TOWARDS SUSTAINABLE CONSUMER-BRAND RELATIONSHIP BUILDING WITHIN HASHTAG-BASED ONLINE BRAND COMMUNITIES

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ABSTRACT

Growing impact of hashtags on rapidly reaching wider audience on social media platforms has called for investigating strategic ways to utilize its power in driving effective consumer engagement and facilitating community feelings attached to the brands. Extant literature has primarily focused on examining how consumers perceive the usage of brand-related hashtags and subsequent attitudinal and behavioral responses to adopt them on their own posts. In line with this effort to uncover the role of brand-related hashtags, such as brand community hashtags, particularly, this dissertation aimed to investigate the role of network structure of individual consumers nested within social media platforms and the interactive relationships with their neighbors that contribute to enhancing brand communication outcomes.

Drawing from social identity theory, optimal distinctiveness theory, and consumer-brand relationship literature, consumers' ego networks built through brand community hashtags on Twitter were examined by employing several computational methods, including data mining, social network analysis, computerized textual analysis, and sentiment analysis. The results revealed the positive impact of consumers' ego network size on enhancing content engagement through brand community hashtags in addition to the significant moderating influence of the strength of interpersonal relationship with their network neighbors on facilitating content reach and engagement on Twitter. In particular, findings shed light on understanding consumer roles in the perspectives of networked brand communication, and provide various theoretical and managerial implications.

DEDICATION

This dissertation is dedicated to my loving family who has been the strongest motivation to me getting through all challenges over the past years: my mom Hyeja Jang, my dad Jeonghoon Park, my husband Joonhyeok Ahn, and my dog Pepper. Mom, you have been my role model for life, teaching me how to become a brave woman with courage and resilience. I am now who I am because you have shown me the path to follow. Dad, your warmest heart and unconditional love have brought me up to be a better person each and every day. Your absolute trust in me has made me come this far. My lovely husband, Joonhyeok, thank you for being everything to me – the only shoulder to lean and cry on when I was breaking down, the warmest hug when I needed it the most, and the anchor keeping my feet on the ground when I was lost in the middle of nowhere. Pepper, the very first and most precious dog in my entire life, you finally and absolutely deserve this title, Dr. Pepper, after long days and nights patiently waiting for me to stop working and take you for a walk. You will never know how much I appreciate you for supporting me mentally and emotionally, even when other human beings cannot do anything for me.

LIST OF ABBREVIATIONS AND SYMBOLS

β	Unstandardized coefficient
z	A number representing how many standard deviations above or below the mean population the score derived from
t	Computed t-test value to determine means differ
p	Probability that a particular measure of an assumed probability distribution being greater/less than or equal to observed value
M	Arithmetic mean
SD	Standard deviation
SE	Standard error
s^2	Variance
$<$	Less than
$>$	More than
$=$	Equal to

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CHAPTER ONE

INTRODUCTION

Brand community hashtags have served as powerful anchors for online brand communication by generating brand awareness and fostering consumer-brand identification in digital platforms (Naraine, Pegoraro, & Wear, 2019). Exponential growth of such hashtags associated with brands, particularly on social media platforms, have influenced online brand reputation and consumer trust by engaging people in continuous conversations related to products or services (CMS Wire, 2020). Incorporating brand community hashtags in strategic communication planning for social media advertising can bring multiple benefits to brands such that brand community hashtags not only facilitate electronic word-of-mouth (eWOM) around the brands, but also get consumers involved in active consumer-brand interaction and relationship building through specific hashtags connecting consumers interested in the brands (B2C, 2021). In particular, popular brand community hashtags relevant to brands boost visibility of the content tagged to such hashtags and increase reach to a better targeted audience, improving conversion rate and growing advertising profit (B2C, 2021; eMarketer, 2017). A recent #PepsiNYCLocal campaign initiated by Pepsi, for instance, exemplifies the power of social media hashtags and how online brand communities developed around the hashtags could facilitate active consumer engagement (PR Newswire, 2021). By using #PepsiNYCLocal hashtag and tagging @Pepsi on social media posts, Pepsi fans could nominate people they know to be honored and recognized by the brand, leading to active engagement with brands and other consumers.

Recognizing the positive impact of brand community hashtags on enhancing overall consumer engagement experience associated with brands, advertising scholars have examined several relevant research agendas, such as the role of online brand community in consumer-brand engagement (CBE) and relationship building (e.g., Hollebeek, Juric, & Tang, 2017), consumer motivations tied to online brand community engagement (e.g., Shin & Perdue, 2021), and the effectiveness of brand community hashtags on advertising and brand outcomes (e.g., Kim & Hyun, 2019; Vermeer, Remmelswaal, & Jacobs, 2017). Hollebeek and colleagues (2017) further conceptualized brand community development in *online* platforms to understand consumers' sense of belonging associated with a brand-related community and to identify such community development as a value creation process wherein the *identity* of consumers is actively engaged in brand-related behaviors. Within the online brand communities, various factors contribute to enhancing consumer-brand engagement. Individual consumers' utilitarian or hedonic motivations, for example, can boost intention to participate in brand-related eWOM behaviors (Kim & Hyun, 2019), and altruism and social identification motivations may also increase consumers' online brand community engagement behaviors (Lee, Kim, & Kim, 2011). More specifically, consumers' intention to use brand community hashtags is influenced by perceived community membership (Yang, Sun, Zhang, & Mei, 2012) and platform usage motivation (Erz, Marder, & Osadchaya, 2018).

Consumer engagement through online brand communities then contributes to developing and maintaining consumer-brand relationships (CBRs) in the long term (Lyu & Kim, 2020). CBRs are conceptualized as consumers' relational commitment developed toward a brand, built upon consumer trust and satisfaction (Fournier & Yao, 1997; Hess & Story, 2005). Several empirical studies have demonstrated that consumer engagement on digital and social platforms

leads to active involvement associated with brands, which then helps strengthen CBRs and foster a sense of belonging or community linked to the brands (Baker & Walsh, 2018; Carlson, Suter, & Brown, 2008; Kim & Hyun, 2019). In that sense, online brand communities serve as one of the influential arenas for CBE and relationship building (Swimberghe, Darrat, Beal, & Astakhova, 2018).

Online brand communities are any online communities developed for people who share common interests around certain brands where consumers can interact with brands as well as other consumers. Moreover, such common interests around brands gradually develop to shape consumers' social identities such that consumers feel psychological connectedness toward brands and identify themselves with shared images or personalities of the brands (Carlson et al., 2008; Lyu & Kim, 2020). Ultimately, consumers' social identities developed with brands in online brand communities then lead to in-group favoritism toward the brands strengthening the group membership, which in turn facilitates active CBE and CBR building over the long period of time.

Previous findings from empirical studies generally support the idea that brand communities built upon consumer-brand identification enhance consumer engagement and that leads to continuous consumer participation in brand-related behaviors (e.g., Wang, Tai, & Chang, 2019). Among various affordances in social and digital platforms, research has also shown that hashtags play significant roles in driving consumer engagement and achieving broader reach (Saxton, Niyirora, Guo, & Waters, 2015). According to Saxton et al. (2015), growing an online community around specific hashtags and promoting such hashtags attached to a brand or organization could advance the effectiveness of social media messaging. Consumers do adopt the hashtags to present their identities associated with the specific community, and that drives more engagement on social media platforms (Erz et al., 2018). As articulated, hashtags

could serve as a symbol of group membership and self-presentation (Baker & Walsh, 2018) and accessible structure for stimulating effective brand communication to build sustainable consumer-brand relationships (Fedushko & Kolos, 2019; Naraine et al., 2019).

Despite the abundance of research on this topic, relatively few empirical studies have demonstrated how consumers' social identities are associated with in-group perception toward online brand communities to develop networked communities associated with brands, consequently facilitating brand-related content sharing centered around brand community hashtags. Specifically, the role of brand community hashtags (e.g., #MiniMonday, #SmoothSquad) that differs from that of general brand hashtags referring to mere brand names or products (e.g., #MiniCooper, #GilletteVenus) warrants further investigation. As a symbolic tool for representing consumer identities associated with certain brands (see An et al., 2019), brand community hashtags can offer an influential forum for consumers to group together with other consumers who identify similarly with the favorable brands. As such, hashtags are important in brand communication context to organize and establish structure to on-going conversations about brands through online brand communities. Furthermore, little is known about what consumer factors in hashtag networks amplify such impact of consumers' social identity on brand community participation and subsequent brand-related communication outcomes (e.g., Erz, Marder, & Osadchaya, 2018). Considering the expanding role of consumers on social media platforms who serve multiple roles going beyond mere content creators (Liu-Thompkins, Maslowska, Ren, & Kim, 2020), it is important to uncover what makes consumers powerful in participating in the networked communities and facilitating conversations about particular brands on social media in addition to understanding the role of major social media affordances, such as brand community hashtags.

The focus of this study is twofold. First, this study hopes to understand how consumers' in-group perception toward online brand communities in social media platforms facilitate content sharing through brand community hashtags. Second, this study aims to extend the scope of understanding consumer perspectives toward online brand community participation to exploring consumers' roles as influential communicators within networked communication by considering interpersonal relationships with network neighbors.

Grounded in social identity theory (Tajfel & Turner, 1979) and optimal distinctiveness theory (Brewer, 1991), consumers' social identities as well as their two conflicting needs for inclusiveness and distinctiveness associated with brands would significantly influence their brand-related behaviors on Twitter through brand community hashtags (Graham & Wilder, 2020; Leonardelli, Pickett, & Brewer, 2010; Kim, Park, Lee, & Park, 2018). Taking a computational approach, this dissertation employs social media data mining, social network analysis, and computerized textual analysis to examine sustainable consumer-brand engagement and relationship building through online brand community hashtags on Twitter. By doing so, this study hopes to contribute to broadening the scope of CBR research and understanding consumer perspectives associated with online brand communities and related hashtags as well as actual behaviors of consumers manifested in social media platforms.

This dissertation is structured as follows: Chapter 2 reviews relevant literature around online brand community and brand community hashtag usage for brand communication on social media. Chapter 3 elaborates the theoretical background of social identity theory and optimal distinctiveness theory applied in the context of online brand community, and proposes hypotheses. Chapter 4 explains methodological approaches employed to test the hypotheses, including several computational methods. Chapter 5 describes and reports findings from the

computational data analyses. Chapter 6 discusses the key findings and implications of this dissertation and suggests directions for future research.

CHAPTER TWO

LITERATURE REVIEW

Vast academic attention has been paid to exploring how consumers engage with online brand communities and the positive impact of consumer engagement behaviors (CEBs) and consumer-brand relationship (CBR) building through online brand communities on advertising and brand outcomes (Kim & Hyun, 2019; Vermeer, Remmelswaal, & Jacobs, 2017). Consumer participation in online brand communities facilitates active engagement involving other consumers and brands such that consumers involved in the communities are likely to identify with the brands favorably and interact with other consumers who share and represent common identities associated with the brands (Carlson, Suter, & Brown, 2008; Swimberghe et al., 2018). Consumers of the brand Jeep, for instance, tend to get involved in their online brand communities around Jeep by using #JeepNation or other brand-associated hashtags to show off their attachment to the Jeep car ownership and sharing community perception with the other fellow consumers who own Jeep cars. This consumer identification with the brands and other consumers through online brand communities, then, leads to fostering meaningful brand-related behaviors, such as spreading positive electronic word-of-mouth (eWOM) about the brand and sharing brand experiences on online platforms such as social media (Kaur, Paruthi, Islam, & Hollebeek, 2020).

Social media as a popular interactive platform offers effective tools for consumers to communicate about brands with others wherein brand community hashtags, in particular, become an influential anchor for conversations (Baker & Walsh, 2018; Naraine et al., 2018). By locating

the shared brand community hashtags and actively adopting them in social media content, those who share common interests around certain brands are spontaneously involved in the ongoing brand-related conversations (Vermeer et al., 2017). As an effective tool for carrying brand communication, brand community hashtags contribute to enhancing advertising and brand outcomes (e.g., brand attitude and loyalty, eWOM and purchase intention, consumer-brand relationship strength) in favor of the earned media actively circulated by consumers that could eventually save brands' advertising spending at large (Baker & Walsh, 2018; Dwyer & Marsh, 2014; Kim & Hyun, 2019).

Therefore, it is worth investigating how consumer use of brand community hashtags facilitated from consumer identification within networked online brand communities ultimately contributes to enhancing advertising and brand outcomes on social media by reaching and engaging a wide range of fellow consumers identified as in-group. In that sense, this dissertation hopes to disentangle how online brand communities thrive with consumer participation and provide empirical evidence of consumers engaging in online brand communities to connect with other consumers as well as brands, and to build and maintain sustainable consumer-brand relationship on a popular social media platform, Twitter. By doing so, this dissertation may extend the current understanding of online brand communities and the role of brand community hashtags by providing useful strategies to leverage active consumer participation that brings positive brand communication outcomes benefiting brands that target consumers on social media. Figure 1.1 below outlines overarching conceptual background of how brand community hashtags serve as effective tools for sustainable online brand engagement.

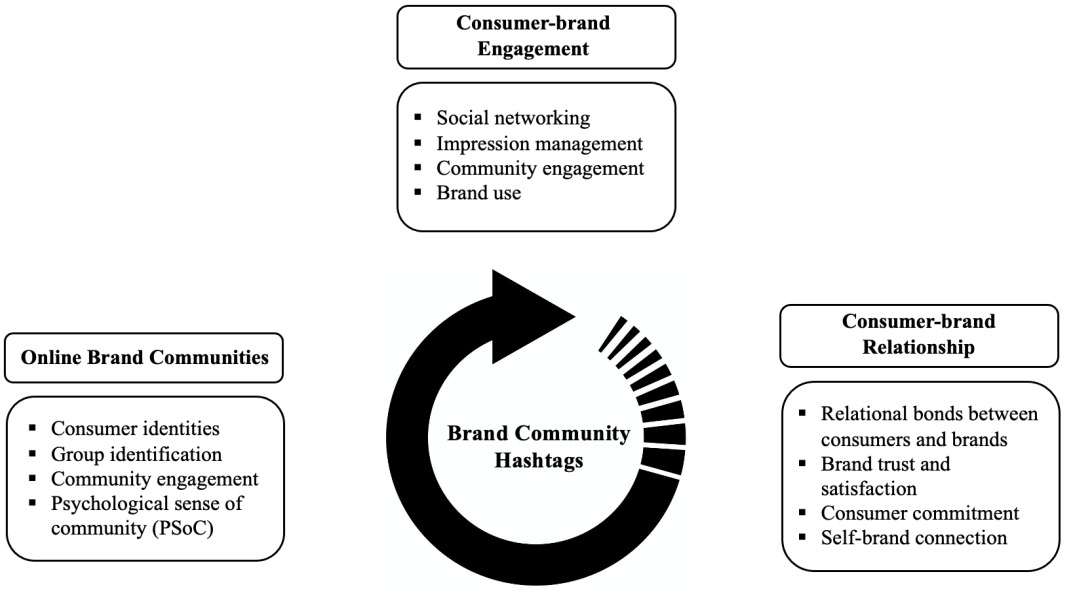

Figure 1.1. Conceptual Background of Sustainable Online Brand Engagement

Online Brand Community and Consumer-brand Engagement

Online brand communities (OBCs) are digital arenas where consumers and brands co-create shared value (Kaur et al., 2020). Within the online brand communities, utilitarian or hedonic values are attached to the brands through continuous consumer participation maintaining close relationships with both brands and other consumers (Wang, Tai, & Chang, 2019). Consumers who join the OBCs and actively engage in brand-related conversations tend to strongly identify themselves with the brand (Carlson et al., 2008; Swimberghe, Darrat, Beal, & Astakhova, 2018). The extent to which consumers identify with the brand (hereafter *consumer identity*), is highly related to OBC affiliation being an essential factor representing consumers' perceived value on digital platforms (Bhattacharya & Sen, 2003). Moreover, those who strongly identify with the OBCs (i.e., group identification) not only develop a sense of belonging to brand and the community, but they also tend to more actively participate and engage in conversations within the communities (Muniz & Schau, 2005; Wirtz, Ambtman, Bloemer, Horvath, Ramaseshan, Van de Klundert, Canli, & Kandampully, 2013).

Extant literature on OBCs has focused on conceptualizing how OBCs function as an effective tool for the consumer-brand co-creation process (Hollebeek, Juric, & Tang, 2017; Madupu & Cooley, 2010). Empirical efforts have followed to further investigate its meaningful impact on consumer engagement (Baldus, Voorhees, & Calantone, 2015) and attitudes and behaviors associated with the brands (Jung, Kim, & Kim, 2014). Jung et al. (2014), for example, found that social and informational benefits tied to OBCs enhanced consumer attitudes toward the community, which subsequently facilitated consumers' continuous community participation and brand trust. Similarly, Wang et al. (2019) illustrate that social media affordances and brand engagement drives continuous engagement by allowing consumers to build connections between community members by tagging or following others. Indeed, previous OBC literature supports the claim that OBCs serve as an interactive and helpful platform for consumers and brands to get together and form a shared community perception around the brands.

In particular, a great deal of studies has focused on discovering how consumer identities have a critical impact on increasing consumers' group identification and, subsequently, community engagement behaviors within the OBCs (Islam et al., 2018; Kaur, Paruthi, Islam, & Hollebeek, 2020; Lee et al., 2011; Shalev & Schrift, 2019). Particularly, the number of social ties an individual consumer has directly connects to the impact of one's consumer identity on other consumers within OBCs (Noyan, 2017; Shalev & Schrift, 2019). That is, those who have a greater number of social ties in an OBC (e.g., influential users who have a high number of followers) are more likely to spread brand-related information to those who have a relatively smaller number of ties on a social network (Noyan, 2017).

Moreover, several empirical studies ascertain the role of consumer identities and the number of social ties attached to them on enhancing brand community identification and

engagement outcomes (Coelho, Rita, & Santos, 2018; Lam et al., 2020; Liao, Yang, Wei, & Guo, 2019; Shalev & Schrift, 2019). Shalev and Schrift (2019), for instance, demonstrated that consumers who have a large number of social ties tend to show higher levels of group identification with the brand community, supporting the notion that strong consumer identities tied to a brand may lead to active brand community engagement. In addition, Islam et al. (2018) conducted an online survey among the members of OBC on Facebook and found that perceived congruity of consumers between the self and brand image significantly facilitated consumer engagement behaviors (CEBs) on Facebook, increasing brand loyalty as a result. Similarly, Kaur et al. (2020) provided additional empirical support to the idea that consumer identification with brand and the presence of reward positively influence consumer brand engagement and brand loyalty. Taken together, findings of the aforementioned studies imply that consumer identity association with brands and consumers' brand community identification significantly influence consumer-brand engagement within online brand communities.

The idea that consumers' sense of belonging is deeply associated with online brand community engagement can be explained through the psychological concept of psychological sense of community (PSoC); PSoC is one's perception of similarity to others where a person develops emotional connectedness and beliefs interdependent with others within a larger community (Hill, 1996; Lyu & Kim, 2020; Sarason, 1974). This perception of connectedness further extends to shared emotion when interacting with others in the community. Therefore, it is imperative to understand consumers' PSoC in the context of consumer engagement behaviors within the OBCs in that one's perceived affiliation with a brand and other consumers within the OBCs (i.e., consumer identities) is amplified through the impact of PSoC developed from any communication and interaction among consumers (Blanchard, 2007; Swimberghe et al., 2018).

In other words, the impact of consumer identities associated with brands and OBCs on consumer engagement and relationship building behaviors is linked cohesively to the role of PSoC in effect throughout the processes (Lyu & Kim, 2020).

Applying the concept of PSoC in OBC context, Lyu and Kim (2020) examined the dynamic interrelationships among social media and consumer factors (e.g., perceived interactivity, consumer-brand relationship) and brand factors (e.g., self-brand connection, brand commitment), and their impact on brand attitude and purchase intention associated with social media advertising. Findings of this study imply that consumers' PSoC around social media brand communities enhances brand attitude and commitment, revealing the critical role of PSoC in leveraging positive advertising and brand outcomes on social media.

Scholarship around consumers' community identification and PSoC, then, extends to examining meaningful consumer-brand engagement behaviors (CEBs) involved in OBCs. Early pioneering efforts to identify CEBs in online brand communities aimed to identify the underlying anatomy of consumers' collective value creation process in brand communities (Hollebeek et al., 2017; Schau, Muniz Jr., & Arnould, 2009). Schau and colleagues' (2019) seminal work systematically analyzed practices of 12 existing brand communities conceptualizing brand community engagement behaviors with four components: social networking, impression management, community engagement, and brand use. Each of these four dimensions connects to the mechanisms of which consumers interact with others and develop relationships within brand communities. In particular, *social networking* represents CEBs creating and sustaining relational ties among brand community members (e.g., welcoming and empathizing members). *Impression management* extends it to any external endeavor (e.g., evangelizing and justifying) of brand enthusiasts who are dedicated to creating positive and favorable brand impressions beyond the

brand community itself. Then, *community engagement* involves practices reinforcing brand community members' active engagement within the community (e.g., staking, milestoning, and documenting). Lastly, *brand use* is associated with any improved use of the brands, such as customizing or commoditizing their products. Essentially, Schau et al. (2009) viewed various types of consumer engagement in brand communities as meaningful collective CEBs that create shared value communicated among consumers, and between consumers and brands.

Among the four identified CEBs, social networking and community engagement elements are particularly helpful to understand how consumers actively engage with other consumers and brands within the *online* brand community. Social networking practices of brand communities focus on creating, enhancing, and maintaining social ties among brand community members (Schau et al., 2009). Community engagement practices foster community members' engagement with the brand community by emphasizing distinctions among community members and providing members with social capital associated with the community (Schau et al., 2009). Later work by Hollebeek et al. (2017) further refined this typology to encompass the unique context of *online* brand community adding four factors (i.e., assisting, appreciating, empathizing, and mingling) specifically dealing with online brand community engagement behaviors. This conceptualization places more importance on the sense of belonging in online platforms than the original model proposed by Schau et al. (2009). In the context of online brand communities, it demonstrates that *consumer identities* are deeply associated with CEBs occurring within the online brand community such that shared consumer identities among fellow consumers facilitate appreciative attitudes toward particular brands in favor of the sense of belonging, which leads to actively getting involved in conversations with consumers about the brands in online platforms.

Consumer involvement in and connection with online brand communities through CEBs are important to building and sustaining lasting consumer-brand relationships.

Sustainable Consumer-brand Relationship Building through Online Brand Community

Consumers not only develop a PSoC and engage in brand-related behaviors, but they also develop relationships with brands built upon continuous interaction (Hess & Story, 2005; Martínez-López et al., 2021; Park & Kim, 2014). CBRs are critical factors to consider when understanding consumers' online brand community participation. It serves as a major driving force for consumers to continuously be involved in ongoing conversations around brands. Fournier and Yao (1997)'s theoretical discussion of CBRs suggests that the consumer-brand relationship should be an alternate and overarching concept of traditional brand loyalty. In their theoretical argument, a CBR is viewed as a dynamic and evolutionary phenomenon wherein the power of both brand and consumer is considered to explain strong relational bonds between the two. A later study by Hess and Story (2005) refined the CBR as a multidimensional concept that indicates relational commitment a consumer develops based upon brand trust and satisfaction (Hess & Story, 2005). Moreover, Khamitov, Wang, and Thomson (2019)'s meta-analysis adds that elasticities of consumer-brand relationship may vary across brand types, brand loyalty, time, and individual consumer characteristics.

Grounded in the theoretical development of CBRs, numerous empirical studies examined significant factors that contribute to CBR building. One of the major factors involved in the process is consumer perception of self-brand connection. Self-brand connection refers to the extent to which one's self-concept is connected to a brand, being symbolically representative of who consumers believe they want to be (Chaplin & John, 2005; Fournier, 1998). This cohesive linkage between the brand and self-concept of consumers has been identified as a significant

driving force of emotional experience with the brand (Park, MacInnis, Priester, Eisingerich, & Iacobucci, 2010). Consequently, consumers with higher level of self-brand connection would respond to brand-related messages more favorably than those with lower level of self-brand connection (Cheng, White, & Chaplin, 2012). Furthermore, Swaminathan, Page, and Gurhan-Canli (2007) pointed out that consumers' self-construal, defined as a "constellation of thoughts, feelings, and actions concerning one's relationship to others such as the self being distinct from others or connected to others" (Singelis, 1994, p. 581), plays an important role in influencing the effects of self-brand connection and cultural orientation. From a CBR perspective, brands as highly symbolic entities are intricately connected to consumers' life, thus shaping how consumers communicate their individual and group identities with others. Likewise, findings of Swaminathan et al. (2007) extended this understanding to reveal that brands could strengthen consumer identities at the individual (i.e., self-brand connection) and group level with the moderating effect of self-construal.

Consumer-brand relationships cultivated over the series of meaningful interactions are important to amplify consumer-engagement behaviors (CEBs) on social media (Confos & Davis, 2016; Hamzah, Wahab, & Waqas, 2021; Hayes, Golan, Britt, & Applequist, 2020; Hayes, Shan, & King, 2018). Empirical evidence suggests that strength of consumer-brand relationships not only contributes to enhancing brand-related content sharing intention on social media by itself (Hayes et al., 2018), but also intertwines with consumer characteristics such as motivations and consumer-brand identification to influence CEBs on social media (Hayes, King, & Ramirez Jr., 2016; Hamzah et al., 2021). Hayes et al. (2020), for example, investigated the role of consumer-brand relationship (CBR) strength in driving positive outcomes toward native advertising on Twitter and revealed that CBR strength directly boosts brand attitude, purchase intention, and

sharing intention. It is noteworthy that such a positive impact was present when the native ad was authored by peers who maintained a certain level of social ties with the consumers. Another study by Hamzah et al. (2021) found that consumer-brand relationship increased CEBs with brand posts on social media by triggering consumers to respond positively to interactive and novel brand posts.

In order to enhance sustainability of consumer-brand relationships, it is also important to note that the quality of consumer-brand relationship depends on various factors to overcome immediate interaction between consumers and brands. Park and Kim (2014), for example, empirically investigated how perceived benefits of a brand's social network website impact consumer's relationship with the brand's social network, enhancing loyalty behaviors. The study found that a more beneficial brand's social network website would positively influence consumer perceptions of relationship investment by brand and enhance the quality of consumer-brand relationship and increase positive WOM intention (Park & Kim, 2014). Similarly, Hudson, Huang, Roth, and Madden (2016) found that consumers' social media use is closely related to consumer-brand relationship building such that those who engage with brands on social media are more likely to develop enhanced consumer-brand relationship quality. Moreover, such an effect is amplified with higher levels of brand anthropomorphism, meaning how much people associate human characteristics with the brands (Hudson et al., 2016). Indeed, a mixed-method study by Kim, Park, and Kim (2014)'s demonstrated that high quality of consumer-brand relationship would further enhance consumer evaluations of brand extensions, particularly for low-fit brand extensions where the extension and parent brand are in similar product categories with different product attributes. Therefore, it is important to scrutinize what determines the overall quality and sustainability of consumer engagement behaviors (CEBs) and relationship

building. In the following section, key determinants of consumer-brand engagement and relationship building are discussed in detail.

Key Determinants of Consumer-Brand Engagement and Relationship Building

Extant literature has attempted to identify key determinants of consumer-brand engagement and relationship building and discussed meaningful advertising and brand outcomes associated with it (Chang & Chieng, 2006; Huber, Vollhardt, Matthes, and Vogel, 2010; Smit, Bronner, & Tolboom, 2007). Among various factors, four key determinants are discussed and summarized in this section: s*elf-concept/congruence*, *commitment*, *norms*, and *demographics/culture*.

Self-concept and congruence. As briefly introduced in the previous section, consumers' self-concept and perceived similarity between themselves and a brand (i.e., congruence) are closely related to how they think or feel about a brand and interact with it, ultimately building a meaningful relationship (Chaplin & John, 2005; Fournier, 1998; Park et al., 2010; Thakur & Kaur, 2015). According to Fournier (1998), self-concept in brand communication context is defined as the extent to which a brand expresses core values and contexts of consumers' self-image and identity. A later empirical investigation of Swaminanthan et al. (2007) then demonstrated how brands can strengthen consumer identities such that consumers can use the brand image as a tool to reflect their self-image and personal interests. This dynamic interaction between consumers' self-concept and brands subsequently influences consumer-brand relationships (Thakur & Kaur, 2015). A cross-sectional survey conducted by Thakur and Kaur (2015) found that consumers' self-concept positively influences female consumers' attitudinal brand loyalty in evaluating luxury fashion brands, also reflected in their purchasing behaviors.

Relevant to self-concept, the extent to which consumers perceive similarity with a brand also becomes essential in consumer-brand relationship building. Huber et al. (2010), for instance, identified significant antecedents of brand relationship quality and found consumers' actual self-congruence, functional congruence, and ideal self-congruence positively predict brand relationship quality, which consequently enhances repurchase intention. On the brand's side, another study by Smit et al. (2007) argued that there are certain brands that are more suitable for relationship building with consumers than others, demonstrating that brands with a unique and hedonic personality would be more likely to be perceived as a partner, decreasing the fear of consumers' inappropriate privacy concerns or protection.

Commitment. Consumers' commitment is another key construct that influences consumer-brand relationships (Hess & Story, 2005). Commitment in the context of consumer-brand relationships refers to "consumers' ultimate relationship disposition, encompassing beliefs, attitudes, and behaviors toward the brand and their relationship with that brand" (Hess & Story, 2005, p. 314). Elaborated as a multidimensional concept, the nature of consumer-brand relationship points to the important role that consumer trust and satisfaction plays to build and shape commitment toward a brand (Delgado-Ballester & Munuera-Alemán, 2001). With this conceptualization, several studies explored how consumer commitment positively reinforces consumer-brand relationship building (Brodie, Ilic, Juric, & Hollebeek, 2013; Sung & Choi, 2010). Sung and Choi (2010), for example, examined the dynamic interplay among significant factors contributing to consumers' commitment to relationship building with brands, such as satisfaction, alternatives, and investment. The findings indicated that consumer satisfaction and investment with lower attractive alternatives would lead to enhancing the level of consumers' commitment to the relationship with a brand. Likewise, Brodie et al. (2013) supported the idea

that actively engaged consumers in brand communities would show greater consumer loyalty, emotional bonding, trust, and commitment, which then helps building consumer-brand relationships.

Norms. Norms also play key roles in determining how consumers engage with brands and build relationships with them in that consumers and brands becoming active primary communicators in online brand communities are largely influenced by how consumers perceive social norms around the interaction (Aggarwal, 2004; Valta, 2013). Treating brands as relationship partners, consumers are likely to mirror human social interactions when interacting with the brands (Chang & Chieng, 2006; Fournier, 1998). Aggarwal (2004) endorsed the theoretical premise that consumers form relationships with brands based on the relational norms of interpersonal relationships which guide subsequent brand evaluations. Additionally, Valta (2013) later found that consumers' relational norms and brand relationship quality would significantly mediate consumer-brand relationships such that relational norms become an important driver for enhancing brand relationship quality, indirectly influencing brand loyalty.

Demographics/culture. Similar to how norms come into play when consumers engage with brands and develop relationships with them, there are also some demographic and cultural influences that are worth noting in consumer-brand relationship literature (Chang & Chieng, 2006; Hudson et al., 2016). Chang and Chieng (2006)'s cross-regional study revealed that one's individual and shared experiences associated with brands affect brand association differently following their own cultural background, which influences brand attitude and shapes consumer-brand relationships in a unique way. Furthermore, one's cultural background could have a meaningful impact on brand anthropomorphism, which refers to the perception of brands associated with actual human beings carrying a variety of emotional states and conscious

behaviors and acting as a member of social ties (Puzakova, Kwak, & Rocereto, 2009). Indeed, a study conducted by Hudson et al. (2016) observed that the perception of brand anthropomorphism increases brand relationship quality such that consumers from higher levels of anthropomorphic culture would experience enhanced quality of the relationship (Hudson et al., 2016).

Role of Brand Community Hashtags in the Era of Computational Advertising

Academic discussion on consumer identities and consumer engagement behaviors through online brand communities was further extended to uncover what specific affordances of popular digital platforms (e.g., social media) may contribute to enhancing consumer-brand engagement and relationship building. One of the primary affordances which consumers interact one another with is hashtags, so-called brand community hashtags, in this specific context. *Brand community hashtag* refers to a unique tagging format with a symbol # that is shared among social media users who have similar interests and opinions about a brand, connecting the users and categorizing brand-related content through its searchable feature (Dwyer & Marsh, 2014; Moorley & Chinn, 2014). Brand community hashtag research has addressed a wide range of topics, including consumer-brand identification and brand community development (Hollebeek, Juric, & Tang, 2017; Schau, Muniz, & Arnould, 2009), consumer engagement within the brand community (Islam, Rahman, & Hollebeek. 2018; Lee, Kim, & Kim, 2011), and the influence of brand community hashtags on advertising and brand outcomes (Baker & Walsh, 2018; Erz, Marder, & Osadchaya, 2018; Kim & Hyun, 2019; Naraine, Pegoraro, & Wear, 2019; Wang, Tai, & Chang, 2019). Studies showed that brand community hashtags allow consumers who share common interests around specific brands to share information and emotions attached to the brands, and serve as a useful tool for any consumers to locate the brand-related content (Baker &

Walsh, 2018; Kim & Hyun, 2019). By sharing common brand community hashtags, online brand communities not only foster continuous and active participation of consumers, but also contribute to increasing consumer-to-consumer interactions associated with the brand-related content within the online brand community networks (Naraine et al., 2019).

In fact, emerging trends in computational advertising research have called for the importance of investigating key anchoring factors driving active CEBs on digital platforms, such as brand community hashtags, to facilitate brand-related content diffusion on social media (Araujo, Copulsky, Hayes, Kim, & Srivastava, 2020; Huh & Malthouse, 2020). In an effort to uncover the dynamics present in social media platforms, several studies have analyzed the role of hashtags, keywords, interactive content, and unique communicators within social media (Araujo, Neijens, & Vliegenthart, 2015; Ibrahim & Wang, 2019; Matz, Segalin, Stillwell, Muller, & Bos, 2019; Yun, Duff, Vargas, Sundaram, & Himelboim, 2020). Araujo et al. (2020) articulated that media planning in this emerging area of computational advertising should consider fostering CEBs and planning meaningful and sustainable interaction with consumers in developing ecosystems. The authors noted that it is essential to understand why consumers engage in brand-related behaviors in various platforms and how non-behavioral dimensions of engagement, such as cognitive, affective, and social elements, become important to influence consumer engagement behaviors in the changing environment (Araujo et al., 2020). Yun et al. (2020) further notes methodological advancement in computational advertising research by reviewing several computational techniques (e.g., topic modeling) applied to effectively identify dominant topics in the content around brands shared in social media platforms.

Specific to the effectiveness of brand community hashtags in this line of research, previous research findings have been fairly consistent, showing that brand community hashtags

are helpful to trigger continuous engagement with branded content shared on social media and to broaden reach by making it easier for consumers to locate information about products and brands (Kywe, Hoang, Lim, & Zhu, 2012; Wang, Tai, & Chang, 2019). On social media platforms, brand community hashtags could bring ongoing brand-related conversations together and make them viral not only limited to the particular brand community, but also in a broader range of audiences present on the platform (e.g., Kywe et al., 2012). Despite the positive impact of brand community hashtags on consumer engagement observed in some studies, a few other studies reported the opposite outcome. Vermeer et al. (2017)'s case study on Heineken's social media reputation management, for instance, revealed that the use of Heineken-related hashtags negatively influenced online consumer engagement. This is contradictory to Kywe et al. (2012) and other studies that found hashtags would generate higher engagement. This contradictory findings in the literature may emerge from various conditions of sample brands and/or context where each study is implemented. For instance, the sample brand (i.e., Heineken) of Vermeer et al. (2017) belongs to low involvement – feeling category brands (Vaughn, 1980) where consumers' effort and involvement are deemed lower than the other categories while other studies, such as Kywe et al. (2012), did not specify the categories or context of each brand examined or consumer characteristics of the specific brands for the hashtag effectiveness.

Among the studies taking consumer-centric approach, Wang et al. (2019) revealed that in consumers' point of view, hashtags and bookmarks are perceived useful to build connections among online brand community members, and found that hashtags could facilitate co-creation experiences, leading to continuous participation. Although a growing amount of computational advertising research implies that hashtags are effective in disseminating brand-related content, what becomes essential is to understand consumers' spontaneous and active participation as an

important driving force that amplifies the impact of brand community hashtags on advertising and brand outcomes. The following section focuses primarily on the expanding role of consumers involved in brand communication on social media and how consumers contribute to creating and sharing content within brand community hashtag networks.

Consumer Participation in Brand Community Hashtag Networks

Consumers in a rapidly changing media environment have become active communicators who serve multiple roles (e.g., creators, metavoicers, propagators; see Liu-Thompkins, Maslowska, Ren, & Kim, 2020) and actively participate in brand-related activities on social media. Liu-Thompkins et al. (2020)'s conceptual framework for user-brand relationships points out that consumers participate in brand communication not only by passively consuming the content, but also by creating, amplifying, and interacting with brand-related messages. Based on this framework (Liu-Thompkins et al., 2020), consumer participation in brand community hashtags can also be considered with multiple roles of consumers adopting the hashtags in their own content (i.e., creator), amplifying the impact of the hashtags (i.e., metavoicer), and actively forwarding and sharing the hashtags (i.e., propagator).

Previous studies have closely explored how consumers use brand community hashtags throughout their social media experience. Baker and Walsh (2018) analyzed Instagram posts to investigate how social media users use hashtags to represent their identities on social media platforms. Findings of the study revealed that Instagram users use hashtags as a tool for self-presentation as well as a symbol of group membership on social media. Similarly, Erz et al. (2018) further identified what motivates social media users to use hashtags on Instagram, and found that social media users produce and click hashtags to present themselves, to seek information, and to boost status on the social media platforms. These studies highlight the role of

hashtags becoming an effective tool for consumers' self-presentation as well as social interaction.

Moreover, a handful of studies also pointed out that hashtag usage is highly related to consumers' intention to actively participate in online brand communities associated with particular brands (Naraine et al., 2019; Wang et al. 2019). Naraine et al. (2019), for instance, found that brand community hashtags could serve as an effective anchor for conversation about particular brands on social media, and facilitate active interactions among the members in online brand communities. Wang et al. (2019) added empirical support to the claim that brand community hashtags enhance continuous consumer-brand engagement on social media platforms and likelihood of product information inquiry. Taken together, previous findings of consumer engagement research suggest that brand community hashtags created for particular brands have a potential to be a powerful tool for consumers interacting with other consumers who share common interests around the brands, and continuously engaging in ongoing and active conversation about the brands on social media platforms.

Influence of Brand Community Hashtags on Brand Communication Outcomes

As illustrated throughout this chapter, the most important questions in brand community hashtag and consumer-brand engagement literature can be summarized to uncover four major subjects: (1) how consumers develop identification with brands on digital platforms and shape psychological sense of community toward online brand communities, (2) what aspects of social media contributes to enhancing consumer-brand engagement behaviors, (3) how effective brand community hashtags are to facilitate brand content diffusion and positive brand communication outcomes, and (4) what determines and motivates consumers to engage in online brand communities and build sustainable relationship with brands.

Consumer-brand engagement through brand community hashtags warrants further investigation in how such engagement and relationship building behaviors consequently bring positive brand communication outcomes of social media advertising. There have been several empirical efforts to explore the influence of consumer-brand engagement via brand community hashtags on consumers' attitudinal and behavioral responses toward the focal brands (Fedushko & Kolos, 2019; Kim & Hyun, 2019; Kywe et al., 2012; Naraine et al., 2019; Luoma-aho, Virolainen, Lievonen, & Halff, 2018). Fedushko and Kolos (2019) indicated that in the year of 2018, hashtags are the most popularly used in Twitter, Instagram, and Facebook among the other social media platforms where hashtags target consumers better in driving more consumer engagement and attracting a number of followers. Zanini, de Moraes, Migueles, Lourenco, and Irigaray (2019) analyzed existing tweets scraped from online brand community on Twitter, and observed that consumers are actively engaged and showed different patterns of engagement behaviors unique in tweeting, retweeting, replying, and liking tweets. In a sport team's brand community hashtag, hashtag served as an effective anchor for leading the conversation around the team and facilitating frequent interactions among the community members (Naraine et al., 2019).

The notable influence of such hashtags, however, is not completely without potential pushbacks on brand evaluation and reputation. Hashtag hijacking through so-called 'bashtags', refers to an undesired kidnapping of brand communication via hashtags as a tool to satirize or negatively critique the original brand associated with the hashtag (Luoma-aho et al., 2018; Gilkerson & Berg, 2017). McDonald's #McDStories campaign, for instance, started as a promotional campaign to inspire consumers and brand fans to share positive and cheerful stories about their personal experiences of McDonald's, but it later turned out to be overflowing with

negative and sarcastic responses by consumers who actively adopted the hashtag (Gilkerson & Berg, 2017). Therefore, it is also important for brands to plan for what strategies need to be involved in promoting a brand community hashtag and how to closely monitor the content shared within the brand community hashtag network in order to derive positive advertising and brand outcomes.

Through the extensive investigation on this area of research, several implications are provided for advertising scholars interested in boosting effective consumer-brand engagement through social media platforms and leveraging the power of online brand communities and hashtags. First, it has been largely supported that consumers do identify with brands, and the consumer-brand identification may lead to forming lasting brand communities among consumers (e.g., Hollebeek et al., 2017). Online brand communities on social media facilitate brand communication among consumers who share common interests about brands, and amplify the effectiveness of consumer-brand engagement by offering accessible tools, such as hashtags, to promote participation in the community (e.g., Wang et al., 2019). In the following chapter, the theoretical framework that is used to further understand this phenomenon will be thoroughly reviewed with seminal work in the literature, followed by the proposed hypotheses of this dissertation.

CHAPTER THREE

THEORETICAL BACKGROUND

In this chapter, consumer-brand relationship building through brand community hashtags within online brand communities is explained in the lens of social identity theory and optimal distinctiveness theory (Brewer, 1991; Tajfel & Turner, 1979). Social identity theory (SIT) sets the conceptual ground for consumer identification with brands and online brand communities and how consumers develop in-group favoritism toward online brand communities. Furthermore, optimal distinctiveness theory supplements the mechanisms behind how consumers actively engage in *intra*group behaviors by adopting brand community hashtags to be involved in the online brand communities. Intersecting the two theories with the theoretical background of consumer-brand relationships, consumers' active and continuous participation through brand community hashtags is examined to disentangle significant factors that contribute to facilitating sustainable consumer-brand relationship building processes built upon brand trust and satisfaction within online brand communities (see Figure 2.1).

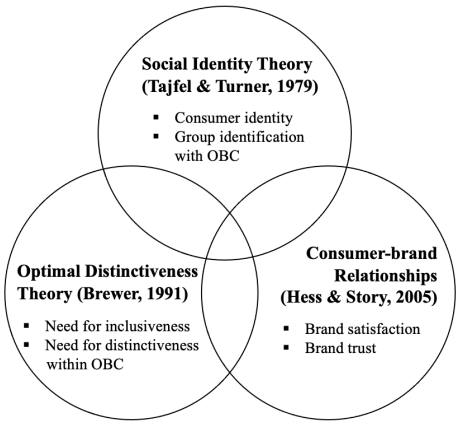

Figure 2.1. Theoretical Frameworks

Through various interactions with brands in online and offline settings, consumers develop a certain level of connectedness with brands and brand images (Carlson, Suter, & Brown, 2008). The perception of connectedness then leads consumers to identifying with the brands, consequently shaping their consumer identity - the extent to which consumers identify with a brand (Bhattacharya & Sen, 2003). Consumer identity and group identification with specific brands or brand-related communities tend to form in-group favoritism toward the brand. In-group favoritism motivates consumers to get together and join online brand communities that allow them to share feelings and opinions about the brands (Swimberghe, Darrat, Beal, & Astakhova, 2018). In that sense, social identity theory is particularly helpful to disentangle how consumer identities are developed and closely tied to a brand and online brand communities that not only enhance their attitudes toward the brand and communities but also ultimately strengthens consumer-brand relationships (Carlson et al., 2008; Elliott & Wattanasuwan, 1998; Kaur, Paruthi, Islam, & Hollebeek, 2020). Moreover, optimal distinctiveness theory supplements SIT's explanation noting motivational drivers involved in online brand communities such that specific consumer motivations seeking optimal level of distinctiveness and inclusiveness within the communities facilitate consumers' active and continuous participation within the online brand communities (Moon & Sung, 2015; Zeng & Wei, 2013).

Grounded in the conceptual background of social identity theory, optimal distinctiveness theory, and consumer-brand relationship building, the following sections will explain theoretical premises of each theory and how each theory guides understanding consumer participation in networked online brand communities through brand community hashtags. The proposed research model below outlines how consumers' involvement within networked brand communities enhances brand-related communication outcomes amplified by the interpersonal relationship

consumers maintain with their neighbors using specific brand community hashtags on a social media platform, Twitter (see Figure 3.1).

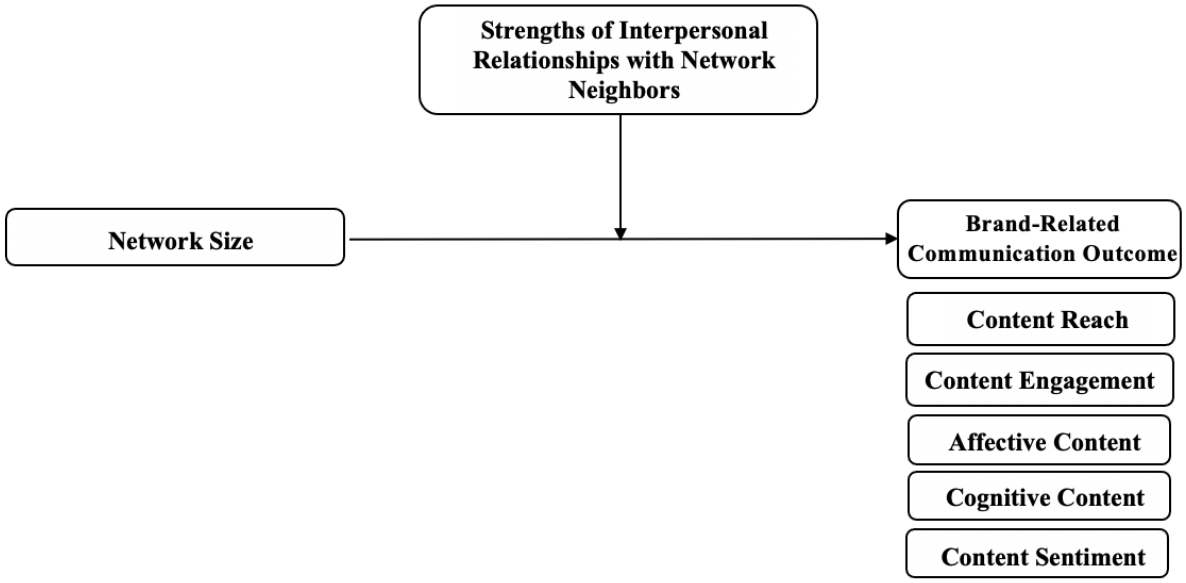

Figure 3.1. Proposed Research Model

Social Identity Theory

Rooted in social psychology, social identity theory explains that individuals tend to categorize themselves into perceived in-groups wherein they identify internally with group membership (i.e., social identity; Turner, 1985) and develop clear distinctions between in-groups and out-groups based on such perception (Tajfel, 1972; Tajfel & Turner, 1979). According to Tajfel and Turner (1979), social identity refers to one's self-image that derives from social categories that one perceives to belong. The in-group is a collection of individuals that an individual categorizes themselves to be part of in terms of social category, shared value-laden attributes, and characteristics (i.e., group identity) (Tajfel & Turner, 1979). Out-groups, on the other hand, are conceptualized as the other relevant group of individuals who are perceived to be distinct and differentiated from the in-group (Tajfel & Turner, 1979).

The discrimination between in-groups and out-groups influences one's attitudes, emotions, and behaviors toward the intergroup relations such that individuals develop favoritism toward in-group and discrimination toward out-groups (Turner, Brown, & Tajfel, 1979). Specifically, once an individual identifies oneself within a group or community, a sense of belongingness and togetherness is developed toward the identified in-group (Tajfel, 1974). Such identification with a group leads to motivating individuals to distinguish themselves from relevant out-groups (i.e., categorization), which subsequently enhances self-esteem by fostering positive social relationships (Brown, 2000; Hogg, Terry, & White, 1995; Turner, 1985). Through the identification processes and continuous positive social interaction with in-group members, individuals tend to form favorable attitudes toward the in-group (i.e., in-group favoritism) constructed upon shared affective and emotional connections among the in-group members (Allen & Meyer, 1996; Turner et al., 1979).

According to Tajfel and Turner (1979), one's social identity becomes effective when the following conditions are met: (1) group membership must be internalized, (2) a social situation allows comparison between groups, and (3) the out-group is relevant enough to provoke a certain extent of similarity and salience. Under these social conditions, individuals tend to manage their social identities and satisfy their self-enhancement motivations by psychologically moving from one group to another to seek inclusiveness with the high-status group, assimilate into the group (i.e., social mobility), change the self-evaluative consequences of current in-group membership (i.e., social change), and find new dimensions to evaluate and compare favorably with the high-status group (i.e., social creativity) (Tajfel, 1981). Turner and his colleagues (1975) explain this with Self-Categorization Theory (SCT) to supplement the *inter*group focus of social identity

theory and extend it to the *intra*group processes by articulating that individuals engage in a self-reference process creating relational social comparisons under the place or position defined within the group (Turner, 1985; Turner, Hogg, Oakes, Reicher, & Wetherell, 1987). Turner et al. (1979) also adds that in-group perception and favoritism can also be evoked by trivial or ad-hoc categorization of social in-groups. In other words, the mere perception of being "us" as in-group, regardless of the *strength* of the perception grouping themselves with others, may be enough for individuals to develop a certain level of in-group perception and favorable attitudes toward the in-group although it may not always lead to stronger attitude or behavioral change. Essentially, through the categorization process, individuals shape thoughts and emotions toward in-groups being more similar and favorable, and those toward out-groups being different and less favorable (Tajfel & Turner, 1979). What this means in consumers' in-group identification with brands and subsequent community behaviors occurring within the in-group is that even simple cues signaling common traits or similarities among individual consumers may serve as triggering tools for "in-group" identification grouping similar interest consumers together. In hashtag-based online brand community context, shared hashtags that consumers commonly use to interact with other peer consumers about specific brands on social media platforms become an accessible tool to form a sort of networked communities, or conversation arena for the online brand communities (Baker & Walsh, 2018; Fedushko & Kolos, 2019).

Social identity and in-group favoritism has been applied in the online brand communication context to uncover how consumers identify with specific brands and brand communities on digital platforms, connecting their social identities with brands and favoring the in-groups shaped around brands (An, Do, Ngo, & Quan, 2019; Lyu & Kim, 2020). Grounded in

social identity theory, An et al. (2019), for example, demonstrated that brands may serve as symbolic tools for consumers to use in creating a link between personal identity and social identity. Particularly, perceived connection between one's social identity and the brand facilitates spreading positive word-of-mouth about the brand (An et al., 2019). Similarly, Graham and Wilder's (2020) experimental study revealed that stronger consumer identification with brands not only enhanced positive perceptions of advertising but also minimized the backlash of negative advertisements on social media. Likewise, consumers who strongly identify with specific brands actively adopt brand community hashtags in order to represent their involvement with the brand as a part of their social identities (Kaur, Paruthi, Islam, & Hollebeek, 2020; Wang, Tai, & Chang, 2019). Brand community hashtags (e.g., #GoProFamily) shaped around online brand communities, then, may serve distinct roles in serving as an identity expression tool when compared to the general hashtags that only indicate the brand name (e.g., #GoPro). For instance, a general brand hashtag #GoPro may be commonly used in general and broad circumstances referring to the brand that encompass (a) one time purchase of the GoPro product, (b) mere indication of the brand GoPro or its products, (c) positive and/or negative consumer experiences related to the brand, and so on. A brand community hashtag #GoProFamily, on the other hand, implies a certain level of inherent positive association and attachment with the brand GoPro by indicating community-based feelings attached to the brand and its products. Furthermore, explicit use of such brand community hashtags can also represent how consumers of GoPro identify and position themselves within the group of GoPro consumers, not the other competitor camera brands (e.g., Canon, Sony) perceived as comparable out-groups. Therefore, by using the brand community hashtag such as #GoProFamily, consumers of the brand GoPro

can positively associate themselves with the brand and the products they own on social platforms and share their experiences with the other fellow GoPro consumers. In this sense, brand community hashtag #GoProFamily can serve as an identification and grouping tool for consumers who participate in the conversation. Moreover, responding to the shared positivity around consumers, brands also participate in the conversations around their brand community hashtags or initiate the community formation around their brands to expand the benefits (Inc 2021; PR Newswire, 2021). #PepsiNYCLocal initiated by the brand Pepsi is a relevant example when the brand explicitly gathers its fans on the social media platforms by creating a brand community hashtag to honor and reward their membership (or even fan-ship) associated with the brand. Thus, it is critical to understand how consumers get to be actively involved in the brand community hashtag usage and its impact on brand-related communication outcomes.

Despite the emerging differences underlying the two types of brand-related hashtags stated above, particularly the role of brand community hashtags, little has been done to theoretically explain the mechanisms behind consumers actively using brand community hashtags throughout their own social media experiences. In an effort to help delineate the differences between the two types of hashtags (i.e., general brand hashtags vs. brand community hashtags) and particularly examine the powerful roles of brand community hashtags, this dissertation borrows theoretical perspectives from social identity theory and optimal distinctiveness theory. In the context of this dissertation concerning consumer identification with online brand communities, consumers' social identity is conceptually defined as one's self-image linked to a particular brand to which the person perceives to belong. With social identity, consumers identify with the brand and categorize themselves to the related online brand

community shaped around the brand. As such, consumers' in-group favoritism is consumers' tendency to favor in-group brand communities over relevant out-group brand communities in terms of consumer attitudes, behaviors, and perception toward the brands and the brand communities. With this conceptualization, this dissertation examines how consumers' social identity is tied to their behaviors associated with other fellow consumers in social media platforms around brand community hashtag usage. Consumer identification with brands and online brand communities is examined by investigating the extent to which consumers interact with each other within the online brand community networks and how it ultimately influences consumer engagement within the networks. Taking a computational approach, this dissertation hopes to provide empirical evidence of consumers' social identities closely related to their behaviors within online brand communities by demonstrating the close relationships observed among the consumers and brands.

Consumer Social Identity and Online Brand Community

As illustrated, the identification with social in-groups and subsequent in-group favoritism theorized in social identity theory (Tajfel & Turner, 1979) is relevant and helpful to predict how consumers identify with certain brands on social media and/or online brand communities around the brands as well as resulting advertising and brand outcomes. Several advertising studies have supported the idea that consumers' social identities constructed around brands positively influence their responses toward advertising and brands (Dimofte, Goodstein, & Brumbaugh, 2015; Graham & Wilder, 2020; Kim, Park, Lee, & Park, 2018). Kim et al. (2018), for instance, examined how consumers' social identity influenced electronic word-of-mouth (eWOM) on Facebook and revealed that sharing social identity with Facebook friends increases perception of

usefulness and intention to adopt eWOM on Facebook. Another recent study by Graham and Wilder (2020) also showed that the degree to which consumers identify with brands not only enhances consumer perceptions of advertising and brands in online platforms but also mitigates the detrimental influence of advertising on attitudes and behavioral intentions. Likewise, consumers' social identities tied to online brand communities enhance brand commitment and perceived connection between the self and brand, which subsequently strengthens oppositional brand loyalty that explains a psychological tendency of consumers holding negative and opposing views toward the rival brands (Kuo & Hou, 2017). Findings of Kuo and Hou (2017)'s study pointed out the noticeable impact of consumers' social identities associated with online brand communities as well as brand loyalty in developing consumer-brand relationship building.

Despite abundant academic effort on understanding consumers' social identity, limited research has empirically demonstrated how it plays into the actual behavior of consumer interactions on social media platforms. Extending previous findings relevant to the substantial impact of consumers' social identities on brand communication, this dissertation aims to empirically demonstrate how consumers' social identity is associated with their perceptions and engagement behaviors among other fellow consumers within social media platforms and how it contributes to enhancing consumer-brand relationships in the long term by examining content and network characteristics of online brand communities. Moving beyond the self-reported measures, employing computational methods allows observing actual consumer perceptions and behaviors interacting with other consumers and brands in the hashtag-based online brand communities. Grounded in social identity theory (Tajfel & Turner, 1979) in the context of online brand communities and brand community hashtag usage, consumers on social media platforms

are likely to categorize themselves into and identify with the group of people who share common interests in specific brands and develop in-group perception toward the online brand community favoring the brands (Chen & Zhao, 2021; Kuo & Hou, 2017). Such identity-based perceptions of consumers also lead to meaningful relationship building with and interactions among fellow consumers who are interested in similar brands, and between consumers and brands on social media platforms. Consequently, the interactions among consumers and brands form a network of relationships within the online brand community (Chen & Zhao, 2021).

Facilitating the community interactions among consumers who share common interests around the brand, the usage of brand community hashtags can be considered as a type of intra-group behaviors in that consumers get to be involved in the brand-related conversations with such hashtags by easily locating brand information as well as sharing similar experiences with the other fellow consumers online (Baker & Walsh, 2018; Erz et al., 2018; Naraine et al., 2019). Although merely including a hashtag about the brand may not always represent a strong identification with the specific brand community or the hashtag itself, hashtag usage as a unique online behavior observed on social media can be understood as a form of identity-associated behaviors on social media platforms. Indeed, supplementing the original social identity theory with self-categorization theory (Turner, 1985), Turner and colleagues (1979) also pointed out that even trivial or ad-hoc categorization of social in-groups given to an individual can be enough to trigger in-group perception and favoritism toward the group. Similarly, brand community hashtag usage can be an observable intra-group consumer behavior happening on social media platforms that may help consumers categorize themselves with the specific brand community hashtags they tend to use throughout their social media experience.

Chen and Zhao (2021) approached the agenda of CEBs through online brand communities with social network analysis involving actual Facebook brand communities and the communicators involved in the conversation on Facebook. Results of the study indicated that brand-related digital dialogue among stakeholders benefits online brand communities such that conversations around brands have a significant potential to mobilize and expand the community, thus stimulating consumer participation (Chen & Zhao, 2021). Therefore, following social identity theory and previous empirical studies supporting the theoretical claims in advertising context (Dimofte et al., 2015; Graham & Wilder, 2020; Kim et al., 2008), it is reasonable to predict that consumers' categorization with other fellow consumers who identify similarly with a certain brand and/or brand community hashtag form a noticeable and interactive network among them based upon the strength of ties developed among the consumers. Moreover, such networked relationships among consumers observed around specific online brand communities then may positively influence reach and engagement of content as well as content characteristics shared within the communities.

Optimal Distinctiveness Theory

Although social identity theory provides overarching explanations to illustrate consumer identification with online brand communities and its effect on brand community hashtag usage, social identity theory by itself lacks detailed explanations on significant motivational factors associated with the behaviors (Brewer, 1991; Brewer & Weber, 1994). Acknowledging the gap in the theory, Brewer (1991) extended its perspectives to a motivational framework, Optimal Distinctiveness Theory (ODT). ODT focuses primarily on what motivates individuals to influence group relationships. The theory purports that individuals strive to satisfy two

conflicting needs for distinctiveness and inclusiveness within their in-groups (Brewer, 1991). Within the in-group, one's *intra*group behavior will likely change depending upon the degree of perceived inclusiveness that meets the optimal level (Brewer, Manzi, & Shaw, 1993). In other words, when the group is highly inclusive over the optimal level, one's identification with the in-group is weakened, and the group is fragmented to in-group members who strive to achieve the other need for distinctiveness (Brewer & Weber, 1994). A later study by Brewer (2001) elaborated further that one's social identities are selected and activated to the extent that they achieve the optimal balance between the need for inclusion and need for differentiation in a social context. Indeed, group identification and group inclusiveness were later observed to have a curvilinear relationship, implying that individuals may possess both needs for inclusion and differentiation during the self-categorization process (Leonardelli, Pickett, & Brewer, 2010).

Need for inclusiveness refers to the need for validation and perceived similarity to the other in-group members, while need for distinctiveness refers to one's drive for individuation distinct from the others (Brewer, 1991). Brewer (1991) emphasized both motivational drivers being rooted in the selection of one's social identity and the strength of it, which is independent of positive evaluation toward the group membership. Ultimately, the interplay of the two conflicting needs is expected to influence perceptions and judgments of the self and others according to the theory (Brewer, 1991; Leonardelli et al. 2010). In order to satisfy both needs, individuals seek optimal levels of inclusiveness and distinctiveness within their in-groups (Brewer, 2001). This striving for balance influences individuals' group identification such that individuals tend to satisfy the optimal equilibrium when they identify with the other in-group members. Individuals balancing the needs for inclusion and differentiation go through a self-

categorization process, showing curvilinear relationships between group identification and group inclusiveness (Leonardelli et al., 2010).

Grounded in optimal distinctiveness theory, in the context of consumers' social identities around online brand communities, need for inclusiveness is conceptually defined as consumer need for validation and perceived similarity to the other consumers within the community, while need for distinctiveness is defined as consumer need for individuation distinct from the other consumers. In conversations on social media platforms, consumers' need for inclusiveness is presented as one's satisfaction tied to the extent to which they are well connected among online brand community members (Lee, Lee, Taylor, & Lee, 2011; Yan, Jing, Yang, & Wang, 2014). On the other hand, consumers' need for distinctiveness is more pronounced by actively creating brand-related content adopting the brand community hashtags commonly shared among the online brand communities to fulfill their satisfaction for their need for distinctiveness (Kim, 2017). The propositions of optimal distinctiveness theory are particularly helpful to understand motivational drivers of consumers who opt to actively participate in brand community hashtag usage. A few advertising studies have employed optimal distinctiveness theory and investigated the effects of consumers' need for distinctiveness and inclusiveness on brand consumption (Moon & Sung, 2015), and consumers' content generation intention on social media (Zeng & Wei, 2013). Moon and Sung (2015) showed that individuals with higher need for distinctiveness were less likely to purchase the brands used by most in-group members. Findings of this study provided empirical evidence for individuals balancing the need for inclusiveness and distinctiveness and ensuring the optimal level of distinctiveness within their in-groups (Moon & Sung, 2015). In addition, Zeng and Wei (2013) found that social media users are more likely to

upload and share less similar content to their in-groups as similarity and popularity of their in-groups grow, implying that users seek to gain uniqueness by sharing different content as the level of group identification increases to certain extent.

Similarly, a handful of studies have demonstrated that consumers within online community networks on social media engage in content sharing behaviors differently depending on their motivations to express their unique commitment within the communities (Levina & Arriaga, 2014; Yang, Li, & Huang, 2017). Levina and Arriaga (2014) revealed that empowering specific groups of consumers and content producers within online communities facilitates content sharing behaviors in favor of their motivations to pursue distinctions among the other community members and establish distinctiveness by enhancing their social status within the communities. Yang et al. (2017) also adds that perceived recognition for contribution to the community and freedom of expression are what makes a particular group of community members actively engage in content sharing behaviors as well as enhances member commitment among the other silent lurkers within the online communities on social media. In this sense, it is worth noting that brand community hashtags become not only a utilitarian tool for consumers to spot brand-related information, but also a social driver for them to stand out among the in-group online brand community members who share common social identities with them.

Consumers' active use of brand community hashtags, consequently, helps diffusion of brand-related content on social media platforms (Fedushko & Kolos, 2019). Theoretically, Bandura (2001)'s discussion on social cognitive theory of mass communication notes that social network structures significantly influence diffusion processes not only fueled by personal relationships, but also clustered networks of individuals interconnected to one another. It is also

noteworthy that Bandura (2001) highlighted the role of both connectedness and separateness observed within social networks in facilitating content diffusion. That is, the number of ties and patterns of structural linkages developed among people affect their impact on what is spreading through each of the users' social networks (Bandura, 2001). Since one's networked relationships consist of multiple linkages of which some are densely interconnected while others are dispersed throughout the social networks (Granovetter, 1983; Rogers & Kincaid, 1981), it is critical to understand how diverse network characteristics coupled with content characteristics foster effective content diffusion.

Indeed, adopting the network theory perspectives, the pattern of consumer engagement behaviors (CEBs) and interactions among other consumers and brands can be empirically observed by examining content characteristics (e.g., affective, cognitive content) (Dhaoui & Webster, 2021; Kim & Phua, 2020; Moran, Muzellec, & Johnson, 2019; Tellis, MacInnis, Tirunillai, & Zhang, 2019) as well as structural characteristics of consumer networks (e.g., strengths of interpersonal relationships with one's network neighbors) (Gavilanes, Flatten, & Brettel, 2018; Peng, Agarwal, Hosanagar, & Iyengar, 2018; Susarla, Oh, & Tan, 2012; Zhu, Su, & Kong, 2015). For instance, Tellis et al. (2019) argue that emotional and affective content perform better to provoke content sharing on social media platforms than informational and cognitive content by increasing positive attitudes toward the advertising messages, leading to enhancing behavioral intentions associated with the promoted brands. Kim and Phua (2020), however, insists that perceived information value of content shared through hashtags is a critical mediator that enhances consumer attitudes and consumer-brand identification through the hashtags.

The aforementioned mixed findings may be possibly due to the lack of understanding unique characteristics of network structures where consumers are embedded within social media networks, implying the necessity of considering both content and network characteristics in tandem. Peng et al. (2018)'s effort on uncovering network structure impact on content sharing on social media platforms found that a message receiver was more likely to share content from a sender who shares more common followers within the social media platforms, and such positive influence of common followers on content sharing was amplified when the content was perceived novel and distinctive. Findings of the aforementioned studies imply that content characteristics of what is being shared within social media platforms would demonstrate the level and depth of consumer engagement, but consumers who strive to post unique and distinctive content may also contribute to spreading the content to fellow consumers by triggering the tendency to share such content within the social media platforms.

Furthermore, several studies in information systems literature have attempted to investigate the cohesive interaction of content and network characteristics on content creation and diffusion by taking network theory perspectives (Natarajan et al., 2013; Sosa, 2011; Susarla et al., 2012; Zhu et al., 2015). Zhu et al. (2015), for example, combined the user status in social media platforms and content generated by the users to identify diffusion of their influence within the networks by employing a user-content bipartite graph algorithm. The study revealed that the influence of users was determined by both structural properties of user roles within social media platforms in addition to characteristics of the content users posted (Zhu et al., 2015). Similarly, Susarla et al. (2012)'s investigation on content diffusion on YouTube found that networked interactions among social media users are important to determine virality of YouTube videos and

the magnitude of the impact. The study also observed that user heterogeneity in the social media platforms meaningfully contributes to fueling content diffusion processes (Susarla et al., 2012). In advertising context, aggregating consumer engagement derived from both content and network characteristics within online brand community networks may provide useful insights to understand how consumer needs for achieving inclusiveness and distinctiveness within social media platforms facilitate consumer engagement behaviors (CEBs) and relationship building processes over time.

As illustrated, consumers' need for inclusiveness and distinctiveness as unique motivational drivers may enhance consumer-brand relationship building within online brand communities. Need for inclusiveness of consumers facilitates their motivation to be involved in the online brand communities where associated community hashtags are popularly adopted to strengthen the community membership of consumers, which then leads to active and continuous involvement in brand communication (Brewer, 1991; Yang, Sun, Zhang, & Mei, 2012). Once consumers are involved in the brand communication through specific online brand communities they identify with, they tend to show higher tendency to keep positive attitudes toward the brand and maintain continuous involvement within the online brand communities (Kim & Hyun, 2019; Wang, Tai, & Chang, 2019). This tendency keeps consumers in the loyalty loop of specific brands and related communities on social media, contributing to enhancing brand trust among the other consumers who share similar interests about the brand (Leonardelli & Loyd, 2016). Throughout this process, consumers are also likely to develop and maintain higher levels of brand satisfaction by sharing similar feelings and opinions about the brands with fellow consumers, which could amplify the in-group favoritism toward the brands and the communities

(Wang et al., 2019). Therefore, the need for inclusiveness of consumers is likely to strengthen consumer-brand relationships as they continue positive interactions and active engagement among the other consumers and brands, cultivating higher levels of brand trust and satisfaction on social media platforms (Zhang & Wang, 2013).

Need for distinctiveness of consumers, on the other hand, plays another significant role in capturing consumers in the online brand communities in favor of social media affordances such as brand community hashtags to help them be distinct and unique within the communities (Naraine, Pegoraro, & Wear, 2019). That is, consumers' motivation to stand out within the online brand communities may boost one's intention to be more engaged in the ongoing brand communication (López, Sicilia, & Moyeda-Carabaza, 2017). Research has shown that consumers with higher levels of brand identification tend to use brand-related hashtags in their own social media posts (Dessart & Duclou, 2019; Stathopoulou, Borel, Christodoulides, & West, 2017; Yang et al., 2012). Particularly, those who wish to show high affiliation with a brand on social media platforms tend to use brand community hashtags to represent their identities associated with the brand (Fedushko & Kolos, 2019; Vermeer, Remmelswaal, & Jacobs, 2017). Likewise, consumers' need for distinctiveness can facilitate active and continuous involvement in brand communication on social media by adopting brand community hashtags that help them stand out among the connected others from the online brand communities.

Taken together, applying social identity theory and optimal distinctiveness theory (Brewer, 2011; Leonardelli et al. 2010; Tajfel & Turner, 1979), this dissertation attempts to uncover how consumers' needs for inclusiveness and distinctiveness within the networked communities amplify the impact of consumer identities on brand community hashtag usage

behaviors. Particularly, network size of one's interaction within online brand communities is expected to predict content diffusion in the network such that those who maintain a large network around them would be more influential in spreading content to other fellow consumers within the network. Furthermore, strengths of interpersonal relationships with one's network neighbors can significantly and positively moderate the impact of network size in facilitating the overall content sharing behaviors as well as characteristics of the shared content through online brand communities.

Hypotheses Development

The primary focus of this dissertation accommodates how social identity of consumers and in-group perception toward online brand communities facilitate engagement behaviors on social media platforms. Although numerous social scientific studies have investigated the role of social identity (Hornsey, 2008) and optimal distinctiveness theory (e.g., Leonardelli & Loyd, 2016), respectively, relatively little attempt has been made to incorporate the two and explain the interplay of social identity and underlying two motivational drivers, such as need for inclusiveness and distinctiveness and how the factors tie together to ultimately enhance brand-related communication outcomes observed from existing social media platforms. In that sense, theoretically, social identity theory and optimal distinctiveness theory are tested in combination to discover significant network factors linked to consumer-brand engagement and its subsequent impact on content diffusion through brand community hashtags. This dissertation attempts to examine consumer-brand engagement through online brand communities by incorporating computational approaches to understand networked communication among consumers within brand community hashtag networks. In doing so, social network analysis allows for exploring how network characteristics, such as consumers' network size aligning with strengths of

interpersonal relationships with network neighbors, enhance meaningful brand-related communication outcomes.

Grounded in social identity theory (Tajfel & Turner, 1979), consumer identities developed and associated with brands are expected to positively influence the size of one's ego network a consumer develops and maintains within brand community hashtag networks. That is, those who identify strongly with brands and/or online brand communities present a larger ego network, amplified by inherent needs for inclusiveness and distinctiveness. Stronger interpersonal relationships consumers develop with their network neighbors may represent unique type of highly involved consumers within the online brand community networks. Moreover, previous literature points to the positive impact of these network structures on consumer engagement, demonstrating that a more interconnected network facilitates engagement and content diffusion among participating users within the network (Kim, 2017; Lee et al., 2011). Similarly, Qu, Saffer, and Riffe (2021) investigated consumers' brand-related discussion networks and demonstrated that consumers' network size positively predicted their content contribution in the brand discussion network. Findings of the study point out the higher tendency of consumer engagement behaviors of content sharing or liking and interaction with other consumers when they discuss the brand with more people (Qu et al., 2021). Thus, following hypothesis is proposed:

> **Hypothesis 1**: Network size of consumers will enhance (a) content reach and (b) engagement.

Along with the stream of social network analysis research, Borgatti, Everett, and Johnson (2013) defines one's ego network as the number of alters that a focal ego is connected directly with where ego is a focal person and alters represent other people connected to the ego within a network. Adopting this social network analysis approach, several studies have indicated that size

of a network may lead to the magnitude of an ego's impact on relevant others within a network, influencing engagement behaviors (Park, 2017; Park & Kaye, 2017; Perry, Pescosolido, & Borgatti, 2018; Qu et al., 2021). Scholars have found that large networks are likely to consist of a mix of strong and weak ties, whereas small networks tend to comprise of highly trusted strong ties (Eveland, Hutchens, & Morey, 2013; Gil de Zúñiga & Valenzuela, 2011; Park, 2017). The size of network, therefore, becomes important to assess how people within the network interact and engage with the conversation. According to Son and Lin (2008), within a large network, people show higher likelihood of encountering weak ties, which facilitates engagement than strong ties. Social identity literature adds support to this idea that individual's network size strengthens identification with a group (Jones & Volpe, 2011), thus exaggerating affection shared among in-group members within social groups such as particular organizations or brand communities (Coelho, Bairrada, & Peres, 2019; Galinsky, Hugenberg, Groom, & Bodenhausen, 2003). In addition to shared positivity and affection among the in-group members, providing virtual and structured places for consumers with similar interests, OBCs gather consumer groups together to communicate and exchange useful information related to brands when needed, thus influencing consumer behaviors engaging with the shared content *within* the communities (Raacke & Bonds-Raacke, 2008). In that sense, as optimal distinctiveness theory suggests, optimal size of network size that is sufficiently large enough to help distribution of resources and information is desired for in-group members to realize advantages of belonging to the effective in-group (Leonardelli et al., 2010). Therefore, following two hypotheses are proposed:

> **Hypothesis 2**: Network size of consumers will positively influence the amount of (a) cognitive content and (b) affective content shared within the brand community hashtag networks.
>
> **Hypothesis 3**: Network size of consumers will positively influence sentiment of content shared within the brand community hashtag networks.

Applying the aforementioned conceptual approach in hashtag-based online brand community context, one's active connections with the *influential* peer consumers within the online community hashtag networks can be interpreted as the extent to which a consumer is actively involved and included in the conversations happening within the networks (i.e., those who maintain a strong ties). The well-connected position of these highly connected users, then, may amplify the impact of one's intention to actively use the brand community hashtags on leveraging positive brand communication outcomes. This is because those who are actively connected and involved to one's in-group are likely to form positive attitudes and behaviors associated with the group behaviors, widely supported by the social identity literature and optimal distinctiveness theory (Brewer, 1991; Tajfel & Turner, 1979). On the other hand, Colladon and Naldi (2020) also suggest that there could be another type of users keeping more connections with the network *periphery*. Scholars argue that those who maintain stronger connections with the peripheral users may become important to avoid fragmentation among users, but keep the network together (Burt 2009; Colladon & Naldi, 2020).

In advertising context, Himelboim and Golan (2019) examined various roles of Twitter users based on their network connectivity in network to spread information of viral advertising. Findings of the study identified three types of influencer roles, namely primary influencers (i.e., retweeted hubs), contextual influencers (i.e., bridges), and low influencers (i.e., network isolates). Per their analysis, a small group of users, especially primary influencers, disproportionately contributed to the ad sharing on Twitter, whereas majority of other users showed limited contribution individually (Himelboim & Golan, 2019). Contextual influencers serving as bridges are those highly mentioned users within a network, and made a meaningful, but passive contribution to the virality of advertising on Twitter (Himelboim & Golan, 2019).

Essentially, the study pointed out the importance of approaching ad distribution as a multi-level process and knowing different role of diverse influencers differing in connectivity to other users within a network to understand content engagement on Twitter. Likewise, within the online brand community hashtag networks, consumers who are more likely to connect with central users (vs. other peripheral users) within the hashtag network may serve distinct roles in how brands are communicated through the associated hashtags by keeping the "in-group" consumers together within the loop of brand-related conversations.

Furthermore, users' connections with their *neighbors* within a network tend to influence how information is shared throughout the network ranging from the center as well as periphery of it (Maharani, Adiwijaya, & Gozali, 2014). Among the various facets of building and maintaining connections with network neighbors, tie strengths of the engaged peers around a consumer may significantly influence one's attitudes and behaviors associated with other consumers in favor of the shared social identity as a consumer (Reed, 2002). Tie strength refers to the magnitude of the bond developed between users of a network, which implies the importance of social relationships, frequency of interactions, or type of the connections (Friedkin, 1990; Granovetter, 1973). Due to its meaningful impact linked to social interaction among network users, several advertising studies have examined the role of tie strengths on various communication outcomes, such as diffusion of word-of-mouth related to brands (e.g., Araujo, Neijens, & Vliegenthart, 2017) and consumers' group-related attitudes and behaviors (e.g., Phua, Jin, & Kim, 2017). Phua et al. (2017), for example, investigated the moderating role of consumers' tie strength on the relationship between consumers' brand-related participation and community-related outcomes, including identification, engagement, commitment, and membership intention. Survey findings of the study indicated that consumers who perceived

higher levels of tie strengths to their peers on social media platforms showed higher levels of identification and membership intention related to their brand participation where Twitter scored the highest score for tendency of consumers' brand community identification among the other three major platforms including Facebook, Instagram, and Snapchat. Moving further, while acknowledging the impact of *tie strengths* of one's neighbors, it is also important to consider the *relationship* connecting the consumer and their peers those who are in the center or periphery of the conversations happening between the two. In other words, it must be two separate discussions looking at the respective strengths of one's neighbors themselves commonly categorized as two types, stronger vs. weaker tie strengths, from examining *intensity of the interpersonal relationship* a consumer builds with such neighbors based upon meaningful interactions occurring between them.

Therefore, the size of consumers' ego network and *strengths of interpersonal relationships* with their network neighbors of the engaged consumers positioned within the network warrant investigation. Insights from the aforementioned studies point to the influential role of consumers connected to the neighbors who maintain stronger tie strengths in leading to relevant brand-related communication outcomes. Grounded in social identity theory perspectives (Tajfel & Turner, 1979; Hogg & Reid, 2006), Reed (2002) argued that consumers tend to perceive positive reinforcement contingencies throughout the self-identification process with other significant consumers within the relevant reference group who share similar interests in brands, driving positive brand attitudes and behavioral intention to purchase the brand. These social identity-based consumer judgments shed light on how *fellow consumers around a consumer* can amplify one's positive association with the brand, and subsequently, influencing attitudes and behaviors. Relevant literature found that *the nearby peers* around a consumer who

have stronger tie strengths tend to interact closely with a consumer at near positions within a network and they will be one of the most influential people to influence one's attitude and behaviors (Hanneman & Riddle, 2005; Reed, 2002). Furthermore, Hanneman and Riddle (2005) added that social actors who have stronger ties to other peers may be advantaged in favor of the strength of ties such that they have more *access* to resources of the network and *ability* to diffuse information to others within the network.

Likewise, considering the *relational dynamics* among a consumer and their peers, strengths of the *interpersonal relationships* one maintains with their network neighbors within a network may also denote a significant impact of close in-group peers on one's subsequent attitude formation and behavioral outcomes (Hanneman & Riddle, 2005; Hossain, Chung, & Murshed, 2007). Therefore, having stronger strengths of interpersonal relationships with one's network neighbors may amplify the impact of one's network size on brand-related communication outcomes in favor of more frequent and active interactions occurring among them that strengthens identification with the in-group members and intensifies the favoritism toward the in-group both parties belong to. It is then logical to predict that one's network characteristics involving interpersonal relationships with network neighbors would enhance how consumers engage with content sharing behaviors through brand community hashtags and thus leveraging brand-related communication outcomes. Thus, following hypothesis is proposed:

> **Hypothesis 4**: Strengths of interpersonal relationships with consumers' network neighbors will amplify the influence of network size of consumers on brand-related communication outcomes, such as (a) content reach, (b) engagement, (c) amount of affective content, (d) cognitive content, and (e) content sentiment.

As illustrated, optimal distinctiveness theory paired with social identity theory provide a robust theoretical ground for explaining how consumers are actively involved in spreading brand-related conversations through brand community hashtags on social media platforms.

Therefore, it is possible that consumers' use of brand community hashtags is highly associated with consumer identities and in-group identification manifested by their network size and positions within the online brand communities, enhancing important brand-related communication outcomes, such as brand-related content reach and engagement, affective and cognitive content, and the sentiment of such content shared within the network. Furthermore, the impact of brand community usage is expected to be even more pronounced with strengths of one's interpersonal relationships with consumers' network neighbors influencing the interactions among the online brand community members. In the following chapter, methodological approaches to test the proposed hypotheses will be introduced in detail.

CHAPTER FOUR

METHODOLOGY

In this chapter, methodological design of this dissertation is overviewed and explained in detail. To address the proposed hypotheses, computational methods were employed to extend the scope of understanding consumer engagement behaviors observed from actual online brand communities that exist on Twitter by scraping tweets associated with the selected brand communities.

Overview of Study Design

This study takes a computational approach that employs social media data mining, social network analysis, and computerized textual analysis followed by sentiment analysis. A set of computational methods were employed to address the impact of brand community hashtag usage on brand-related communication outcomes, such as content reach and engagement, and characteristics of the content shared within the brand community hashtag networks.

Independent variables include consumers' ego network size and strengths of interpersonal relationships with their network neighbors, which were measured by collecting the number of followers the focal consumer has (i.e., network size) and calculating Bonacich power centrality of the focal user (Bonacich, 2007).

Dependent variables include content reach and engagement of which the number of retweets and replies, respectively, scraped from publicly available data through Twitter API, proportional amount of affective and cognitive language calculated by using LIWC 2022 software, and content sentiment calculated by using VADER package that returns three scores of

positivity, negativity, and neutrality in Python. Below is the detailed information about each step of the overall methodological procedure.

Description of the Sampled Brand Community Hashtags

Among various brand community hashtags on Twitter, the following eight brand communities were selected to include four different product categories (see Vaughn, 1980): High Involvement-Think brands (GoPro; #GoProFamily, Jeep; #JeepNation), High Involvement-Feel brands (Aerie; #AerieReal, Fossil; #FossilStyle), Low Involvement-Think brands (Puffs; #PassThePuffs, Charmin; #TweetFromTheSeat), and Low Involvement-Feel brands (KFC; #NationalFriedChickenDay, Heineken; #OpenYourWorld) (see Table 1.1).

Table 1.1
Description of the Eight Sampled Brand Community Hashtag Networks

Brands (Number of Followers*)	Brand Community Hashtags	Total Number of Tweets
@GoPro (2.1M)	#GoProFamily	3,111
@Jeep (1M)	#JeepNation	2,673
@Aerie (95.8K)	#AerieReal	832
@Fossil (101.5K)	#FossilStyle	311
@Puffs (30.3K)	#PassThePuffs	52
@Charmin (83.9K)	#TweetFromTheSeat	137
@KFC (1.5M)	#NationalFriedChickenDay	631
@Heineken (168.8K)	#OpenYourWorld	453
Total		8,200

Note. The number of followers indicated in this table is recorded in December 2021.*

According to the FCB Grid model introduced by Vaughn (1980), high involvement-think brand category (i.e., Quadrant 1) entails products or services involving consumers' effort on thinking and economic considerations, therefore informative strategy is effective (e.g., cars, appliances, cameras). For instance, GoPro is one of the highly present camera and photography brands on Twitter, while Jeep is a car brand included in the samples of this study. These brands tend to promote objective details of the product quality and inform consumers of the updated features of products (see Appendices for sample tweets). High involvement-feel brand category

(i.e., Quadrant 2) includes products or services that fulfill consumers' psychological needs and ego-related purchases, such as cosmetics or apparels, and jewelry. In this study, Aerie and Fossil were included as apparel and cosmetics brands. Aerie, for example, tend to promote tweets including copies that appeal to consumers' emotional state or mood related to their brand or product usage (see Appendices). Low involvement-think brand category (i.e., Quadrant 3) consists of habitual products or services that consumers need in their routinized behaviors, such as household products, cleaners, or paper products. Brands for this category include Puffs and Charmin. Brands in this quadrant are likely to share the routinized and daily uses of their products with informational tips (see Appendices). Lastly, low involvement-feel brand category (i.e., Quadrant 4) embraces products of personal taste or pleasure, including beer, cigarettes, food, or candy bars. KFC, for instance, actively promotes their signature taste of products appealing to its consumers' taste and pleasure (see Appendices). In this study, KFC and Heineken were included as food-related and brands.

The brands were selected also because they have maintained a relatively stronger presence with active and popular brand community hashtags on Twitter among other brands: @GoPro; 2.1M followers, @Jeep; 1M followers, @Aerie; 95.8K followers, @Fossil; 101.5K followers, @Puffs; 30.3K followers, @Charmin; 83.9K followers, @KFC; 1.5M followers, @Heineken; 168.8K followers at the time of December 2021. Any tweets that contain both the brand community hashtags and the corresponding brand names during the 1-year period of each hashtag from March 31, 2021 to March 31, 2022 were collected. Although majority of the brand community hashtags included brand names by themselves, not all of them included their brand names (e.g., #NationalFriedChickenDay for KFC, #OpenYourWorld for Heineken, #TweetFromTheSeat for Charmin). To ensure each hashtag was indeed associated with the

particular brand, it was a necessary decision to include tweets that contained both brand names and the hashtags. In addition, the 1-year period was set to include all of the selected brand community hashtags being in use that is comparable regardless of the start of each hashtag during the specific period of time. Twitter API script was prepared to scrape existing tweets within each of the hashtag networks. Scraped dataset was then cleaned and used to explore content and network characteristics of each hashtag network by identifying linguistic content characteristics (e.g., affective and cognitive content) of tweet content using Linguistic Inquiry and Word Count (LIWC) 2022 software. In addition, network characteristics (i.e., network size, Bonacich power centrality) were measured by using the NetworkX package in Python (see Table 2.1 for operationalization of the variables).

The following section describes the computational methods employed to assess the proposed hypotheses in detail.

Table 2.1
Operationalization of the Variables

Variables	Operationalization
Network size	The number of a focal user's followers
Strengths of interpersonal relationships with one's network neighbors	Bonacich power centrality of a focal user
Content reach	The number of retweets attached to each tweet
Content engagement	The number of replies attached to each tweet
Affective content	The amount of affective language expressed in the textual content
Cognitive content	The amount of cognitive language expressed in the textual content
Content sentiment	The overall intensity of sentiment expressed in the textual content

Data Preparation and Processing

After importing data into Python, undirected weighted retweet and reply networks were constructed for each brand community hashtag with individual consumers represented as nodes by using NetworkX package. The graphs were then exported as a compatible format to import it in R using igraph packages (i.e., python-igraph in Python, igraph in R). For edges, only the weight of edges (i.e., based on the number of interactions) was constructed, while the direction of the edges was omitted. This is because measuring the interactions between source and destination, regardless of who is tweeting to whom, is enough to operationalize *strengths* of the relationship between the two alters. Having the direction of such interactions would provide additional insights to the specific role of each alter within the interactions, but it is not what this dissertation aims to investigate.

In doing so, a Python script was prepared to download user information and public metrics attached to each user appearing within the eight brand community hashtag networks. Particularly, scraped information included: (1) tweet id, (2) user id, (3) username, (4) number of followers, (5) number of followings, (6) number of retweets, (7) number of replies, (8) tweet content, (9) posted time, (10) mention user id(s), (11) retweet user id(s), and (12) reply user id(s). Dataframes were then constructed by using pandas package in Python. Downloaded data was saved as a csv file and used for the subsequent analyses. Appendices include all of the Python scripts used in this dissertation.

Among the collected data, number of retweets represents content reach whereas number of replies corresponds to content engagement. The number of retweets and replies can serve as effective proxy measures for reach and engagement, respectively. That is because retweets refer to tweets that are republished by other users for the purpose of sharing the content to reach wider

audiences, while replies refer to tweets published by users as direct responses to particular tweets to engage actively with the selected content (Park, Reber, & Chon, 2016).

Network size variable was measured by the number of followers of focal consumers at the time of each tweet. For both retweet and reply networks, edges were weighted by the number of interactions each consumer has with one's direct neighbors. This method allows for taking the influence of different consumers within a network into account (Bonacich, 2007). The weighted centralities of network neighbors were then saved as a variable representing strength of interpersonal relationships with one's network neighbors (see Appendices for the script).

Data Mining and Computational Data Analysis

Data Mining. Twitter data that contains eight brand community hashtags (i.e., #GoProFamily, #JeepNation, #AerieReal, #FossilStyle, #PassThePuffs, #TweetFromTheSeat, #NationalFriedChickenDay, #OpenYourWorld) during the 1-year period were collected by using Twitter API for the purpose of ethical and valid data mining.

Computational Data Analysis. Network metrics (i.e., network size, strength of interpersonal relationships with network neighbors of consumers) and overall sentiment of each tweet content containing a particular brand community hashtag were calculated by using VADER (Valence Aware Dictionary and sEntiment Reasoner) package's three sentiment values of positivity, negativity, and neutrality in Python. LWIC also offers sentiment assessment, however, some scholars have questioned the validity of its AI algorithms that fail to deliver consistent and reliable results (e.g., Boukes, van de Velde, Araujo, & Vliegenthart, 2020). As an effective alternative, VADER is useful in analyzing sentiment of textual content in that it helps computationally determining whether textual content in social media is positive, negative, or neutral (Hutto & Gilbert, 2014). Since algorithms of VADER is specifically trained on social

media data for both polarity and intensity of emotional tones within human text, it is appropriate and relevant to use it for investigating social media content. Based on sentiment lexicon and algorithmic rules, VADER package analyzes semantic orientation of textual content as positive, negative, or neutral, and returns three scores of positive, negative, and neutral content in addition to the overall compound score of all three. This dissertation particularly adopts overall compound sentiment score which is a metric calculated by summing up all of the lexicon ratings and normalizing the scores between -1 (extremely negative) and 1 (extremely positive).

Network Size. One's network size was measured by collecting the number of followers of the focal user from the scraped Twitter dataset.

Strength of Interpersonal Relationships with Network Neighbors. Strength of interpersonal relationships with network neighbors was measured by calculating Bonacich power centrality (Bonacich, 1987; Himelboim & Golan, 2019). According to Bonacich (1987), the role of a users' centrality needs to take a function of status of *connected others* into account. Bonacich power centrality, therefore, accounts for a user's centrality by summing connections to others that are weighted by the number of interactions. This approach aligns well with the purpose of this dissertation that delineates one's connected others being more or less influential, which then influences their impact on content diffusion within a brand community hashtag network. Therefore, by using power_centrality() function in R with specific parameters set to account for the influence of connected neighbors, positive Bonacich power centrality with positive attenuation of 0.25 was calculated to include the impact of *those who have influence over the conversation as a whole through other well-connected others*, whereas negative Bonacich power centrality with negative attenuation of -0.25 was calculated for the impact of

those who rather have power over peripheral others who are highly dependent on the given user within the networks.

Content Reach and Engagement. Content reach was measured by retrieving the number of retweets attached to each tweet scraped from Twitter API. Similarly, content engagement was measured by retrieving the number of replies attached to each tweet scraped from Twitter API.

Content Characteristics. Content sentiment was calculated by using VADER package in Python to get the quantified sentiment of textual content by accounting for the intensity of emotion (i.e., positive, negative, and neutral). Affective and cognitive content characteristics were identified by running Linguistic Inquiry and Word Count (LIWC) 2022 software to conduct computerized textual analysis. When textual content of the scraped tweets is imported in the software, LIWC 2022 analyzes the focal psychometric properties of linguistic content in a given text by assessing a dictionary including over 12,000-word corpus, word stems, and emojis (Boyd, Ashokkumar, Seraj, & Pennebaker, 2022). Every textual content of the scraped tweets was analyzed for the proportional amount of affective and cognitive content calculated from the given text.

Control Variables. In order to control for the potential product category and brand presence effects, product category and the number of Twitter followers of the selected brands were included as control variables in all of the performed analyses for hypotheses testing.

Data Analysis Plans

First, when treating the number of retweets and replies as dependent variables to assess content reach and engagement, distribution of the count data was found to be overdispersed where variances were significantly larger than their corresponding means (retweets: M=58.5, s^2=157370.885; replies: M=.2439, s^2=35.921) (see Table 2.2). Therefore, negative binomial

regression analyses are appropriate to test hypotheses involving retweets and replies count data as dependent variables. Thus, the pscl R package (Jackman, 2020) was used to test Hypothesis 1 and Hypothesis 4a-b.

Table 2.2
Descriptive Statistics of the Variables

Variables	M	SD	s^2
Network size	40723.44	280560.75	7820000000
Affective content	5.94	5.11	26.08
Cognitive content	3.79	4.77	22.78
Retweets	58.5	396.7	157370.89
Replies	.2439	5.99	35.92
Positive sentiment	.0999	.1103	.0122
Negative sentiment	.0185	.0462	.0021
Neutral sentiment	.8816	.1196	.0143
Strength of interpersonal relationships with well-connected network neighbors (Retweet network)	-.6546	1.2945	1.6758
Strength of interpersonal relationships with peripheral network neighbors (Retweet network)	.4337	1.3276	1.7626
Strength of interpersonal relationships with well-connected network neighbors (Reply network)	-.1065	0.8532	0.7279
Strength of interpersonal relationships with peripheral network neighbors (Reply network)	.0985	0.9975	0.9950

Next, textual content of each tweet was analyzed to investigate the proportional amount of affective and cognitive content each tweet contains. By using the Linguistic Inquiry and Word Count 2022 (LIWC 2022) software, sampled tweets were analyzed for affective and cognitive processing content, employing a Bag-Of-Words approach based on the LIWC 2022's dictionary that contains 12,000-word corpus (Boyd et al., 2022). Since LIWC measures for affective and cognitive content are proportional data in nature, returned scores of affective and cognitive content variables were converted to range from 0 to 1 to perform beta regression analyses using

gamlss package to test Hypothesis 2 and Hypothesis 4c-d (Stasinopoulos, Rigby, & Akantziliotou, 2008).

Finally, three sentiment scores of each textual content (i.e., positivity, negativity, neutrality) were calculated and saved by using VADER package in Python (see Appendices for the script). Since the three sentiment scores sum up to 1 for the overall sentiment of every textual content, Dirichlet regression analysis is considered appropriate to test the variable for Hypothesis 3 and Hypothesis 4e. Therefore, the DirichletReg package was used for the analyses, using common parameterization. Product category and the number of brand followers were included as control variables across all of the analyses testing the proposed hypotheses.

CHAPTER FIVE

RESULTS

This chapter will describe the details of data preparation and processing, followed by reporting results examining the four hypotheses proposed in this dissertation. A series of computational data analyses aimed to test how network size of consumers and strength of interpersonal relationships with network neighbors of consumers formed around brand community hashtags influence brand-related content diffusion on Twitter. By investigating the eight sampled brand community hashtag networks, the goal of this dissertation is to uncover the impact of individual consumers' network characteristics and relationships with other fellow consumers on spreading brand-related content.

Hypothesis 1: Network Size Influence on Content Reach and Engagement

Hypothesis 1 predicted that consumers' network size would positively influence content reach and engagement. First, to test the impact of network size on content *reach* (i.e., the number of retweets), a negative binomial regression analysis was employed while product category and the number of brand followers were held constant. Results showed that network size did not have a statistically significant influence on the number of retweets (p=.596) (see Table 3.1).

Similarly, to test the impact of network size on content *engagement* (i.e., the number of replies), a negative binomial regression was employed. Results indicated that network size did have a statistically significant and positive influence on the number of replies (β=0.56029, SE=0.02280, z=24.577, p<.001) (see Table 3.2). Therefore, Hypothesis 1 was only partially supported for the positive impact of network size on content *engagement*, demonstrating that

a larger network size of consumers may enhance consumers' engagement with the shared content by fostering active replies among consumers within the brand community hashtag networks.

Table 3.1
Regression Analysis Results of Network Size Impact on Content Reach

Variables	*β*	*SE*	*z*	*p*
Intercept	-4.321e-01	6.328e-02	-6.828	<.001
Network size	-3.533e-08	6.667e-08	-0.530	.596
Prodcat2	4.233	7.809e-02	54.205	<.001
Prodcat3	7.659	1.381e-01	55.477	<.001
Prodcat4	2.796	5.925e-02	47.182	<.001
Brand followers	1.815e-06	3.834e-08	47.326	<.001

Note. * indicates statistically significant findings. Product category as a nominal control variable has been dummy-coded and presented as Prodcat2, Prodcat3, and Prodcat4.

Table 3.2
Regression Analysis Results of Network Size Impact on Content Engagement

Variables	*β*	*SE*	*z*	*p*
Intercept	-5.10473	1.41468	-3.608	<.001
Network size	0.56029	0.02280	24.577	<.001*
Prodcat2	0.55673	0.30161	1.846	<.001
Prodcat3	1.70382	0.43282	3.937	0.065
Prodcat4	0.95316	0.17446	5.463	<.001
Brand followers	-0.11834	0.09918	-1.193	.233

Note. * indicates statistically significant findings. Product category as a nominal control variable has been dummy-coded and presented as Prodcat2, Prodcat3, and Prodcat4.

Hypothesis 2: Network Size Influence on Characteristics of Shared Content

Hypothesis 2 predicted that consumers' network size would increase the amount of cognitive content and affective content shared within the network. To test this hypothesis, a series of beta regression analyses were performed. Results indicated that network size did not have a significant influence on the amount of cognitive content (p=.908), however, it did have a significant and positive influence on the amount of affective content (β=1.260e-08, SE=1.693e-09, t= 7.448, p<.001) shared within the brand community hashtag networks (see Table 3.3). Therefore, Hypothesis 2 was partially supported for the positive influence of consumers' network size on increasing the amount of *affective* content shared within the brand community hashtag networks.

Table 3.3

Regression Analysis Results of Network Size Impact on Content Characteristics

Variables	*β*	*SE*	*t*	*p*
Cognitive content				
Intercept	3.910e-02	1.715e-03	22.793	<.001
Network size	-2.146e-10	1.852e-09	-0.116	.908
Prodcat2	1.834e-03	2.142e-03	.856	.392
Prodcat3	6.312e-02	3.840e-03	16.439	<.001
Prodcat4	8.289e-04	1.638e-03	.506	.613
Brand followers	-2.518e-09	1.051e-09	-2.397	.017
Affective content				
Intercept	9.758e-02	1.568e-03	62.246	<.001
Network size	1.260e-08	1.693e-09	7.448	<.001*
Prodcat2	9.876e-03	1.957e-03	5.045	<.001
Prodcat3	-3.015e-02	3.509e-03	-8.593	<.001
Prodcat4	2.573e-02	1.497e-03	17.187	<.001
Brand followers	-3.440e-08	9.600e-10	-35.830	<.001

Note. * indicates statistically significant findings. Product category as a nominal control variable has been dummy-coded and presented as Prodcat2, Prodcat3, and Prodcat4.

Hypothesis 3: Network Size Influence on Content Sentiment

Hypothesis 3 predicted that consumers' network size would enhance sentiment of the content shared within the network (see Table 2.2 for descriptive statistics). To test this hypothesis, a Dirichlet regression analysis was employed with three VADER scores of positivity (p=.766), negativity (p=.510), and neutrality (p=.195) that sum up to 1, controlling for the product category and brand follower effects. Results showed that network size did not have statistically significant influence on any of the positive, negative, and neutral sentiment of the shared content (see Table 3.4, 3.5, 3.6). Thus, Hypothesis 3 was not supported.

Table 3.4

Regression Analysis Results of Network Size Impact on Positive Sentiment of Content

Variables	*β*	*SE*	*z*	*p*
Intercept	-1.402	3.957e-02	-35.420	<.001
Network size	1.180e-08	3.972e-08	.297	.766
Prodcat2	1.621e-01	4.918e-02	3.296	<.001
Prodcat3	1.043	9.086e-02	11.473	<.001
Prodcat4	-6.259e-02	3.896e-02	-1.606	.108
Brand followers	1.127e-09	2.372e-08	.048	.962

Note. * indicates statistically significant findings. Product category as a nominal control variable has been dummy-coded and presented as Prodcat2, Prodcat3, and Prodcat4.

Table 3.5

Regression Analysis Results of Network Size Impact on Negative Sentiment of Content

Variables	*β*	*SE*	*z*	*p*
Intercept	-2.195	3.804e-02	-57.707	<.001
Network size	2.651e-08	4.029e-08	.658	.510
Prodcat2	1.145e-01	4.710e-02	2.432	.015
Prodcat3	4.813e-01	8.340e-02	5.771	<.001
Prodcat4	2.623e-01	3.758e-02	6.980	<.001
Brand followers	1.397e-07	2.294e-08	6.089	<.001

Note. * indicates statistically significant findings. Product category as a nominal control variable has been dummy-coded and presented as Prodcat2, Prodcat3, and Prodcat4.

Table 3.6

Regression Analysis Results of Network Size Impact on Neutral Sentiment of Content

Variables	*β*	*SE*	*z*	*p*
Intercept	1.124	6.019e-02	18.677	<.001
Network size	8.604e-08	6.643e-08	1.295	.195
Prodcat2	-2.726e-01	7.338e-02	-3.715	<.001
Prodcat3	4.008e-01	1.158e-01	3.462	<.001
Prodcat4	-3.813e-01	5.268e-02	-7.239	<.001
Brand followers	1.143e-07	3.797e-08	3.010	.003

Note. * indicates statistically significant findings. Product category as a nominal control variable has been dummy-coded and presented as Prodcat2, Prodcat3, and Prodcat4.

Hypothesis 4: Moderating Influence of Strength of Interpersonal Relationships with Network Neighbors

Hypothesis 4 predicted that strengths of interpersonal relationships with one's network neighbors (i.e., Bonacich centrality) would amplify the positive influence of consumers' network size on (a) content reach, (b) content engagement, (c) amount of affective content, (d) amount of cognitive content, and (e) sentiment of the content shared within the network. To test this hypothesis, a series of negative binomial regression (to assess the impact on content reach and engagement), beta regression (to assess the impact on the amount of affective and cognitive content), and Dirichlet regression (to assess the impact on content sentiment) analyses were performed respectively for retweet networks and reply networks. In particular, in order to assess the impact of *those who have influence over the conversation as a whole* through other well-

connected others in comparison to *those who rather have power over peripheral others* who are highly dependent on the given user and may have detached from the conversation otherwise, two types of Bonacich centralities were calculated respectively by adding *positive* exponent of 0.25 for *those influencing well-connected others*, and *negative* exponent of -0.25 for *those influencing peripheral others*. Arbitrary exponents of 0.25 and -0.25 were added to avoid matrix singularity while successfully accounting for the influence of connections with others.

First of all, the moderating effects of those influencing well-connected others (i.e., Bonacich centrality with *positive* attenuation of 0.25) and those influencing peripheral others (i.e., Bonacich centrality with *negative* attenuation of -0.25) between network size and content reach and engagement were examined by employing negative binomial regression analysis, controlling for the product category and brand follower effects. The results showed that the interaction between one's network size and *stronger* strength of interpersonal relationships well-connected with its network neighbors would have significant and positive influence on content *reach* (β=1.898e-07, SE=6.528e-08, z=2.908, p=.004) as well as content *engagement* (β=0.19884, SE=0.07253, z=2.741, p=.006). On the other hand, the interaction between one's network size and *weaker* strength of interpersonal relationships that are connected with peripheral neighbors would have significant and negative influence on content *reach* (β=-4.255e-07, SE=1.107e-07, z=-3.843, p<.001), while such negative influence was not statistically significant on content *engagement* (p=.182) (see Table 3.7, 3.8).

Table 3.7

Regression Analysis Results of Strength of Interpersonal Relationships with Network Neighbors x Network Size Impact on Content Reach

Variables	*β*	*SE*	*z*	*p*
Those influencing well-connected others				
Intercept	-5.948e-01	6.397e-02	-9.298	<.001
Network size	4.629e-07	2.978e-07	1.554	.120
Prodcat2	4.337	7.789e-02	55.685	<.001
Prodcat3	7.823	1.377e-01	56.811	<.001
Prodcat4	2.964	6.010e-02	49.318	<.001
Brand followers	1.789e-06	3.829e-08	46.715	<.001
Network size * SIR	1.898e-07	6.528e-08	2.908	.004*
Those influencing peripheral others				
Intercept	-3.870e-01	6.284e-02	-6.159	<.001
Network size	-7.907e-07	3.131e-07	-2.525	.012
Prodcat2	4.118	7.744e-02	53.172	<.001
Prodcat3	7.628	1.367e-01	55.812	<.001
Prodcat4	2.779	5.887e-02	47.214	<.001
Brand followers	1.660e-06	3.879e-08	42.802	<.001
Network size * SIR	-4.255e-07	1.107e-07	-3.843	<.001*

Note. * indicates statistically significant findings. Product category as a nominal control variable has been dummy-coded and presented as Prodcat2, Prodcat3, and Prodcat4. SIR denotes strength of interpersonal relationships with network neighbors.

Table 3.8

Regression Analysis Results of Strength of Interpersonal Relationships with Network Neighbors x Network Size Impact on Content Engagement

Variables	*β*	*SE*	*z*	*p*
Those influencing well-connected others				
Intercept	2.82406	2.04703	1.380	.168
Network size	0.14930	0.12716	1.174	.240
Prodcat2	0.56997	0.28780	1.980	.048
Prodcat3	1.67592	0.41451	4.043	<.001
Prodcat4	1.21424	0.16834	7.213	<.001
Brand followers	-0.20160	0.09519	-2.118	.034
Network size * SIR	0.19884	0.07253	2.741	.006*
Those influencing peripheral others				
Intercept	-2.240216	2.406069	-0.931	.352
Network size	0.747735	0.177731	4.207	<.001
Prodcat2	-0.001324	0.294846	-0.004	.996
Prodcat3	0.712075	0.426800	1.668	.095
Prodcat4	0.880183	0.170612	5.159	<.001
Brand followers	-0.365072	0.097197	-3.756	<.001
Network size * SIR	-0.138993	0.104212	-1.334	.182

Note. * indicates statistically significant findings. Product category as a nominal control variable has been dummy-coded and presented as Prodcat2, Prodcat3, and Prodcat4. SIR denotes strength of interpersonal relationships with network neighbors.

Table 3.9

Regression Analysis Results of Interaction Effects on Content in Retweet Networks

Variables	*β*	*SE*	*t*	*p*
Those influencing well-connected others				
Affective content				
Intercept	9.987e-02	1.577e-03	63.331	<.001
Network size	-2.041e-09	7.583e-09	-0.269	.788
Prodcat2	9.732e-03	1.947e-03	4.999	<.001
Prodcat3	-3.168e-02	3.493e-03	-9.070	<.001
Prodcat4	2.309e-02	1.513e-03	15.258	<.001
Brand followers	-3.400e-08	9.565e-10	-35.547	<.001
Network size * SIR	-4.833e-09	1.661e-09	-2.910	.004*
Cognitive content				
Intercept	3.785e-02	1.733e-03	21.840	<.001
Network size	2.056e-08	8.333e-09	2.467	.014
Prodcat2	1.835e-03	2.139e-03	0.858	.391
Prodcat3	6.395e-02	3.838e-03	16.662	<.001
Prodcat4	2.127e-03	1.663e-03	1.279	.201
Brand followers	-2.639e-09	1.051e-09	-2.511	.012
Network size * SIR	5.378e-09	1.825e-09	2.946	.003*
Those influencing peripheral others				
Affective content				
Intercept	9.756e-02	1.569e-03	62.173	<.001
Network size	6.173e-09	7.855e-09	0.786	.432
Prodcat2	9.863e-03	1.957e-03	5.040	<.001
Prodcat3	-3.012e-02	3.508e-03	-8.584	<.001
Prodcat4	2.552e-02	1.500e-03	17.016	<.001
Brand followers	-3.403e-08	9.824e-10	-34.636	<.001
Network size * SIR	-1.803e-09	2.779e-09	-0.649	.517
Cognitive content				
Intercept	3.899e-02	1.717e-03	22.708	<.001
Network size	1.636e-08	8.595e-09	1.903	.057
Prodcat2	1.843e-03	2.141e-03	0.861	.389
Prodcat3	6.318e-02	3.839e-03	16.458	<.001
Prodcat4	9.438e-04	1.641e-03	0.575	.565
Brand followers	-2.651e-09	1.075e-09	-2.467	.014
Network size * SIR	5.659e-09	3.041e-09	1.861	.063

Note. * indicates statistically significant findings. Product category as a nominal control variable has been dummy-coded and presented as Prodcat2, Prodcat3, and Prodcat4. SIR denotes strength of interpersonal relationships with network neighbors.

Table 3.10

Regression Analysis Results of Interaction Effects on Content in Reply Networks

Variables	*β*	*SE*	*t*	*p*
Those influencing well-connected others				
Affective content				
Intercept	9.743e-02	1.579e-03	61.710	<.001
Network size	3.455e-09	6.592e-09	0.524	.600
Prodcat2	1.044e-02	1.979e-03	5.272	<.001
Prodcat3	-2.981e-02	3.520e-03	-8.467	<.001
Prodcat4	2.591e-02	1.502e-03	17.249	<.001
Brand followers	-3.438e-08	9.633e-10	-35.685	<.001
Network size * SIR	-1.911e-09	1.731e-09	-1.104	.270
Cognitive content				
Intercept	3.957e-02	1.726e-03	22.925	<.001
Network size	1.614e-08	7.206e-09	2.239	.025
Prodcat2	4.576e-04	2.164e-03	0.211	.833
Prodcat3	6.214e-02	3.849e-03	16.146	<.001
Prodcat4	3.370e-04	1.642e-03	0.205	.837
Brand followers	-2.636e-09	1.053e-09	-2.503	.012
Network size * SIR	2.994e-09	1.893e-09	1.582	.114
Those influencing peripheral others				
Affective content				
Intercept	9.783e-02	1.570e-03	62.307	<.001
Network size	3.053e-09	7.062e-09	0.432	.666
Prodcat2	1.048e-02	1.970e-03	5.319	<.001
Prodcat3	-3.033e-02	3.508e-03	-8.646	<.001
Prodcat4	2.566e-02	1.497e-03	17.141	<.001
Brand followers	-3.451e-08	9.607e-10	-35.925	<.001
Network size * SIR	-3.239e-09	2.715e-09	-1.193	.233
Cognitive content				
Intercept	3.836e-02	1.714e-03	22.382	<.001
Network size	2.220e-08	7.709e-09	2.880	.004
Prodcat2	1.456e-04	2.151e-03	0.068	.946
Prodcat3	6.365e-02	3.830e-03	16.620	<.001
Prodcat4	1.049e-03	1.634e-03	0.642	.521
Brand followers	-2.201e-09	1.049e-09	-2.098	.036
Network size * SIR	7.262e-09	2.964e-09	2.450	.014*

Note. * indicates statistically significant findings. Product category as a nominal control variable has been dummy-coded and presented as Prodcat2, Prodcat3, and Prodcat4. SIR denotes strength of interpersonal relationships with network neighbors.

Next, the interaction effects between network size and interpersonal relationships with network neighbors on content characteristics (i.e., affective content, cognitive content) were examined by employing a series of beta regression analyses. In retweet networks, the interaction

between one's network size and *stronger* strength of interpersonal relationships well-connected with its network neighbors would have significant and *negative* impact on the amount of affective content (β=-4.833e-09, *SE*=1.661e-09, *t*=-2.910, *p*=.004), while it had significant and *positive* impact on the amount of cognitive content (β=5.378e-09, *SE*=1.825e-09, *t*=2.946, *p*=.003). However, none of such interaction effects were significant between network size and *weaker* strength of interpersonal relationships connected with one's peripheral neighbors (see Table 3.9). In reply networks, the interaction effects between network size and stronger interpersonal relationships with well-connected others did not have any significant results besides the significant and *positive* interaction between network size and weaker interpersonal relationships on the amount of cognitive content (β=7.262e-09, *SE*=2.964e-09, *t*=2.450, *p*=.014) (see Table 3.10).

Finally, the interaction effects between network size and interpersonal relationships with network neighbors on sentiment of the shared content was examined by employing a series of Dirichlet regression analyses. In retweet networks, interaction effects between one's network size and interpersonal relationships with well-connected others were significant in reducing negative content (β=-0.04869, *SE*=0.02138, *z*=-2.277, *p*=.023) while it also had similar detrimental impact on positive content (β=-0.122086, *SE*=0.021878, *z*=-5.580, *p*<.001). In reply networks, however, none of the interaction effects were found to be significant (see Table 3.12). Thus, Hypothesis 4 was partially supported for the significant and positive moderating impact of strength of interpersonal relationships with one's network neighbors on enhancing content *reach* and *engagement*.

Table 3.11

Regression Analysis Results of Interaction Effects on Content Sentiment in Retweet Networks

Variables	*β*	*SE*	*z*	*p*
Those influencing well-connected others				
Positive content				
Intercept	-5.166092	0.642752	-8.037	<.001
Network size	0.256372	0.044826	5.719	<.001
Prodcat2	0.344082	0.072157	4.769	<.001
Prodcat3	1.218476	0.110722	11.005	<.001
Prodcat4	0.006284	0.043368	0.145	.885
Brand followers	0.077547	0.023312	3.326	<.001
Network size * SIR	-0.122086	0.021878	-5.580	<.001*
Negative content				
Intercept	-5.41963	0.62107	-8.726	<.001
Network size	0.08930	0.04422	2.019	.044
Prodcat2	0.37315	0.07018	5.317	<.001
Prodcat3	0.74971	0.10111	7.415	<.001
Prodcat4	0.34779	0.04101	8.480	<.001
Brand followers	0.17784	0.02271	7.832	<.001
Network size * SIR	-0.04869	0.02138	-2.277	.023*
Neutral content				
Intercept	2.51262	0.95516	2.631	.009
Network size	-0.11909	0.06864	-1.735	.083
Prodcat2	-0.31726	0.11574	-2.741	.006
Prodcat3	0.35363	0.16040	2.205	.027
Prodcat4	-0.32687	0.05645	-5.791	<.001
Brand followers	0.04031	0.03824	1.054	.292
Network size * SIR	0.05370	0.03274	1.640	.101
Those influencing peripheral others				
Positive content				
Intercept	1.26589	0.74856	1.691	.091
Network size	-0.29967	0.07519	-3.986	<.001
Prodcat2	0.44063	0.07357	5.990	<.001
Prodcat3	1.31991	0.11101	11.890	<.001
Prodcat4	0.03485	0.04209	0.828	.408
Brand followers	0.11816	0.02431	4.860	<.001
Network size * SIR	0.13212	0.03319	3.981	<.001*
Negative content				
Intercept	-3.75821	0.69372	-5.417	<.001
Network size	-0.04725	0.06776	-0.697	.486
Prodcat2	0.38767	0.07126	5.440	<.001
Prodcat3	0.76808	0.10148	7.569	<.001
Prodcat4	0.35405	0.04051	8.740	<.001
Brand followers	0.18273	0.02339	7.811	<.001
Network size * SIR	0.01573	0.02997	0.525	.600
Neutral content				
Intercept	-1.64817	1.06348	-1.550	.121
Network size	0.30439	0.09906	3.073	.002

Prodcat2	-0.37185	0.11665	-3.188	.001
Prodcat3	0.29377	0.16092	1.826	.068
Prodcat4	-0.34723	0.05580	-6.223	<.001
Brand followers	0.02876	0.03884	0.740	.459
Network size * SIR	-0.13628	0.04410	-3.090	.002*

Note. * indicates statistically significant findings. Product category as a nominal control variable has been dummy-coded and presented as Prodcat2, Prodcat3, and Prodcat4. SIR denotes strength of interpersonal relationships with network neighbors.

Table 3.12

Regression Analysis Results of Interaction Effects on Content Sentiment in Reply Networks

Variables	*β*	*SE*	*z*	*p*
Those influencing well-connected others				
Positive content				
Intercept	-2.669022	0.527828	-5.057	<.001
Network size	0.005688	0.035631	0.160	.873
Prodcat2	0.360981	0.072240	4.997	<.001
Prodcat3	1.280651	0.111431	11.493	<.001
Prodcat4	0.025559	0.042756	0.598	.550
Brand followers	0.073230	0.023281	3.145	.002
Network size * SIR	0.004558	0.019656	0.232	.817
Negative content				
Intercept	-4.152502	0.514744	-8.067	<.001
Network size	-0.006447	0.034906	-0.185	.853
Prodcat2	0.384222	0.070142	5.478	<.001
Prodcat3	0.762404	0.101610	7.503	<.001
Prodcat4	0.357245	0.040886	8.738	<.001
Brand followers	0.172291	0.022709	7.587	<.001
Network size * SIR	-0.002576	0.019239	-0.134	.893
Neutral content				
Intercept	-0.22331	0.80823	-0.276	.782
Network size	0.08086	0.05328	1.518	.129
Prodcat2	-0.30695	0.11460	-2.678	.007
Prodcat3	0.36301	0.16072	2.259	.24
Prodcat4	-0.36474	0.05549	-6.573	<.001
Brand followers	0.04531	0.03843	1.179	.238
Network size * SIR	-0.04261	0.02935	-1.452	.147
Those influencing peripheral others				
Positive content				
Intercept	-3.04342	0.61713	-4.932	<.001
Network size	0.01197	0.04568	0.262	.793
Prodcat2	0.36760	0.07201	5.105	<.001
Prodcat3	1.30036	0.11094	11.721	<.001
Prodcat4	0.03200	0.04271	0.749	.454
Brand followers	0.07681	0.02323	3.307	<.001
Network size * SIR	0.00139	0.02574	0.054	.957
Negative content				
Intercept	-4.86560	0.60080	-8.099	<.001

Network size	0.04471	0.04421	1.011	.312
Prodcat2	0.38772	0.06978	5.557	<.001
Prodcat3	0.76769	0.10117	7.588	<.001
Prodcat4	0.35570	0.04072	8.735	<.001
Brand followers	0.17343	0.02260	7.675	<.001
Network size * SIR	-0.03007	0.02484	-1.211	.226
Neutral content				
Intercept	-0.63444	0.91748	-0.692	.489
Network size	0.09518	0.06607	1.441	.150
Prodcat2	-0.27433	0.11388	-2.409	.016
Prodcat3	0.41500	0.15930	2.605	.009
Prodcat4	-0.35064	0.05536	-6.333	<.001
Brand followers	0.05477	0.03817	1.435	.151
Network size * SIR	-0.05025	0.03689	-1.362	.173

Note. * indicates statistically significant findings. Product category as a nominal control variable has been dummy-coded and presented as Prodcat2, Prodcat3, and Prodcat4. SIR denotes strength of interpersonal relationships with network neighbors.

CHAPTER SIX

DISCUSSION

The primary goal of this research was to extend the understanding of consumers' roles within brand community hashtag networks grounded in the perspectives of consumer identities and subsequent intragroup behaviors observed on social media. Consumers' in-group perception toward specific online brand communities formed around brand community hashtags was examined by looking at the network size of individual consumers within the brand community hashtag networks as well as strength of the relationships that consumers maintain with their neighbors through the network. Based on the theoretical guidance of social identity theory (Tajfel & Turner, 1979) and optimal distinctiveness theory (Brewer, 1991), consumers' interaction with other fellow consumers and relationship building processes were investigated in the context of networked brand communication on social media.

Findings indicated that a larger network size of consumers alone may enhance consumers' *engagement* with the shared content within the brand community hashtag networks by facilitating consumers' tendency to reply to the content, but it was not the case when it comes to content reach. In addition, consistent with previous findings (e.g., Britt et al., 2020), a larger network size of consumers tended to facilitate higher proportion of *affective* content shared within the brand community hashtag networks, whereas it didn't have any noticeable impact on the amount of *cognitive* content and sentiment of the overall content. Moreover, findings of this dissertation uncovered the significant role of interpersonal relationships with network neighbors emerged such that interaction effect between consumers network size and stronger strengths of

interpersonal relationships actively connected with their network neighbors would significantly enhance both content *reach* and *engagement*. This finding demonstrates that consumers who have larger network connected strongly with their neighbors would not only help spreading brand-related content to wider audience through brand community hashtags, but also play significant roles in engaging consumers with such content.

In terms of content characteristics, interaction effect of network size and strengths of interpersonal relationships with network neighbors was found to reduce affective content, but increase cognitive content shared within retweet networks while such tendency was not prominent in reply networks. In terms of sentiment of the shared content, one's network size and *stronger* strengths of interpersonal relationships with network neighbors tie together to reduce negativity, but also decrease positivity at the same time. As such, consumers who have a large network size and maintain active interactions with their neighbors within the brand community hashtag networks tend to elicit more retweets including cognitive language, but less retweets containing affective language. Although these results do not support the proposed direction of hypotheses, it is worth noting that consumers' network size and strengths of interpersonal relationships with network neighbors altogether may have distinct effects on fostering cognition-laden communication through the brand community hashtag networks.

Networked Relationship among Consumers

Previous literature on consumer interactions observed through social media revealed that consumers identify with brands, form communities with other consumers linked to those brands, and spread electronic word-of-mouth (eWOM) spontaneously (Carlson et al., 2008; Kaur et al., 2020). As the role of consumers expands alongside the rapid change and development of social media platforms (Liu-Thompkins et al., 2020), consumer interaction behaviors on social media

can be understood by closely examining the networked structure of the relationship consumers develop and maintain through social media platforms (Kim & Hyun, 2019). Particularly, increasing popularity of shared hashtags among consumers contribute to documenting relevant information related to brands, bringing consumers together in an online arena to continue sharing experiences and opinions about brands, and reinforcing consumer identification with brands over time (Baker & Walsh, 2018; Naraine et al., 2018). In this sense, findings of this dissertation provide fruitful insights in that individual consumers' networks formed within brand community hashtags were examined to highlight the networked relationships among consumers who identify similarly with certain brands on Twitter. This research is one of the few advertising studies that provide empirical evidence showing consumer identities are grouped together on social media platforms to form meaningful communities that influence brand-related content diffusion outcomes.

Consumer Network Size

When understanding networked relationships among consumers, one of the primary traits a consumer has on social media platforms is the size of one's network (Borgatti et al., 2013). Qu et al. (2021)'s social network analysis, for instance, supported the idea that consumers' network size would positively predict brand-related content discussion by facilitating content sharing or liking behaviors on social media platforms. In particular, respective consumers are considered as influential egos within social networks, which in turn imposes noticeable impact on how other consumers connect and engage with them (Perry et al., 2018; Qu et al., 2021). As such, network size of individual consumers within a social network may subsequently influence the overall engagement behaviors (Park & Kaye, 2017). Following this line of research, consistent with the previous findings (Kim, 2017; Lee et al., 2011; Qu et al., 2021), findings of this dissertation also

showed that a larger network size of consumers can facilitate content engagement with other fellow consumers through shared brand community hashtags by inducing higher likelihood of retweets. Furthermore, by incorporating the impact of network size on content characteristics, it is also noteworthy that a large network size of consumers can facilitate *affective* content shared within brand community hashtag networks. This finding adds support to the existing literature such that a large *size* of consumers' network could be a driving force to facilitate affective language shared among the other consumers who are actively engaged within the network (Britt et al., 2020; Qu et al., 2021).

Role of Networked Neighbors in Brand-Related Content Diffusion

Interpersonal relationships consumers develop and maintain with their neighbor consumers connected through brand community hashtags play important roles in brand-related content diffusion process. Given that consumers form their networked relationships with other fellow consumers on social media platforms (Bandura, 2001; Reed, 2002), understanding those who are connected *closely* with each consumer may provide useful guidance to uncover how individual consumers' connections with others may help content diffusion through brand community hashtags. Findings of this dissertation demonstrated that stronger strengths of interpersonal relationships developed with well-connected network neighbors had significant and positive influence coupled with a large network size of consumers on enhancing content reach and engagement within brand community hashtag networks. This significant interaction effect between strengths of interpersonal relationships with consumer's network neighbors and network size implies that not only the large size of consumer network, but strong interpersonal relationships with one's network neighbors must also be considered together to effectively increase brand-related communication outcomes on Twitter.

Interestingly, even more so, such content diffusion through the large size of consumer network with strong strengths of interpersonal relationships with network neighbors will facilitate cognitive language shared within the brand community hashtag networks. Cognitive and affective language, and the sentiment of such language shared in communication has been largely studied in a various context of brand communication (Britt et al., 2020; Dhaoui & Webster, 2021; Moran et al., 2019). Advertising literature indeed has offered an underlying mechanism addressing the role of cognition and affection in sharing brand-related content in digital platforms and discussed ad effectiveness in engaging others through the content (see Tellis et al., 2019). In line with this research context, previous empirical research points to the notable impact of affect-laden and emotional conversations on driving consumer engagement and positive attitudinal and behavioral intentions (e.g., Eckler & Bolls, 2011). It is also essential to recognize that hashtags as an effective and accessible tool for consumers to locate and share information related to brands by triggering more cognition-laden conversations that can benefit both consumers and brands to exchange useful information (e.g., Kim & Phua, 2020). In that sense, the findings of this dissertation may suggest that brand content diffusion through consumers who maintain a large size of network with connected influential neighboring consumers would work as effective bridges between consumers and brands not only for reaching wider consumer audience, but also for driving cognitive engagement around brand communication on Twitter.

Theoretical and Managerial Implications

Findings of this dissertation suggest several theoretical and managerial implications. First of all, this research provides empirical evidence of consumer interaction and engagement within "consumer groups" on social media shaped around specific hashtag networks. Extant literature

around consumer identity in brand communication context has explored in-group perception of consumers grouping themselves with other consumers and its impact on the following brand-related decision making and evaluations (Reed, 2002; Yang et al., 2017). The discussion has been extended to investigate how consumers utilize social media platforms for the purpose of sharing brand experiences with others and the consequences of such consumer-brand interactions through social media platforms (Araujo et al., 2017; Fedushko & Kolos, 2019; Phua et al., 2017).

Despite the continuous academic effort in uncovering the underlying dynamics of consumer perceptions and behaviors linked to brand communication through social media platforms, limited attention has been paid to empirically demonstrate consumers' social identities grouped together on such platforms to develop and maintain networked relationships among other consumers (e.g., Qu et al., 2021). Grounded in social identity theory and optimal distinctiveness theory, this dissertation may fill this gap in the literature by demonstrating the role of individual consumers' network size on content diffusion processes in addition to dismantling the influence of strengths of interpersonal relationships with network neighbors. This empirical evidence of consumer social identities associated with particular brands and online brand communities may help extend the understanding of community-related consumer behaviors through the lens of social identity perspectives. Specifically, moving beyond community identification and in-group consumer behaviors, significant moderating influence of strengths of interpersonal relationships with network neighbors observed in this research may shed light on the importance of investigating "who" are connected within social in-groups in brand communication context, which links to the propositions of optimal distinctiveness theory.

It is also worthwhile to note that findings revealed significant relationships between one's network characteristics involved within the brand community hashtags and the subsequent

content characteristics shared within the networks. By exploring the existing conversations around eight brands that incorporate four different brand categories (Vaughn, 1980), findings of this dissertation imply cohesive relationship between individual consumers' egocentric network characteristics, such as network size, and content diffusion outcomes as well as characteristics of shared content. In particular, positive influence of consumers' network size on increasing *affective* content shared within the brand community hashtag networks extend the previous findings on brand-related content diffusion literature (Britt et al., 2020; Qu et al., 2021) by uncovering what type of content is more likely to be shared along with the joint effect of one's network size.

In managerial perspectives, the observed impact of consumers' network size and the strengths of interpersonal relationships with network neighbors on content diffusion may help guiding advertising practitioners' communication planning and decision-making processes. As growing industrial effort has been made to engage consumers with social media content through specific hashtags linked to brands (B2C, 2021), it is essential to incorporate strategic approach in planning and executing hashtag advertising through social media. Findings of this research imply brand community hashtags provide an effective structure to ongoing brand-related conversation by developing and maintaining networked relationships among consumers who share similar interests around the brands on social media platforms. The structure that consumers appearing within brand community hashtag networks form with other consumers through the hashtags was found to amplify engagement among their members. Particularly, it is important to note that consumers who are actively involved in the brand community hashtag networks with a large size of followers and their influential adjacent network neighbors may serve as effective bridges in *reaching* and *engaging* other fellow consumers through the content shared within the brand

community hashtag networks. Therefore, advertising and marketing practitioners who plan to grow brand-related hashtags for content diffusion purposes are advised to plan specific communication objectives and action plans that match well with the network characteristics of target audience.

Limitations and Directions for Future Research

Although findings of this dissertation provide meaningful implications for academics and industry professionals, it is not without limitations. First, samples of this study may not be completely representative of all brand community hashtags that exist on Twitter. For the purpose of this study, only eight particular brands and their corresponding brand community hashtags were examined. Brand personalities specific to each brand may have confounding effect on how consumers engage and interact with other fellow consumers and/or the shared content on Twitter. Relatedly, one particular brand community hashtag (e.g., #JeepNation) was sampled for each brand, meaning other potential hashtags associated with the brands (e.g., #JeepLife, #JeepCreep) were not considered in this dissertation. Following FCB Grid model (Vaughn, 1980), four different product categories were controlled and held constant for its potential effects on the proposed relationships. Future studies can investigate the effect of different product categories on brand content diffusion through brand community hashtags on social media platforms. Second, in order to implement ethical data mining using Twitter API, only publicly available user accounts and tweets were scraped and included in the samples. Therefore, private user accounts or tweets were not included. In addition, it should be noted that Twitter algorithms may have converted the number of followers since late March 2022, which might have affected the samples collected in May 2022. Twitter was selected as a social media platform because of its high potential in facilitating content diffusion through hashtags for the purpose of this

dissertation (see Kwon, Han, & Kim, 2017). The results, however, may not be the same with other social media platforms pertaining to their unique characteristics, such as TikTok or Instagram. Future studies may examine the platform impact on how consumers interact with other consumers who share similar interests around particular brands and its subsequent influence on brand communication outcomes. Moreover, it is worth examining the specific role of official brand accounts in facilitating brand-related conversations within the brand community hashtag networks and their active and/or passive involvement to achieve desirable reach and engagement. Moving further, longitudinal perspectives on consumer interaction and relationship building behaviors through the brand community hashtags would also provide extensive understanding of how brand communication can be developed and sustained over time on social media.

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APPENDICES

Script 1: Data Scraping from Twitter API

```
import time
import requests
import pandas as pd

def next_search(
    url,
    query = None,
    max_results = 100,
    tweet_fields = None,
    user_fields = None,
    start_time = None,
    end_time = None,
    since_id = None,
    max_id = None,
    expansions = None,
    token = { 'name': 'next_token', 'value': ''}):

    params = {
        'query': query,
        'max_results': max_results,
        'tweet.fields': tweet_fields,
        'user.fields': user_fields,
        'start_time': start_time,
        'end_time': end_time,
        'since_id': since_id,
        'max_id': max_id,
        'expansions': expansions
    }

    if token['value']:
        params[token['name']] = token['value']

    headers = {
        'Authorization': 'Bearer Token' #Put Valid Bearer Token
    }
    r = requests.get(url, headers=headers, params=params)
    print('--------------------------------\nrequest url: {}\nresponse: {}\n\n\n------
--------------------------'.format(r.request.url, r.json()))

    return r.json()

def get_user_object(r):
    user_objects = {}
    for user in r['includes']['users']:
        user_objects[user['id']] = {
            'userid': user['id'],
            'username': user['username'],
            'followers': user['public_metrics']['followers_count'],
            'followings': user['public_metrics']['following_count']
```

```
        }
    return user_objects

# unlike user object (guaranteed to have), we need to make sure 'mention' key exists
def get_mention_objects(r):
    entity_objects = []
    if 'mentions' in r['entities']:
       for mention in r['entities']['mentions']:
            entity_objects.append(mention['id'])
    return list(set(entity_objects)) if entity_objects else []

def get_retweet_user_objects(tweet_id):
    # make sure to pause 1s not to go over the rate limit
    retweet_user_objects = []

    next_token = ''
    while True:
        time.sleep(1)
        r = next_search(
            url = '/'.join(('https://api.twitter.com/2/tweets', tweet_id,
'retweeted_by?')),
            token = { 'name': 'pagination_token', 'value': next_token }
        )
        if 'title' in r and r['title'] == 'Too Many Requests':
            print('sleep for 15m to get around the rate limit')
            for i in range(900,0,-60):
                print('{} seconds are left'.format(i))
                time.sleep(60)

        if 'data' in r:
            retweets = r['data']
            for retweet in retweets:
                retweet_user_objects.append(retweet['id'])

        next_token = parse_meta(r)
        if not next_token:
            break

    return list(set(retweet_user_objects)) if retweet_user_objects else []

def get_reply_user_objects(username, userid, tweet_id):
    reply_user_objects = []

    next_token= ''
    while True:
        time.sleep(1)
        r = next_search(
            url = 'https://api.twitter.com/2/tweets/search/all',
            query = ''.join(['conversation_id:', tweet_id]),
            tweet_fields = ','.join(['lang', 'in_reply_to_user_id', 'author_id',
'conversation_id']),
            since_id = tweet_id,
            token    = { 'name': 'next_token', 'value': next_token }
        )

        if 'title' in r and r['title'] == 'Too Many Requests':
            print('sleep for 15s to get around the rate limit')
            time.sleep(15)

        if 'data' in r:
            replies = r['data']
```

```
            for reply in replies:
                if reply['lang'] == 'en':
                # if 'in_reply_to_user_id' in r and  r['in_reply_to_user_id'] ==
userid and r['conversation_id'] == tweet_id:
                    reply_user_objects.append(reply['author_id'])
        next_token = parse_meta(r)
        if not next_token:
            break
    return list(set(reply_user_objects)) if reply_user_objects else []

# make sure that the response contains 'data' key and exit early if not existed
def parse_data(r):
    if 'data' not in r:
        return pd.DataFrame()
    tweets = r['data']
    ids = []
    userids = []
    usernames = []
    followers = []
    followings = []
    retweets = []
    likes = []
    replies = []
    texts = []
    created_ats = []

    num_unique_mentions = []
    unique_mention_user_ids = []
    num_unique_retweets = []
    unique_retweet_user_ids = []
    num_unique_replies = []
    unique_reply_user_ids = []

    for tweet in tweets:
        if tweet['lang'] == 'en':
            ids.append(tweet['id'])
            user_objects = get_user_object(r)
            userids.append(user_objects[tweet['author_id']]['userid'])
            usernames.append(user_objects[tweet['author_id']]['username'])
            followers.append(user_objects[tweet['author_id']]['followers'])
            followings.append(user_objects[tweet['author_id']]['followings'])

            retweets.append(tweet['public_metrics']['retweet_count'])
            likes.append(tweet['public_metrics']['like_count'])
            replies.append(tweet['public_metrics']['reply_count'])
            texts.append(tweet['text'])
            created_ats.append(tweet['created_at'])

            # mentions
            mention_objects = get_mention_objects(tweet)
            num_unique_mentions.append(len(mention_objects))
            unique_mention_user_ids.append(mention_objects)

            # retweets
            # only look up retweet if retweet_count > 0
            # not to encounter rate limits too often
            if tweet['public_metrics']['retweet_count'] > 0:
                print('--------------------------------tweet_id: {}, retweet_count:
{}, look up--------------------------------'.format(tweet['id'],
tweet['public_metrics']['retweet_count']))
                retweet_user_objects = get_retweet_user_objects(tweet['id'])
```

```
                num_unique_retweets.append(len(retweet_user_objects))
                unique_retweet_user_ids.append(retweet_user_objects)
            else:
                print('--------------------------------tweet_id:{}, retweet_count: 0,
PASS look up--------------------------------'.format(tweet['id']))
                num_unique_retweets.append(0)
                unique_retweet_user_ids.append([])

            # replies
            reply_user_objects = get_reply_user_objects(
                user_objects[tweet['author_id']]['username'],
                user_objects[tweet['author_id']]['userid'],
                tweet['id']
            )

            num_unique_replies.append(len(reply_user_objects))
            unique_reply_user_ids.append(reply_user_objects)

    data = {
        'tweet_id': ids,
        'user_id': userids,
        'user_name': usernames,
        'followers': followers,
        'followings': followings,
        'retweets': retweets,
        'likes': likes,
        'replies': replies,
        'text': texts,
        'created_at': created_ats,
        'num_unique_mentions': num_unique_mentions,
        'unique_mention_user_ids': unique_mention_user_ids,
        'num_unique_retweets': num_unique_retweets,
        'unique_retweet_user_ids': unique_retweet_user_ids,
        'num_unique_replies': num_unique_replies,
        'unique_reply_user_ids': unique_reply_user_ids
    }

    return pd.DataFrame(data)

# make sure that the response contains 'meta' key then confirm the next_token exists
or not
def parse_meta(r):
    if 'meta' not in r:
        return ''
    return r['meta']['next_token'] if 'next_token' in r['meta'] else ''

def main():
    query_topic = '#HASHTAG BRAND'
    # initial save only with headers
    df = pd.DataFrame(columns=[
        'tweet_id',
        'user_id',
        'user_name',
        'followers',
        'followings',
        'retweets',
        'likes',
        'replies',
        'text',
        'created_at',
        'num_unique_mentions',
```

```
        'unique_mention_user_ids',
        'num_unique_retweet_users',
        'unique_retweet_user_ids',
        'num_unique_reply_users',
        'unique_reply_user_ids'
    ])
    df.to_csv(query_topic+ '.csv', index=False, mode='w')

    next_token = ''
    while True:
        time.sleep(1)
        # initial search
        r = next_search(
            url = 'https://api.twitter.com/2/tweets/search/all',
            query = query_topic,
            max_results = 100,
            tweet_fields= ','.join(['lang', 'created_at', 'author_id', 'entities',
'public_metrics']),
            user_fields = 'public_metrics',
            start_time = '2021-03-31T00:00:00+00:00',
            end_time = '2022-03-31T00:00:00+00:00',
            expansions = 'author_id',
            token = { 'name': 'next_token', 'value': next_token }
        )

        if 'title' in r and r['title'] == 'Too Many Requests':
            print('sleep for 15s to get around the rate limit')
            time.sleep(15)

        df = parse_data(r)
        df.to_csv(query_topic+ '.csv', header=False, index=False, mode='a')
        print('-------------------------------- {}.csv is saved!----------------------
----------\n'.format(query_topic))

        # inspect the next token to see whether the further search is needed
        next_token = parse_meta(r)
        print('next_token: {}'.format(next_token))
        if not next_token:
            break

if __name__ == "__main__":
    main()
```

Script 2: Sentiment Analysis using VADER

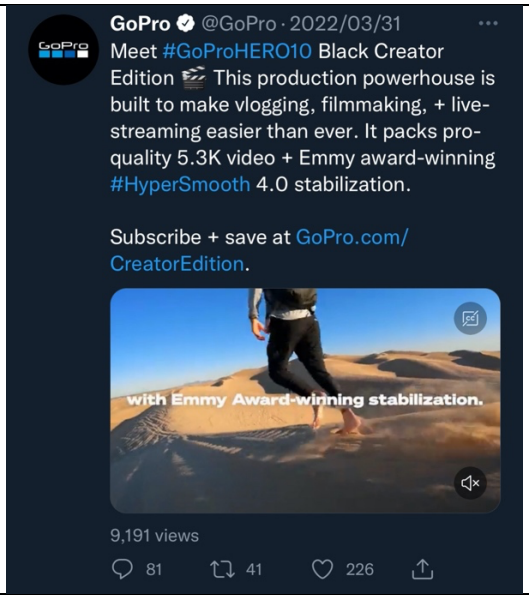
```
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
import pandas as pd

def main():
    df = pd.read_csv('#Hashtag Brand.csv')
    df['text'].fillna(0, inplace=True)
    df["positivity"] = df["text"].apply(positivity_scores)
    df["negativity"] = df["text"].apply(negativity_scores)
    df["neutrality"] = df["text"].apply(neutrality_scores)
    df.to_csv("#Hashtag_VADER.csv", index=False)

def positivity_scores(sentence):
    sid_obj = SentimentIntensityAnalyzer()
    return sid_obj.polarity_scores(sentence)["pos"]
```

```
def negativity_scores(sentence):
    sid_obj = SentimentIntensityAnalyzer()
    return sid_obj.polarity_scores(sentence)["neg"]

def neutrality_scores(sentence):
    sid_obj = SentimentIntensityAnalyzer()
    return sid_obj.polarity_scores(sentence)["neu"]

main()
```

Script 3: Network Analysis using NetworkX

```
import networkx as nx
import igraph
from ast import literal_eval
import pandas as pd

def main():
    G_reply_dc = nx.Graph()
    G_retweet_dc = nx.Graph()

    file_name = '#Hashtag Brand.csv'
    df = pd.read_csv(file_name)

    for index, row in df.iterrows():
        unique_reply_user_ids = literal_eval(row['unique_reply_user_ids'])
        for unique_reply_user_id in unique_reply_user_ids:
            if G_reply_dc.has_edge(str(row['user_id']), unique_reply_user_id):
                G_reply_dc[str(row['user_id'])][unique_reply_user_id]['weight'] += 1
                print('userid: {}, unique_reply_user_id: {}, weight:
{}'.format(str(row['user_id']), unique_reply_user_id,
G_reply_dc[str(row['user_id'])][unique_reply_user_id]['weight']))
            else:
                G_reply_dc.add_edge(str(row['user_id']), unique_reply_user_id,
weight=1)

    for index, row in df.iterrows():
        unique_retweet_user_ids = literal_eval(row['unique_retweet_user_ids'])
        for unique_retweet_user_id in unique_retweet_user_ids:
            if G_retweet_dc.has_edge(str(row['user_id']), unique_retweet_user_id):
                G_retweet_dc[str(row['user_id'])][unique_retweet_user_id]['weight'] +=
1
                print('userid: {}, unique_retweet_user_id: {}, weight:
{}'.format(str(row['user_id']), unique_retweet_user_id,
G_retweet_dc[str(row['user_id'])][unique_retweet_user_id]['weight']))
            else:
                G_retweet_dc.add_edge(str(row['user_id']), unique_retweet_user_id,
weight=1)
    nx.write_weighted_edgelist(G_reply_dc, "brand_reply_edgelist.csv", delimiter= ",")
    nx.write_weighted_edgelist(G_retweet_dc, "brand_retweet_edgelist.csv", delimiter=
",")

if __name__ == "__main__":
    main()
```

Sample Tweets from Official Brand Accounts

	Think	Feel
High Involvement		
Low Involvement