certain limitations. First, the results of the API analysis indicate that the eBGT Facebook was involved in an information delivery hub. Downloading network data from large Facebook group pages can easily max out an individual computer's system memory if one does not limit the number of reactions, likes, and shares when setting up the data importer, which will result in a scattered network [62] (Müller & Thiesing, 2011). Second, Facebook is a commercial property and as such is not obliged to provide data. Many of the "edges" NodeXL extracted from Facebook are no longer available due to Facebook's changes in API public disclosure as of 2016. Reducing data access lessens the credibility and desirability of Facebook as a platform. As substitutes, several open-source SNA programs such as Ucinet, Pajek, Gephi, SNAP, and NetworkX provide diverse functions for merchandising informatics. Third, the results are limited in that a combination of words and nodes in a two-mode network would potentially provide a richer representation of the emerging field of big data science [63] (Leydesdorff, 2010). In the case of an eco-friendly market driven by policy initiatives, a combination of geographic and semantic perspectives

may be more informative. Therefore, such a perspective might complement merchandising informatics research in addressing questions concerning the emergence and interdisciplinarity of big data research. Given these limitations, future research should make possible a broader understanding of eco-friendly communication by focusing on its coordination and the cooperation among citizens, media outlets, and organizations. These entities are likely to play critical roles in providing an in-depth understanding of social networking driven by social media.

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