MPC MAJOR RESEARCH PAPER

#JustDoIt: Brand-to-Consumer Interaction via Twitter

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Abstract

Nike's "Possibilities" campaign has become a prime example for social media adoption in marketing. In August 2013, Nike had asked its consumers to redefine "Just Do It" by taking to Twitter and sharing their athletic achievements under the #JustDoIt hashtag. The iconic slogan has since then evolved from a mere promotional message to a trending Twitter topic that continues to engage consumers today. By examining Nike's #JustDoIt Twitter conversation, marketing professionals and scholars alike can develop a more informed understanding of how Twitter facilitates interaction between a brand and its consumers. The paper aims to explore how Twitter can be used to develop and maintain relationships between businesses and consumers by examining the interactions within Nike's #JustDoIt conversation. Using Bakhtin's (1981) notion of heteroglossia and Zappavigna's (2011) interpretation of the imagined audience and ambient affiliation, this paper will conceptualize the interactions that took place and demonstrate their applications to the practice of social business (Rajagopal, 2013) and Integrated Marketing Communication (Kapoor, Jayasimha, and Sadh, 2013). The research questions are:

(1) How does #JustDoIt facilitate interaction between Nike and its consumers?

(2) What are Twitter users saying in Nike's #JustDoIt conversation?

(3) To what ends does #JustDoIt serve in Nike's overall mission?

Heteroglossia, the imagined audience, and ambient affiliation are all concepts that can be used to describe user interactions within Twitter hashtags. For businesses, these terms provide a framework for better understanding how branded content can reach audiences on Twitter, thus informing strategies that seek to engage consumers and spark conversations.

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1. Introduction

Celebrating the 25th year of spreading its trademark message, Nike released its *Possibilities* campaign in August 2013 to "inspire viewers to push their limits and strive to reach new goals" (NIKE Inc., 2013a). The campaign was released with a video sequence that proposes a series of progressively challenging goals aimed to motivate the audience to push themselves to achieve more. The video's conclusion summarizes the images and overall message by displaying the organization's popular slogan: "Just Do It." (NIKE Inc., 2013e).

Through the campaign, Nike put out a call to action asking viewers to engage with their series of Nike+Running and NikeFuel products. Viewers were encouraged to share their achievements by taking to Twitter and posting to the #JustDoIt hashtag. The goal of the campaign was to celebrate personal successes and in the process, help others to "realize new possibilities" (NIKE Inc., 2013a).

As a result, Nike's trademark message had evolved from a mere promotional message intended to persuade consumers to purchase products, to a Twitter topic designed to motivate and inspire participants far beyond the campaign period.[1]

In a larger context, by investigating the Twitter interactions that have taken place since the campaign's launch, marketing professionals can glean from the #JustDoIt conversation how consumers were interacting with one another and with the brand. A similar study examined the use of Twitter for entrepreneurs and concluded that "social media can provide a means of 'observing' customers, getting closer to customers, and developing personal and company brands" (Fischer & Reuber, 2011, p. 16). The #JustDoIt conversation serves as a prime event for investigating these conclusions, as well as for investigating whether and how the message has changed in its intended meaning. Research into this area can directly inform communication scholars and marketing professionals on how Twitter can facilitate Brand-to-Consumer (B2C) engagement, and become a foundation for bridging research in Computer-Mediated Communication (CMC) tools for businesses in the context of online and digital social networking.

As a business, Nike has made it clear within their quarterly reports and investor statements that the organization continues to focus on tying their digital strategy to bottom line revenues. Mark Parker, President and Chief Executive Officer at NIKE Inc., stated in the 2013 NIKE Investor Meeting: "As the world becomes increasingly digital, we thrive because of our deep consumer connections" (NIKE Inc., 2013b, p. 1). To put this into context, Parker references "digital" in terms of Nike's broader "Digital Ecosystem" which includes "consumer connections, e-commerce, and digital products and services" (NIKE Inc., 2013b, p. 2). In the same investor meeting, Parker attributed the company's ongoing innovation to Nike's digital products and services, noting that the Nike+ brand category has over 20 million members who collectively ran over one billion miles (NIKE Inc., 2013b, p. 4). Moreover, Parker has claimed that the NikeFuel and Nike+ product lines, along with their encompassing Fuel Points system,[2] are "the global currency of movement" (NIKE Inc., 2013b; NIKE Inc., 2013c).

So how does this claim tie back to Nike's overall mission? The company's *About* page reads: "Our mission: To bring inspiration and innovation to every athlete* in the world. *If you have a body, you are an athlete" (NIKE Inc., 2014a). Guided by this mission statement, Nike's operational strategy revolves around offering products and services designed to help their consumers reach their personal goals (NIKE Inc., 2014a). Indeed, motivating consumers to interact with one another via the brand aligns with a strategy that Trevor Edwards, President of the NIKE Brand, refers to as the "category offense" – a "consumer-segmented growth strategy that enables [NIKE] to grow business by serving the consumers with innovative products and services through the language of sport that they are most passionate about" (NIKE Inc., 2013c). Perhaps this language, in the form of hashtags and fuel points, is what Nike refers to as the "global currency of movement" (NIKE Inc., 2014b). If so, then vast amounts of transactions using this currency have been indexed on Twitter via the #JustDoIt conversation. Not only are users posting quotes, opinions, and stories, but tweets about the Nike+ and NikeFuel points can also be found on Twitter.

It can thus be said that Nike's venture into the digital space is a strategy to connect with the everyday athlete. Edwards asserts that for Nike, "Digital is like oxygen: it's omnipresent and indispensable. It's everywhere and it's always on" (NIKE Inc., 2013c). He goes on to state:

> For us at Nike, we see digital as an opportunity to better connect and better serve our consumers, a way to have a more personal relationship with them. We're always finding new and better ways to help our consumers engage with our brand through social communities, finding inspiring stories about athletes. (NIKE Inc., 2013c).

Leveraging the power of the web, the company created the Nike Community Forums[3] to bring consumers together through motivation and encouragement. Extending the forums onto other social media platforms, members in each category (e.g., running) can use hashtags to share progress and motivation.

Figure 1: *Sample tweet in the #JustDoIt conversation*

1.1. Relevance and Larger Context

Much like Nike, many organizations have begun to realize the advantages of incorporating a social media strategy (Burton & Soboleva, 2011). This Major Research Paper (MRP) focuses on a specific social media campaign by following Nike's #JustDoIt Twitter hashtag. By examining Nike's #JustDoIt campaign, this paper aims to provide insights into the B2C relationship in social networks, as well as social media returns. In this MRP, the term *social media returns* will be used loosely to refer to the non-financial goals and objectives of Nike as they were found on the organization's websites and publicly available documents. These goals and objectives include what Edwards mentioned in the Investor Meeting: "finding new and better ways to help our consumers engage with the brand through social communities" and to "better connect and better serve our consumers" (NIKE Inc., 2013b, p. 9). While this paper places less emphasis on returns in terms of financial revenue, on a theoretical level, this paper's research findings can bridge the knowledge between communication studies and studies in marketing by illustrating how theoretical concepts can be applied in the field. Other studies have also examined the relationship between communication studies and marketing on social media. Kapoor, Jayasimha, and Sadh (2013) for example, discussed the shift in consumer influence that took place with the advent of social media, claiming that social media had "empowered consumers by connecting them all together into conversational webs" (p. 54). In another study, Fischer and Reuber (2011) examined how user interaction on Twitter affected consumer influence and concluded that "without doubt, Twitter and other social media have the potential to be valuable tools that, if deployed well, can positively affect business outcomes such as sales growth, brand image, and company reputation" (p. 16). Through this MRP, observed patterns and behaviours can be used to validate or challenge concepts within existing studies on social media, ultimately deepening the understanding of B2C communication on Twitter.

While scholars have often referred to social media as websites where users engage with their networked connections (Mangold & Faulds, 2009; Marwick & boyd, 2010), this paper focuses specifically on the interactions that took place on Twitter. Twitter is particularly interesting because of its ability to facilitate networking and also because users are able to view and comment on posts from other users outside of their network. Gillen and Merchant (2013) refer to Twitter as a Social Networking Site (SNS) because it allows users to "follow" one another, and distinguishes Twitter from other forms of social media like Facebook and LinkedIn where the user-to-user relationship is symmetrical (p. 51-52). In other words, Twitter users are not required to follow-back those who have followed them (asymmetrical), whereas on Facebook and LinkedIn, the connection is necessarily mutual.

2. Literature Review

This MRP examines the interactions that took place within Nike's #JustDoIt Twitter conversation and compares the findings to Nike's overall mission and objectives. To cover the exploratory nature of this MRP, the literature review will draw from studies on Twitter and social media, communication, and Integrated Marketing Communication (IMC). First, this literature review will examine Twitter as a platform for social interaction, and more specifically, examine the communicative features afforded by the hashtag feature. This will become the foundation for studying Nike's Twitter campaign which took place using the #JustDoIt hashtag. Next, the literature review will discuss two concepts in which this MRP's study of Twitter has been framed: the first is heteroglossia; the second is imagined audience. Lastly, the concept of "social business" (Rajagopal, 2013) will be reviewed to illustrate the connection between Twitter and IMC.

2.1. Twitter

Twitter is defined as a social networking and microblogging site, known for its strict 140-character long messages called “tweets” (Gruzd, Wellman, & Takhteyev, 2011, p. 1296). Twitter’s style of networking differs from other social networking sites in so far as the user-to-user relationship does not have to be mutual: users can subscribe to the tweets of other users without requiring them to follow back (Gruzd et al., 2011; Naaman, Boase, & Lai, 2010). This indirect user-to-user relationship is different from other social networking sites like Facebook or LinkedIn, which are “structured to allow people who know each other – now or in the past – to keep in contact” (Gruzd et al., 2011, p. 1296). Any tweet sent by the user would in turn appear on the stream of all of his or her followers. Conversely, any tweets from profiles that the user follows would appear on the user’s stream (Naaman et al., 2010).

Moreover, Twitter’s @Username and hashtag functions are both communicative features that can connect and expand a user’s social network in various ways. Bruns and Moe (2014) distinguished between the micro-layer of communication, which can be identified by tweets that are directed at specific users via the @Username function; the macro-layer, which are all tweets within a hashtag, and; the meso-layer, which are tweets that do not contain the username or hashtag (p. 19). Scholars have noted that the @Username feature functions not only as a way to target and direct messages (Honeycutt & Herring, 2009), but it also acts as a hyperlink to the user’s profile page (Gillen & Merchant, 2013). Hashtags on the other hand allow users to label and follow specific topics on Twitter. Scholars have been interested in the hashtag functionality because each hashtag becomes a way to create metadata (Zappavigna, 2011, p. 791). In other words, should a person be interested in the 2014 Ontario Elections, he or she could search for the #ONPoli hashtag on Twitter and view all tweets on the discussion.

Building on this thought, Jones (2014) researched instances where multiple hashtags were used in one post to investigate how, through hashtags, networks can leverage resources from other networks. Jones (2014) found that, “examining the operation of these [hashtagged] exchanges can help us better understand the multiple purposes involved in their use” (p. 103).

Indeed, the way in which brands can communicate with consumers has been made easier with Twitter’s features. Hyperlinks, @ replies, retweets, and hashtags allow for conversations to be both directed and interactive. Zappavigna (2011) calls these features "linguistic markers” and suggests that they “bring other voices into tweets by addressing other users, republishing others’ tweets, and flagging topics that may be adopted by multiple users” (p. 790). Zappavigna (2011) claims that the hashtag in particular “is also broadly involved in construing *heteroglossia*[4] in the sense that it “presupposes a virtual community of interested listeners who are actively following [a] keyword or who may use it as a search term” (p. 791). Through this lens, three important concepts emerge in which this MRP will be framed: (1) brand communication on Twitter, (2) the concept of heteroglossia, and (3) the notion of the imagined community.

2.2. Heteroglossia: A Mix of Voices

In *The Dialogic Imagination*, Bakhtin (1981) refers to heteroglossia as “the problem of internal differentiation, the stratification characteristic of any national language” (p. 67). Heteroglossia is a term for describing those diverse voices that add to the intended meanings of speech. Within a much broader framework, heteroglossia lends itself to Bakhtin’s (1981) concept of dialogism, which suggests that a word or a message is “a dialogue between points of view, each with its own concrete language” (p. 76). Bakhtin (1981) adds that this language “is not a neutral medium that passes freely and easily into the private property of the speaker’s intentions; it is populated – overpopulated – with the intentions of others” (p. 294). Zappavigna (2011) claimed that a topic, indexed via hashtags, facilitates heteroglossia via the republishing of tweets (retweets) and through the adaptation of a single topic by multiple users (p. 790). Gillen and Merchant (2013) adds that each tweet in the hashtag becomes what Bakhtin (1986) conceptualizes as "a link in the chain of speech communion" that can be organized and added on to by the users (p. 75-76). Thus, hashtags have been argued to engender heteroglossia through the shared usage of the tag from one user to the next.

Originally used to differentiate between the epic and the novel, the notion of heteroglossia can also apply to Twitter in that "utterances" (Bakhtin, 1981), like #JustDoIt for example, can be interpreted differently depending on each individual user. Bakhtin (1981) suggests that heteroglossia occurs when users incorporate "novelistic layers of literary language… permeated with laughter, irony, humour, elements of self-parody… a certain openendedness [sic], a living contact with unfinished, still-evolving contemporary reality" (p. 7). In other words, while Twitter users are able to follow and contribute to conversations of the same topic by including a hashtag, the hashtag itself becomes heteroglossic by having a variety of intended meanings and uses.

The hashtag thus becomes an important Twitter convention in itself. Bakhtin (1981) suggests that "[the] languages of heteroglossia intersect each other in a variety of ways, forming new socially typifying languages" (p. 291). Zappavigna (2011) advances this claim on to hashtags by suggesting that the # symbol allows the keyword to be searchable, thus amplifying the tweet and opens up "a new kind of sociality where microbloggers engage in ambient affiliation" (p. 802). The meaning of the hashtag can thus be defined by the multiple voices that adopt and use the term. Hashtags and their accompanying contexts would "encounter one another and co-exist in the consciousness of real people" (Bakhtin, 1981, pp. 291-292). In essence, heteroglossia celebrates the presence of different voices, styles, and points of views. As such, heteroglossia is a relevant and reasonable term that can explain the significance of the #JustDoIt hashtag: by having multiple participants, Nike's original "Just Do It" message may very well experience shifts in meanings whenever a user embeds the hashtag to their post. Consider the following tweets for example:

> @UserA: Day 1 of DC #TrainingMode starts tomorrow. #EatClean #Run #Fitness #Fresh #WeRunDC #JustDoIt http://instagram.com/p/lWFv4xqi0m/
>
> @UserB: 20 years from now you will be more disappointed by the things that you didn't do than by the ones you did do. #JustDoIt ✓
>
> @UserC: If someone could print out a sheet of 200x143 graph paper and bring it to me, you'd be my hero. #dontaskquestions #justdoit

@UserA in the first tweet used the #JustDoIt hashtag in conjunction with other tags (e.g., #EatClean, #Run, #Fitness) to promote a healthy lifestyle, whereas @UserB in the second tweet engaged the #JustDoIt tag by sharing a few words of wisdom. While it may be true that both tweets have a motivational undertone, one can speculate that perhaps @UserA interpreted #JustDoIt as more fitness-related, while @UserB saw the #JustDoIt tag as a way to spread general motivation. In contrast, @UserC used the #JustDoIt hashtag as a part-of-speech—"Don't ask questions, just do it"—rather than to promote fitness or general motivation like users A and B. Zappavigna (2011) agrees that outside of its ability to index tweets of the same topic, hashtags can also be used to replace classifiers (#children), processes (#hate), or a thing (#brocolli) (p. 792). Within the digital sphere, the Twitter hashtag should be of particular interest because it is user-defined rather than prescribed. That is, a user can essentially start a hashtag using any combination of characters so long as it follows the hashtag convention (e.g., no special characters or no spaces may be used). Androutsopoulos (2011) posits that these "intentional" vs. "emergent" topics are a characteristic of heteroglossia in the digital space (p. 294).

2.3. The Imagined Community and the Imagined Audience

Drawing from Bakhtin's (1986) imagined community, a single utterance equates to a tweet that starts a chain in which other users can react and respond to. These chains can be observed within Twitter via the user's social awareness streams (Naaman et al., 2010) where users can respond, ignore, retweet, or quote specific tweets from other users. Audiences on Twitter, however, are unique from other social networking sites such as Facebook. Zappavigna (2011) asserts that unlike other forms of social media, Twitter is unique in that the expectation for someone to respond is not there – thus "the metaphor of 'Twittering' continuously like a bird implies" (p. 790).

In the context of social media, Litt (2012) describes the imagined audience as "the mental conceptualization of people with whom we are communicating, our audience" (p. 331). In other words, the imagined audience consists of all of the user's followers who the user thinks he or she is communicating with as well as all other users that the tweet may be visible to. Thus, the hashtag plays a crucial role in communicating with the imagined audience. Zappavigna (2011) suggests that the indexing of tweets (via hashtags, for example) merely allows users to participate in conversations, feeding the "affiliation" aspect of ambient affiliation; the "ambient" nature of tweets is observed through the idea that "users may not have interacted directly and likely do not know each other, and may not interact again" (p. 802). Zappavigna (2011) used the #Obama hashtag as an example to show "if you are interested in values about Obama search for me" (p. 801). Other scholars also seem to agree with this notion by claiming that hashtag participants "do not necessarily know each other, but have been brought together by a shared theme, interest, or concern" (Bruns & Moe, 2014, p. 19), and that hashtags "draw the attention of other users to a particular message within a wider network" (Jones, 2014, p. 104). Studies have shown that the imagined audience does in fact hold influence on user behaviour (Litt, 2012). Other scholars have noted that despite having no prior relationship with one another, people can be motivated to act simply by observing others (Long, Gable, Boerstler, & Albee, 2012, p. 284). Marwick and boyd (2010) add one further distinction between the "imagined audience" and the "networked audience" by claiming that the latter is both public and personal. The networked audience, as Marwick and boyd (2010) suggests, includes connections with whom the user is familiar with, as well as individuals who have random or unknown connections to the user (p. 129). The imagined audience on the other hand, are all Twitter profiles that the user is not directly aware of, thus users "imagine it" (Marwick & boyd, 2010, p. 117). In other words, users on Twitter are able to socialize and interact with other users that they may not be aware of.

In *Theorizing Twitter* (2012), Murthy suggests that the "social" aspect of social media is "designed to facilitate social interaction, the sharing of digital media, and collaboration" (p. 1061). Murthy (2012) also draws on Bakhtin's (1981) concept of heteroglossia by suggesting that Twitter "provides ways for individuals to assert and construct the self which [is] contingent on a larger dialogic community" (p. 1061). This dialogic community Murthy (2012) refers to is composed of all Twitter users that are contributing to conversations, the network of followers, and the list of those that a user follows. All of the users are connected via the @replies, retweets (RTs), and the hashtagging of conversations.

Murthy (2012) discusses two main reasons why such functionalities are interesting when compared to face-to-face communication: (1) Twitter offers the capacity to re-embed tweets, and (2) users may wrongfully attribute the owner of the utterance. First, unlike face-to-face communication, re-embedding tweets essentially places the conversation back into the present (p. 1067). In other words, @UserB can respond to a tweet sent by @UserA one week ago: the response would be re-situated on both users' streams as the present rather than the past. While this is not only characteristic of Twitter (consider receiving a response to an e-mail you sent days ago), Murthy (2012) adds that retweeting or responding to a tweet not only situates the message into the sender and receiver's present, but also in the present time of the networked audience. That is, all of @UserA and @UserB's followers see the response as if it was a recent conversation. This brings us to the second idea Murthy (2012) theorizes which is that "an 'everyday' tweet posted by an ordinary individual has a potentially large readership if it is retweeted" (p. 1069). While retweeting by default attributes the tweet to the original sender (e.g., "RT @Nike…."), Murthy (2012) suggests that there is a possibility that new audiences ignore this piece of information, ultimately misattributing the tweet (p. 1067). Combining these two ideas together, the following metaphor fittingly describes what some may envision a Twitter conversation to be:

> Having a conversation on Twitter can be more like sitting in a room with a door, not knowing who is going to pop their head around and respond or who is listening behind the door. Additionally, it could be several people coming through that door within seconds of each other. This is compounded by the fact that the number of other rooms grows larger every time someone retweets your tweets to their followers. (Murthy, 2012, p. 1069)

2.4. Twitter as a Focus for Research

Scholars have conceptualized Twitter as another realm of social interaction (Murthy, 2012) in relation to imagined audiences (Marwick & boyd, 2010; Litt, 2012). Other studies have taken a linguistic perspective on language use on Twitter as a means for building identification (Page, 2012) and ambient affiliation (Zappavigna, 2011). In terms of user interaction, Naaman et al. (2010) examined communication patterns between users through the use of "social awareness stream" (SAS), and Gruzd et al. (2011) explored the notion of the imagined community and how

Twitter facilitates a sense of community (SoC). These and other studies illuminate the appeal and feasibility of studying Twitter as a communication technology that promotes social connections.

2.4.1. Qualitative Studies on Twitter.

Numerous scholars have used a qualitative approach to study Twitter. In one study, Litt (2012) explored aspects of the imagined audience as it relates to Twitter by examining factors that influence interactivity. Marwick and boyd (2010) also investigated the imagined audience by asking their own Twitter followers questions such as, "Who do you imagine [is] reading your tweets?" (p. 118). Other qualitative studies examined how Twitter can shape social interaction (Murthy, 2012), influence others (Kapoor et al., 2013; Mostafa, 2013), and facilitate the co-creation of meaning (Gillen & Merchant, 2013).

In a study that examined what Twitter users were saying, Dann (2010) used an inductive method to develop a six-category classification system that described the types of content users were posting. Altogether, Dann (2010) proposed 23 possible classifications based on four previous studies (see Appendix A). His six top-level categories include: (1) conversational, (2) pass along, (3) news, (4) status, (5) phatic communications, and (6) spam. Tweets that were information-seeking or had addressivity through including the @Username tag (Honeycutt & Herring, 2009; Zappavigna, 2011) were classified as *conversational* content. The *pass along* category included tweets that were intended to share information or had a URL, as were tweets that were self-promoting and/or advertising information. Headlines, event coverage, or other reporting of information were classified as *news*, while those that answered "*what are you doing now*?" were classified as *statuses*. Within the *phatic* category were greetings, monologues, or opinions. Finally, the *spam* category encompasses tweets that were automated or unsolicited posts from malware or bots. In Dann's (2010) study, the qualitative approach was used to explore and identify a more encompassing model for content classification. These studies illustrate the viability of using inductive approaches to conceptualize the processes and content of Twitter communication.

2.4.2. Quantitative studies on twitter.

There also exists a body of quantitative research on Twitter. Bruns and Stieglitz (2012) for example, collected and analyzed over 40 hashtagged conversations to identify and compare communicative patterns amongst users on Twitter. In another study, Greer and Ferguson (2011) conducted a large-scale analysis to find a relationship between Twitter interactivity and TV viewership. The study examined Twitter sites of 488 television stations and found that public stations and commercial stations utilized different promotional branding strategies (Greer & Ferguson, 2011, p. 207). Like some of the aforementioned qualitative studies, some quantitative studies examined the co-creation of meaning (Zappavigna, 2011) and user influence (Hawthorne, Houston, & McKinney, 2013, p. 557). These studies showed that the quantitative approach can be useful for identifying usage patterns and behaviours.

2.5. Integrated Marketing Communications

Existing marketing literature has defined Integrated Marketing Communications (IMC) as “a guiding principle organizations follow to communicate with their target markets…. It attempts to coordinate and control various elements of the promotional mix – advertising, personal selling, public relations, publicity, direct marketing, and so forth” (Mangold & Faulds, 2009, p. 357). Even still, these researchers have claimed that the traditional IMC model excludes B2C interaction, though recent studies suggest that “online communication in particular is an ideal avenue for fostering dialogue” (Rybalko & Seltzer, 2010, p. 336). These studies have proposed an alternative approach which “combines some of the characteristics of traditional IMC tools with a highly magnified form of word-of-mouth communication” (Mangold & Faulds, 2009, p. 359). The approach accounts for the interactions that take place between the brand and the consumer, as well as the consumer to other consumers (Rajagopal, 2013, p. 112).

Scholars have claimed that Twitter and other social networking sites have changed the way marketing professionals and organizations communicate with consumers, sometimes using the term "consumer-generated media" to refer to social media (Mangold & Faulds, 2009, p. 357). A study conducted in 2011 that compared organizational use of Twitter in six companies with an American and an Australian account (twelve accounts in total) acknowledged that "Twitter and other social media platforms create additional marketing communication channels" (Burton & Soboleva, 2011, p. 491). The same study found that companies were not consistent in their use of Twitter, revealing in one company, that the Australian Twitter account used hashtags more frequently than its American profile. Burton and Soboleva (2011) suggested that one of the key issues for this discrepancy is that "for organizations attempting to develop an effective and efficient Twitter strategy, there is the lack of theoretical or empirical evidence on [the] use of Twitter" (p. 491). Mangold and Faulds (2009) echo this claim, suggesting that "the popular business press and academic literature offers marketing managers very little guidance for incorporating social media into their IMC strategies" (p. 358).

Indeed, the advent of social media and social networking sites has caused somewhat of a crisis for marketers worldwide. While the traditional marketing and promotion mix mirrored the one-to-many broadcast approach to communication, studies in Twitter and consumer behaviour have revealed that with the advent of communication technology, the one-to-many approach is no longer effective (Nitins & Burgess, 2014, p. 294). That is, no longer is it logical to think that the organization controls the message. Instead, scholars have contended that professionals should actively monitor, facilitate, and/or interject into user conversations that are taking place (Nitins & Burgess, 2014; Mangold & Faulds, 2009).

As a starting point, scholars have already recognized that with the advent of social media and social networking sites, consumer-generated messages "have become a major factor in influencing various aspects of consumer behaviour including awareness, information acquisition, opinions, attitudes, purchase behaviour, and post-purchase communication and evaluation" (Mangold & Faulds, 2009, p. 358). Burton and Soboleva (2011) conclude that, "it is unsurprising, then, that more organizations are developing Twitter accounts as an additional way of communicating with customers" (p. 492).

2.6. Making Business Social

Twitter and other social networking platforms present a variety of alternate engagement opportunities, including disseminating coupons or initiating contests. These activities can be categorized as *social business* (Rajagopal, 2013, p. 111). The concept of social business can be helpful to organizations seeking to build and maintain consumer relationships. One of the ways organizations can benefit from social media is by understanding user expectations. Rajagopal (2013) explains that "people want to connect with other people, not with companies" (p. 110). Other research echoes this sentiment, claiming that effective brand-to-consumer relationships form out of the needs of the consumer (Long et al., 2012, p.281). Long et al. (2012) examined how the regulation of goals facilitated the connection between the brand and the consumer. Pertaining to Nike, studies claim that, "noticing others pursuing a goal makes people more likely to pursue the same goal, even if they have no prior relationship with the observed actor" (Long et al., 2012, p. 284). Zappavigna (2011) refers to this process of influence as the ambient affiliation among members of Twitter's imagined audience within hashtagged conversations.

Another way organizations can benefit from a social media strategy within their business operations is to "read" Twitter from a business perspective. Hutchby (2001) claims that by reading technology as if it were text, users can use the technology to "best suit the purposes they have in mind for the artefact" (p. 445). In other words, organizations can benefit from using Twitter if they begin to start "reading" the technology for business purposes. Fischer and Reuber (2011) echo this claim, suggesting that "those who will benefit the most from social media will regard them not solely as a means of communicating with stakeholders, but also as a potential avenue for seeing or making opportunities" (p. 17). Indeed, if organizations were to read Twitter as a tool for connecting and engaging with consumers rather than merely a personal microblogging site, then perhaps there could be much more value in the platform than simple broadcasting and self-promotion.

eWord-of-Mouth (eWOM). Organizations have already begun to realize the shift in consumer interaction. As Mangold and Faulds (2009) put it, "consumers like to network with people who have interests and desires that are similar to their own" (p. 361). For consumers, Twitter has opened a door for soliciting and exchanging information and experiences. In a study about brand-related consumer communication via social media, researchers have found that consumers tend to share information and experiences in part because of altruism (Kapoor et al., 2013, p. 54). The study examined consumer-to-consumer influence on purchasing decisions in the online environment, and defined eWOM as internet-enabled communication from a potential, actual, or former customer about a product or company (p. 49). As an evolution of traditional face-to-face word-of-mouth (WOM), eWOM is not specifically confined to social media, but also extends to product review websites, retailer websites, blogs, and message boards (Kapoor et al., 2013, p.48). Scholars in professional communication as well as business have repeatedly claimed that organizations need not control conversations, but instead entice engagement and stimulate conversation (Smith, Fischer, & Yongjian, 2012, p. 111).

Much of the literature reviewed highlighted Twitter as a platform for social interaction that is particularly useful for engaging consumers online. Concepts like eWOM (Kapoor et al., 2013) and social business (Rajagopal, 2013) can be used to contribute to existing work on Twitter and communication. As consumers continue to take to Twitter to share product reviews and experiences, it becomes even more important for organizations to understand the conversations that may take place. As a platform, Twitter's ability to facilitate interaction between members of otherwise unconnected audiences – the imagined audience – makes for a worthwhile subject of study, especially in the context of B2C relationships. While it is important to have models and conceptualizations of communication on Twitter (Dann, 2010; Naaman et al., 2010; Zappavigna, 2011), it is also important for scholars to analyze discussions in detail so as to gain a better understanding of how and in what ways B2C relationships manifests. This MRP explores the link between communication theory and professional practice by examining Nike's #JustDoIt conversation through Bakhtin's (1981) concept of heteroglossia and Zappavigna's (2011) notion of ambient affiliation among the imagined audiences.

3. Research Questions

Based on the literature review of Twitter, IMC, and business studies, this MRP focuses on observing the emergent conversations within Nike's #JustDoIt topic and investigates the interactions between the brand and its consumers. The research questions are:

RQ1: How does #JustDoIt facilitate interaction between Nike as a brand and its consumers?

RQ2: What are Twitter users saying in Nike's #JustDoIt conversation?

RQ3: What role does #JustDoIt serve in Nike's overall mission?

Research Question 1 seeks to identify and understand the types of interaction that transpired within the #JustDoIt conversation. This knowledge is valuable because it informs an organization's operational strategies, and also benefits the scholarly community by either confirming or challenging previous findings on Twitter and interaction.

Research Question 2 examines whether the #JustDoIt conversation is purely confined to Nike; by examining the conversations that took place, this research paper aims to identify emerging topics to see if any shifts in the meaning of "Just Do It" took place, and if so, what were they? Having multiple topics within the #JustDoIt conversation may indicate heteroglossia is present. Moreover, findings from RQ2 will contribute to a better understanding of what users are talking about.

Research Question 3 aims to relate the results and conclusions from RQ1 and RQ2 to the concept of social business and IMC. Thus, RQ3 will explore why marketing professionals should care about interaction on social media (Page, 2012; Rybalko and Seltzer, 2010; Mangold and Faulds, 2009). Drawing from RQ1 for example, levels and types of interactions in the frame of original content or retweets can provide insights into user behaviour within hashtags, and more broadly, social media campaigns. Topic analyses from RQ2 are also important in order to understand how conversations take shape, and more importantly, how conversations inform marketing professionals about how to leverage aspects of heteroglossia and the imagined audience to control the overall topics within the hashtag.

4. Method

This MRP applies the concepts of heteroglossia, social business, and the imagined community to conceptualize the patterns of interaction among the participants of the #JustDoIt hashtag. Based on the literature reviewed, no tools or methods were found that can quantify heteroglossia, the imagined community, or social business in statistical terms. The primary research questions are, however, more concerned with exploring and describing the interactions within Nike's #JustDoIt conversation than they are at measuring these concepts. Therefore, this MRP uses a mixed-method approach to analyze Nike's #JustDoIt conversation. Findings of this research will be supported through qualitative analyses as well as empirical evidence gained from quantitative analyses.

Previous studies that examined the interactivity of Twitter users were conducted based on a content analysis of Twitter messages. These studies used and built upon existing models of content categories and required manual coding of selected tweet samples (see Dann, 2010; Naaman et. al., 2010; Page, 2012). Other studies opted for a more quantitative approach that allowed researchers to analyze large quantities of data using various software, resulting in empirical evidence to support some claims (Bruns, A., 2012; Gruzd et. al., 2011; Herdagdelen, 2013). In a study that investigated the use of computer-assisted content analysis in examining aspects of speech act theory, Einspänner, Dang-Anh, and Thimm (2014) argued that the use of Computer-Assisted Qualitative Analysis Software (CAQDAS[5]) for Twitter research can be more efficient when dealing with large datasets (p. 99). The researchers concluded that a mixed-methods approach may be appealing as the quantitative and qualitative elements would "minimize [each other's] shortcomings" (Einspänner et al., 2014, p.105).

4.1. Data Collection

The main source of data for this study came directly from Twitter, specifically the #JustDoIt hashtag. Tweets were collected using Gruzd's Netlytic platform (Netlytic.org, 2014) and exported into a .csv file. Netlytic is a non-proprietary, web-based platform that can import data from Twitter and analyze the information using a suite of built-in tools including network visualizations, and frequency-driven word clouds and topic analysis. In order to collect a sufficient and representative amount of data, the collection phase spanned two months from March 1, 2014 to April 30, 2014. Due to Twitter API restrictions, Netlytic required a manual renewal of data imports; queries were renewed every six days to ensure that the collection process was continuous. Netlytic collected 1,000 tweets per hour, but was unable to collect tweets retroactively (i.e., historical data). Tweets were only collected from public profiles at the time of collection.[6]

It should be noted that scholars have been debating what constitutes a representative corpus. Twitter researchers have cited reasons such as data limitations, access to historical data, scalability, storage space, computing power, and timeline issues to argue that "no dataset captured using the Twitter API is guaranteed to be completely comprehensive" (Bruns & Liang, 2012). This seems particularly true for research on hashtags. Bruns and Stieglitz (2014) noted that hashtag corpora "contain only a selection of all communication taking place on Twitter… hashtag datasets do not contain all relevant tweets, but only those whose authors knew of and felt motivated enough to include the hashtag in the tweet" (p. 75). Even so, scholars argue that research on Twitter remains "valid and important" (Bruns & Liang, 2012) when appropriate methods are used (Bruns & Stieglitz, 2014; Einspänner et al., 2014).

While it would be interesting to compare findings from the actual campaign period to the timeframe in this study, historical tweets dating back to the campaign period were not available to all users. In an online search for viable tools to collect Twitter data for this MRP, it was discovered that only a handful of tools, licensed by Twitter, were available for mining historical tweets. Even still, these tools were quite expensive for the scope of this MRP. Furthermore, it was determined that historical data was not required for answering this MRP's research questions: interactivity, emerging topics, and trends could still be detected using existing and real-time data. As a result, Netlytic was the most appealing platform for harnessing data for this study because it allowed for a continuous collection of tweets and provided analytic tools. Since searchable tweets are visible to the general public, the data collected are considered public documents. Netlytic provided the following nine data points per tweet (see Netlytic.org, 2014):

- *ID* – a numerical identifier of the string of data collected (e.g., 1, 2, 3)
- *[Guide]*– a full URL to the tweet
- *Link* – a full URL to the tweet
- *Pubdate* – the full date that the tweet was published
- *Author* – the user who published the tweet
- *Title* – the content within the tweet
- *Description* – the content within the tweet
- *Source* – the method in which the post was published (e.g., iPhone, desktop, web)
- *Code* – a codified identifier of the tweet

For the purposes of this MRP, the *guide*, *title*, and *code* columns were excluded because the information was either repeated (e.g., *guide* and *link* both provided URLs to the tweet, and *title* and *description* both provided the tweet content), or the information was irrelevant to the study (*code*).

	A	B	C	D	E	F	G	H	I	J	K	L
1	id	guid	link	pubdate	author	title	descriptic	source	code	descriptic		
2	4	http://twi	http://twi	3/1/2014 20:27	QuayBae	#justdoit I	#justdoit I	Twitter fo	ad72ab909b60e1a5789fe47aef5276bf			
3	6	http://twi	http://twi	3/1/2014 20:26	JaimeRive	My color v	My color v	Instagram	59abfe40e6dc808729feab52d68d41ce			
4	9	http://twi	http://twi	3/1/2014 20:25	CSparksXt	You scare	You scare	Twitter fo	bdc1f193a522e5c6cd99ab94d16c1af6			

Figure 2: *Screenshot of Netlytic Export*

4.2. Quantitative Methods

The Netlytic platform was used to analyze the main corpus as a whole. The platform reported the top mentioned usernames as well as the most common words found within the corpus by frequency.

Netlytic's Name Network visualization tool was also used, which counts all of the usernames found in the corpus and visualizes the data in a network graph. Each user is represented as a node, and is connected to other users via edges or ties if interaction through username mentions took place (Gruzd & Haythornthwaite, 2013). This is particularly useful because it visualizes the connection between users, or "node-to-node connections" (Gruzd & Haythornthwaite, 2013). The size of each node depends on the number of interactions that the user initiated or received; the more interaction, the larger the node. Users who posted content without addressing, replying, or mentioning other users were represented as a node with zero ties – an "isolated node" (Gruzd & Haythornthwaite, 2013, para. 23). These distinctions are important to make on Netlytic; The Name Network tool can produce visualizations based on the number of times a user mentions or replies to another user – referred to as the *out-degree* centrality – or it can visualize the number of times a user receives a mention or retweet – the *in-degree* centrality (Gruzd & Haythornthwaite, 2013). At the time of study, Netlytic had the option of visualizing the data using *total-degree* centrality, which is a combination of the aforementioned methods (Gruzd, 2014).

In addition to Netlytic, the AntConc Corpus Toolkit[7] was also used for quantitative analysis. The AntConc Corpus Toolkit is a non-propriety software developed by Laurence Anthony (Anthony, 2005) that can perform statistical analyses on large bodies of text. Specifically, AntConc is capable of generating frequency-driven wordlists, and is able to perform keyword, concordance, collocation, and cluster analyses. Einspänner et al. (2014) claim that though

CAQDAS (such as AntConc) is not commonly used in Twitter research, its analytic tools can help to interpret large amounts of data by introducing statistical measures (p. 105). In the scope of this MRP, AntConc was used to identify emerging topics using the keyword, collocation, and cluster analyses.

Finding keywords that emerge from Nike's #JustDoIt conversation was crucial for understanding how specific words are used, thus identifying what the conversations were about. Keyword analyses are different from regular wordlist generators (e.g., a word cloud) because keyword lists require a reference corpus (that is significantly larger than the study corpus) which is used to generate a *keyness score* for each word. A word's *keyness score* is usually calculated using log likelihood (or also chi-square) tests, and identifies words that have unusually high or unusually low frequency of appearance when compared to the same word and its frequency in the reference corpus (Anthony, 2005, pp. 732-734). In effect, a high keyness score indicates that the word occurs significantly more times than it does in the reference corpus, while a negative keyness score (e.g., -10) indicates an unusually infrequent appearance of a word when compared to the reference corpus. In a study comparing the usefulness of keyword lists versus regular word lists, Baker (2006) concluded that keyword lists are "likely to be more useful in suggesting lexical items that could warrant further examination" (p. 2). This 'further examination' can be done through the concordancing tool, which identifies the words that surround the keyword, ultimately providing greater context as to how the word is being used (Baker, 2006, p. 3).

During the data analysis phase of this MRP, it was determined that while the concordance tool identified how keywords were used, the collocation tool was easier to use and provided more useful information. The concordance analysis simply shows the entire sentence in which a search term was used (e.g., *Nike*) and highlights the words to the left or right depending on the user settings (Anthony, 2005, p. 730). On the other hand, the collocation tool provided frequencies in which words were found to co-occur with the search term, thus indicating a possible relationship. While Baker (2006) suggested that these word relationships may need to be validated through additional concordance analyses (p. 24), it was found that the cluster tool mirrored the concordance tool in that it provided the words immediately to the left or right of the search term. The cluster tool, however, also provided frequencies of appearance, which the concordance tool did not. For these reasons, this MRP favoured the collocation and cluster analyses over the concordance tool.

4.3. Qualitative Methods

For the qualitative analysis, the main corpus was divided into two subcorpora using Microsoft Excel. Using the filtering function, the *description* column was filtered to identify tweets with "RT @" within the body of the text. Tweets containing "RT @" were placed in the retweet-only (RT) corpus, while those without were placed in the original-content (OC) corpus.

The next step was to create a sample size for analysis. In examining the use of CAQDAS for Twitter research, Einspänner et al. (2014) claimed that extracting a subsample of data from the larger corpus for qualitative analyses would be appropriate within the mixed-method framework (p. 105). For the scope of this MRP, a random sample of 96 tweets per subcorpus was created using a number randomizer.[8] Tweets were selected using the generated numbers, which were matched with the *ID* field from the Netlytic data export. Using a web-based statistical calculator,[9] it was determined that a sample size of 96 tweets per subcorpus was sufficient to produce a 95% confidence level with a 10% confidence interval relative to corpus size. As a result, 196 tweets in total were analyzed with an expected 85% accuracy (95% ± 10%).

The codebook consists of six categories: (1) Author, (2) Forms of Interaction, (3) Content Structure, (4) Source Device, (5) Topics and Themes, and finally, (6) Unit of analysis. These categories were developed using an inductive approach with the data points provided by Netlytic, as well as emergent categories from manually reviewing the samples. The Topics and Themes category for example, consists of seven sub-classifications that were developed based on the content's relation to Nike, fitness, and motivation. Other scholars have used this inductive approach for coding content. Vickey, Ginis, and Dabrowski (2013) used this method to develop a classification model for analyzing two million fitness tweets. Similarly, the Content Structure category in this study adapted six sub-classifications from Dann's (2010) review of Twitter literature.

4.4. Operationalizing the Research Questions

Methods Used to Explore Research Questions

Research Question	Tools	Quantitative Analysis	Qualitative Analysis
RQ1 - How does #justdoit facilitate interaction between Nike as a brand and its consumers?	Netlytic	Name Network Analysis	
	Excel	Term Frequency Analysis	Content Analysis
RQ2 - What are Twitter users saying in Nike's #justdoit conversation?	AntConc	Corpus Linguistic Text Analyses	Content Analysis / Topic Analysis
RQ 3 - To what ends does #justdoit serve in Nike's overall mission?	N/A		Meta-Analysis

Table 1: *Operationalizing the Research Questions*

This MRP used a combination of quantitative, statistical analysis via the AntConc Corpus Toolkit and qualitative content analysis of tweets to produce a mixed-methods approach for answering the research questions. The mixed-methods approach was ideal for this MRP as the study seeks to explore patterns and behaviours within the *#JustDoIt* conversation, and uses statistically-driven analyses to support qualitative observations.

The following section describes how each of the research questions were operationalized using the different tools (Table 1), and describes the qualitative and quantitative methods used.

RQ1: How does #JustDoIt facilitate interaction between Nike as a brand and its consumers?

At the quantitative level, Netlytic's Name Network tool visualizes the amount of users as well as the nodes and ties between them. This MRP uses the total-degree centrality for visualizing these relationships, which includes the number of @mentions each user sent as well as received (see: Gruzd & Roy, 2014). Using Microsoft Excel's filtering function, the number of retweets and original tweets can reveal whether users in the #JustDoIt conversation tend to publish original content or retweet content. The AntConc Corpus Toolkit can also show how often keywords would appear within each subcorpus. At the qualitative level, the hand-coded content analyses can reveal different levels of interactivity based on the tweet's structure and characteristics (e.g., URLs), which will facilitate a theoretical exploration of heteroglossia and the imagined audience.

RQ2: What are Twitter users saying in Nike's #JustDoIt conversation?

Using traditional methods from corpus linguistics, AntConc can extract keywords from the RT and OC subcorpora, which can be further analyzed to identify contexts using the cluster and collocation tools. First, keywords will be identified using AntConc's keyword generator. The reference corpus contained 1.6 million words that were extracted from Twitter.[10] Identifying keywords would inform the research on the emerging themes within conversations. Next, collocation analyses will be performed on the extracted keywords to identify the words that precede and proceed the keyword in question. This will identify possible relationships between the keyword and other words, indicating how these words were used. Finally, cluster analyses will be used to identify groups of words (e.g., sentences) that the keyword appears in, thus providing a better understanding of what users are "talking about" within the corpora.

RQ3: To what ends does #JustDoIt serve in Nike's overall mission?

Research Question 3 seeks to identify whether the conversations in #JustDoIt are aligned with Nike's mission and objectives. Information regarding Nike's mission and objectives has been collected from published and publicly available data on NikeInc.com. Transcripts from their Investor Meeting (NIKE Inc., 2013b), and Quarterly Meeting (NIKE Inc., 2013c) were particularly helpful in identifying Nike's high-level strategies for consumer engagement. Other objectives were identified by combing through Nike's website, including statements such as "to inspire everyone in their personal achievements" in the official *Possibilities* campaign press release (NIKE Inc., 2013a), "to motivate athletes at all levels to move more" from a November 2013 press release (NIKE Inc., 2013d), and "to achieve goals" on the Nike Community Forums (NIKE Inc., 2014b).

Findings from RQ1 and RQ2 will be used to conceptualize the observed interactions in terms of social business (Rajagopal, 2013) and eWOM (Kapoor et al., 2013). Through the discussion portion of this MRP, Research Question 3 will ultimately answer whether the observed interactions (RQ1) and conversations (RQ2) had any impact on Nike's digital strategy.

5. Findings

The aim of this MRP was to identify and analyze the various levels and types of interactions that took place within the #JustDoIt conversation. Results of the mixed-method analyses have been divided into subsections according to the relevant research questions and the methods used.

5.1. RQ1: Patterns in User Interaction

This section will first discuss the volume of original content and retweets captured in the main Netlytic corpus. Next, visualizations generated from Netlytic's Name Network tool will be explained, briefly alluding to the concepts of heteroglossia and the imagined audience. An in-depth analysis of the hand-coded results will follow and conclude findings for RQ1.

5.1.1. Original Content vs. Retweets.

The main corpus from Netlytic contained a total of 118,608 tweets collected from March 1, 2014 to April 30, 2014. Compared to other studies, the size of this MRP's corpus seemed sufficient given that the search term was confined to one hashtag. The size of other corpora used in previous studies have varied significantly: A study on the 2011 Canadian Federal Election only collected 5,918 tweets over a two-day period (Gruzd & Roy, 2014), while another study used a corpus with 34,770,790 tweets for sentiment analysis (Thelwall, Buckley, & Paltoglou, 2011).

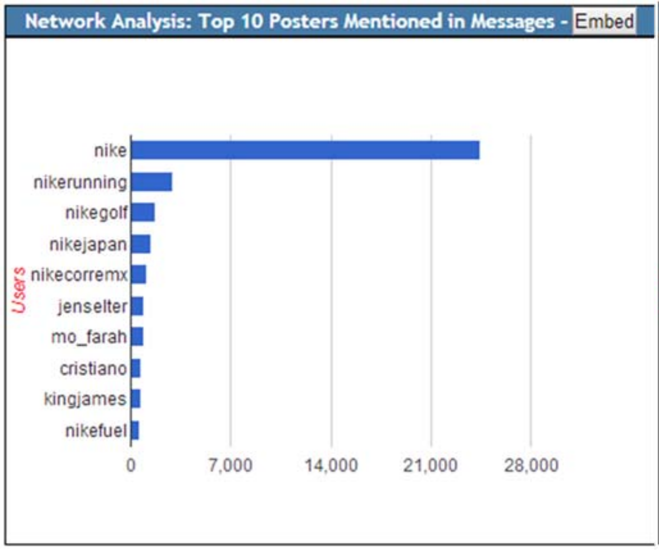

Figure 4: Top 10 Mentioned Users

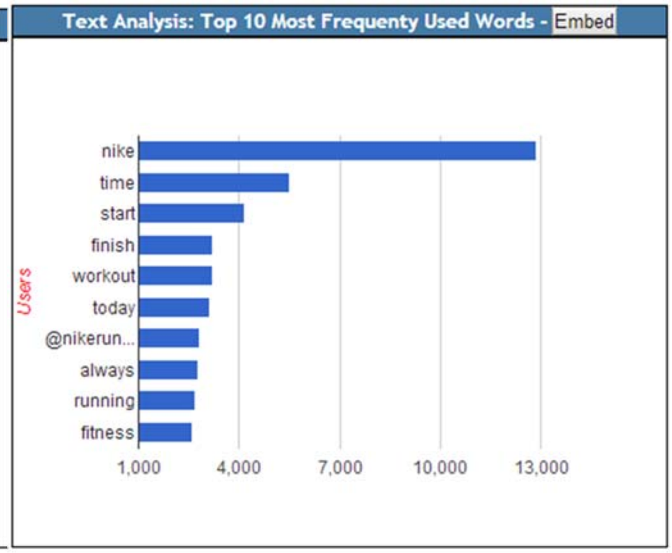

Figure 3: Top 10 Frequently Used Words

Figure 3 and Figure 4 (above) depict that @Nike was the most mentioned user, and *Nike* was the most frequently used word within the corpus. On their own, these basic findings may not say much about the interactions, especially when these analyses were frequency-driven. At the very least, these findings hint that Nike was a frequently discussed topic.

To find out more, a copy of the corpus was downloaded into a .csv file, which was then divided into the RT and OC subcorpora for individual examination. The RT corpus contained 54,530 tweets (46%), while the OC subcorpus contained 64,078 tweets (54%). Examining tweets and retweets can help assess interactivity on Twitter. Much like hashtags, retweets are an important function for expanding the content's visibility; retweets widens a tweet's exposure from one mutually exclusive network to another (Bruns & Moe, 2014, p. 19). For example, @UserA and @UserZ can each have 1,000 followers – none of which are shared between the two. If @UserA tweets a status update, the tweet would only be visible to his 1,000 followers. If @UserZ retweets @UserA's status update, then the original tweet would be seen by 2,000 followers (@UserA's audience + @UserZ's audience).

Retweets are also interesting because they act as a form of acknowledgement. Himelboim, McCreery, and Smith (2013) claim that unlike original content, retweets "indicate actual attention given to a message" (p. 163). In other words, when @UserZ retweets @UserA's status, Twitter notifies @UserA that his content has been retweeted. With original content, on the one/other hand, @UserA would not know whether his 1,000 followers have seen his tweet.

In sum, the initial division of the corpus into the RT and OC subcorpora revealed that while users posted original content more often than they retweeted, retweeted content may account for more interaction between users. This differs from a previous study in which Bruns and Stieglitz (2014) found that 90% of the activity in the #StopKony conversation were retweeted content from "Twitter celebrities" (the remaining 10%), thus concluding that the bulk of the users' involvement in that particular conversation were "marginal" (p. 78). In the same study, Bruns and Stieglitz (2014) found that the #AusPol and #MasterChef conversations had a flush of non-retweeted content (p. 76). It could be said, then, that dividing the main corpus into the RT and OC subcorpora only scrapes the surface in understanding how participants interact in hashtagged conversations.

5.1.2. Visualizing User Interaction via Name Networks.

Netlytic reported a total of 99,973 usernames within the *author* and *description* fields. A total of 59,772 nodes were found, along with 90,564 ties between them. The discrepancy between the total number of users and the total number of nodes can be a result of either (1) the #JustDoIt hashtag was not included in replies, or (2) that not all users replied to tweets. Take for example, if @UserA mentions @UserB and @UserC in a tweet, one node and three usernames would be identified. If @UserA posts a simple status update without mentioning another user, there would be only one node and one username. From an interactivity standpoint, the discrepancy between the total number of usernames compared to the total number of nodes may be indicative that not all users were responding to tweets. However, Netlytic's tools were not able to validate this claim given that the tool was configured to only catch all tweets with #JustDoIt in post. Assuming that users did not respond would be inaccurate if in some cases users responded without including the hashtag. This situation is quite possible considering that the single collection criterion for this MRP was limited to tweets with the #JustDoIt hashtag. For example, only the last tweet in the following conversation would be collected because it was the only one with the #JustDoIt hashtag.

€lkin Sanabria □ @ElkinSanabria7 Jun 28
Monserrate paso constante 2.3K up--> 28'45" with @NikeRunning #SportWatchGPS #nikeplus #YoCreo: http://go.nike.com/036ocjeo

Nike Running @NikeRunning Jun 28
@ElkinSanabria7 That 2.3k set your legs right for tomorrow's half. Feeling ready to take it on?

€lkin Sanabria □ @ElkinSanabria7 Jun 28
@NikeRunning tks! If Colombia Wins today in FIFA WCup I'll be better 👊😎#JUSTDOIT

***Figure** 5: Sample conversation. Hashtag corpora only collects tweets with the search term. In this case, only the last tweet was collected rather than all three messages in the conversation.*

Figures 5-8 are the name network visualizations, starting with the overall #JustDoIt conversation, and ending with the @NikeFuel node. The areas of concentration in the centre – much brighter than the outer areas – are nodes that contain the most influential users within the #JustDoIt hashtag. Users @Nike (Figure 6), @DarkeyTj (Figure 7), and @NikeFuel (Figure 8) were among these influencers. A meta-analysis comparing @DarkeyTJ and @NikeFuel, profiles that should be representative of a user node and a brand-affiliated node respectively, will be discussed in a later section.

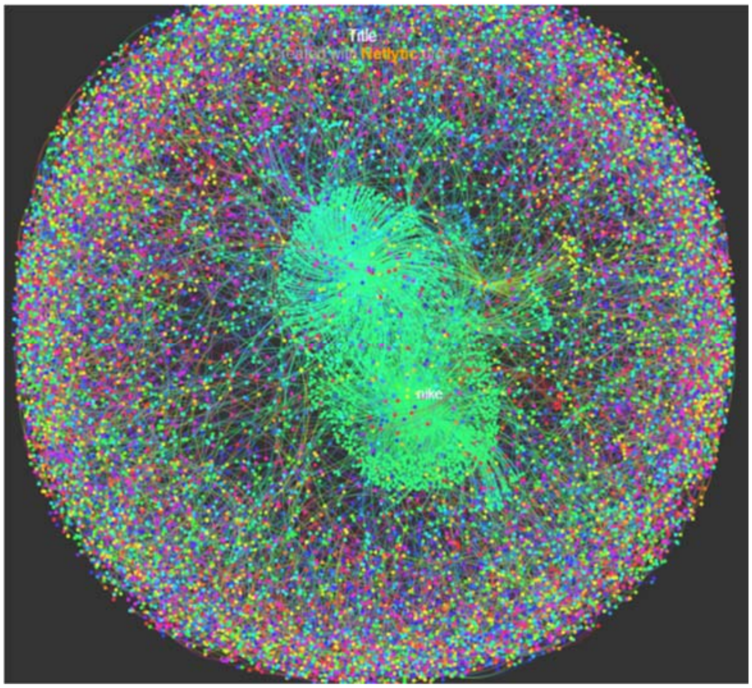

Figure 5*: Name Network Visualization #JustDoIt*

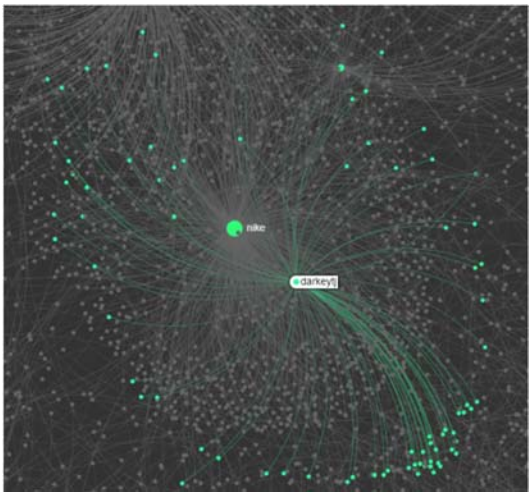

Figure 6: *Name Network for @DarkeyTJ*

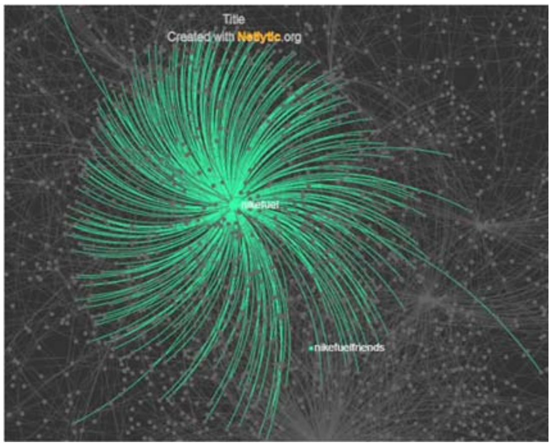

Figure 7: *Name Network for @NikeFuel*

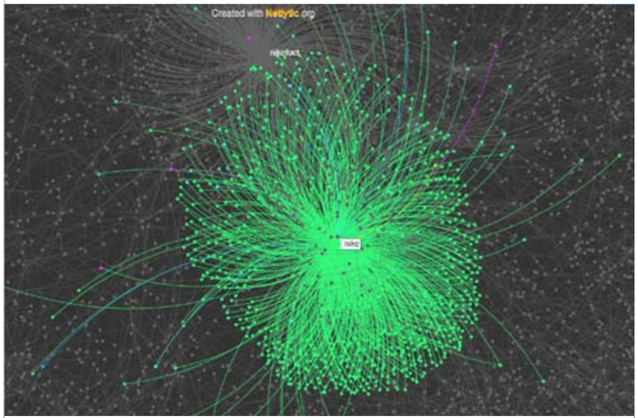

Figure 8: *Name Network for @Nike*

5.1.3. Detecting User Interaction using Qualitative Coding.

The following section details the results of the hand-coded qualitative analysis performed on the two corpora. Table 14 in Appendix B summarizes the results across all coding categories.

Authorship. Using Microsoft Excel's filtering functions, the *author* column was filtered to include all names containing "Nike". The random sampling showed that the entire RT corpus consisted of non-Nike affiliated users – that is, no usernames were found to contain "Nike". On the other hand, the OC corpus had four tweets that were from an official Nike account, namely *@NikeRunning*, *@NikeClassics*, *@NikeFuel*, and *@Nikerun_jp*.

Analysis of Authorship of Sample Tweets in RT and OC Subcorpora

		RT Subcorpus		OC Subcorpus	
Code	Category/Description	Total	%	Total	%
1	@User - Individual/Consumer	96	100.0%	92	95.8%
2	@Nike - Organization	0	0.0%	0	0.0%
3	@Nike - Affiliate	0	0.0%	4	4.2%
9	Other	0	0.0%	0	0.0%

Table 2: *Results of manual hand-coding: Authorship*

Analyzing the authorship of retweets is important because at the most basic level, it identifies who tends to publish content. The hand-coded analysis above identified the "who" by classifying users as either Nike, a Nike-affiliate, or a user that is not affiliated with Nike (i.e., a former, current, or future consumer). Based on authorship alone, these findings suggest that Nike rarely, if at all, retweets content from the conversation. This may make sense if the original content came from a Nike-affiliated account. In addition, these findings suggest that users are indeed retweeting content. Moreover, the results from the OC corpus indicates that the conversation is dominated by users rather than the brand (recall that only four tweets with original content were from a Nike-affiliated account). Together, these results indicate that the liveliness of the conversation can be attributed mostly to user-generated content.

Forms of interaction. The forms of interaction category seeks to identify how often Nike was mentioned in the body of tweets. This criterion focused specifically on the *description* column of the corpus, and filtered tweets by either direct, indirect, or no mention. Unlike the *authorship* category, searching for usernames within the description field identifies with whom users interacted with.

Analysis of the Forms of Interaction Found in RT and OC Subcorpora

		RT Subcorpus		OC Subcorpus	
Code	Category/Description	Total	%	Total	%
1	Original Tweet - Direct mention	0	0.0%	6	6.3%
2	Original Tweet - Indirect mention	0	0.0%	15	15.6%
3	Original Tweet - No mention	0	0.0%	75	78.1%
4	Retweet - Direct mention	3	3.1%	0	0.0%
5	Retweet - Nike Direct	54	56.3%	0	0.0%
6	Retweet- Indirect mention	8	8.3%	0	0.0%
7	Retweet - No mention	31	29.2%	0	0.0%
9	N/A - Spam/Junk Data	0	0.0%	0	0.0%

***Table 3**: Results of manual hand-coding: Forms of Interaction*

The direct mention categories (codes 1, 4, and 5) filtered the body of tweets containing "@Nike" or a variation such as "@NikeFuel", The indirect mention categories (codes 2 and 6) contained "Nike" but not "@Nike" within the body of the tweet. The *no mentions* categories (3 and 7) did not mention Nike within the body of the tweet. Lastly, it should be noted that the *Junk/Spam* category (Code 9) was not applicable because the nature of the filtering method simply searched for any mentions of Nike; language was irrelevant in this frequency-driven search because the @reply, hashtag, and spelling of Nike remains the same across languages. [11]

It was observed that 59.4% of the tweets analyzed in the RT subcorpus mentioned Nike; 54 tweets (56.3%) were a direct retweet of Nike content, noted with "RT @Nike", and three tweets (3.1%) contained "@Nike" but not immediately prefixed with "RT @Nike". The OC subcorpus on the other hand, only had 21.9% of its tweets mentioning Nike: 15 tweets (15.6%) contained

"Nike", but only six (6.3%) contained "@Nike". More than 75% of tweets in the OC corpus had no mention of the brand at all, compared to only 32.3% from the RT subcorpus.

These findings suggest that users are not always interacting with @Nike within the #JustDoIt conversation. The data also shows that users are more likely to directly interact with Nike (i.e., @Nike) via retweets rather than original-content tweets. Finally, the analysis suggests that Nike is indirectly mentioned – or talked about – twice as much in original tweets compared to retweets (15.6% indirect mentions in the OC corpus, compared to 8.3% in RT corpus).

Content Structure. The content structure analysis seeks to classify the types of tweets based on the post's content. These categories were borrowed from Dann's (2010) *Twitter Content Classification,* which were modeled from his own comprehensive review of previous studies on Twitter. His six top-level categories include: (1) conversational, (2) pass along, (3) news, (4) status, (5) phatic communications, and (6) spam. Tweets that were information-seeking or had addressivity (i.e., mentioning a username) were classified as *conversational* content. The *pass along* category included tweets that were intended to share information or had a URL. Other studies cited by Dann (2010) classified tweets that were self-promoting and/or advertising information were also categorized as the pass along category. Headlines, event coverage, or other reporting of information were classified as *news,* while those that answered "*what are you doing now*?" were classified as *statuses*. Within the *phatic* category were greetings, monologues, or opinions. Finally, the *spam* category encompasses tweets that were automated posts.

Analysis of the Content Structures within the RT and OC Subcorpora

		RT Subcorpus		OC Subcorpus	
Code	Category/Description	Total	%	Total	%
1	Conversational	19	19.8%	27	28.1%
2	Pass along	52	54.2%	15	15.6%
3	News	3	3.1%	1	1.0%
4	Status	3	3.1%	22	22.9%
5	Phatic	3	3.1%	15	15.6%
9	Spam	16	16.7%	16	16.7%

Table 4: *Results of manual hand-coding: Content Structures*

Among the RT corpus, the highest observed structure was the *pass along* category with 52 tweets (54.2%). Trailing by 33 tweets was the *conversational* structure with 19 tweets (19.8%). The *news*, *status*, and *phatic* categories had 3 tweets each, accounting for 9.3% of the total RT corpus. Contrasting this with the OC corpus, the highest observed structure was the *conversational* style, accounting for 27 tweets (28.1%) that were addressed to others via an "@" symbol. The second highest ranking category in the OC corpus was the *status* category, accounting for 22 tweets (22.9%). Information sharing and self-promotion – the *pass along* and *phatic* categories— ranked third, accounting for 15 tweets each (totaling 31.2% of the OC corpus). Within both subcorpora, 16 tweets were classified as *spam* due them being in different languages; the content structure was indeterminable. Moreover, links within the tweets were not opened or analyzed in the scope of this MRP because some URLs direct users to images, while others directed users to a webpage.

Not surprisingly, the RT corpus consisted mainly of tweets that have the *pass along* structure. According to Twitter conventions, retweets are mainly for disseminating information and showing an endorsement of content (Naaman et al., 2010). Take the following retweet for example:

> RT @AVGraham14: Let\'s prove him wrong! #RETWEET #RT #JustDoIt *http://t.co/IV7qpZhCp6*

The tweet was classified as having a *pass along* structure because it promotes user-generated content. The example post above calls viewers to action by asking them to #RETWEET. The most surprising finding was that most of the retweets categorized as having a *conversational* structure were of content from @Nike. Of the 19 retweets identified as *conversational,* 13 (68%) contained “RT @Nike”, including the following:

Sample Retweets within the RT Subcorpus

Author	**Content**
ShannonBreck	RT @Nike: @busygirl4k Set. Reach. Repeat. #justdoit
JerryEspinosa2	RT @Nike: @HappyAppyGSA On to the next one. #justdoit
LawDDown	RT @Nike: @RealSaintNick6 A sign of many miles. Here’s to many more. #justdoit

***Table** 5: Sample Retweets*

These tweets are interesting not only because users are retweeting official Nike content, but also because the content of the tweet sees that Nike is addressing a different user. This suggests that (1) Nike engages with users regularly, (2) the addressee is invited to engage with Nike, and (3) other users are endorsing Nike’s engagement. From a theoretical standpoint, these tweets exemplify the notion of the imagined audience (Litt, 2012) in that the content reached individuals that neither Nike nor the addressee were aware of. Moreover, these tweets also illustrate the concept of ambient affiliation (Zappavigna, 2011): third level users—neither the sender nor receiver—are viewing and acting on tweets.

Source Device. More than half of the tweets in both subcorpora came from the official Twitter application for mobile devices (75% in the RT corpus, 54.2% in the OC corpus). The RT subcorpora also had 11 tweets (11.5%) from Twitter on the desktop (identified as Twitter or “web”), one tweet (1%) from a third-party application such as Hootsuite and Tweetdeck, and 12 (12.5%) from another, unknown application. Conversely, the OC corpus had six tweets (6.3%)

from the desktop, 16 (16.7%) from applications like Tweetdeck and Hootsuite, one tweet (1%) from an official Nike+ Application, and 21 tweets (21.9%) from social media channels.

Analysis of the Source Device for Sample RT and OC Tweets

		RT Subcorpus		OC Subcorpus	
Code	Category/Description	Total	%	Total	%
1	Twitter on mobile device	72	75.0%	52	54.2%
2	Twitter on the web	11	11.5%	6	6.3%
3	Twitter application	1	1.0%	16	16.7%
4	Nike / related application	0	0.0%	1	1.0%
5	Other Social Media	0	0.0%	21	21.9%
9	Other	12	12.5%	0	0.0%

Table 6: *Results of manual hand-coding: Source Device*

The difference in source devices is perhaps not all that telling. The one statistic that may be of value to Nike is perhaps the one (and only) original-content tweet posted from a Nike+ application. Relying solely on the hand-coded analysis above, this result indicates very low engagement levels with the Nike+ application. From the cluster analyses and meta-analysis discussed later on, however, it is clear that tweets from the Nike+ application are not being attributed to the #JustDoIt conversation.

Unit of analysis. The unit of analysis category seeks to understand *how* users were participating in the conversations. To measure this, the RT and OC sample tweets were assessed based on their textual elements. Tweets were coded: 1 for *text-only* tweets; 2 for *link-only* tweets; 3 for tweets that contained *text-and-link*, and; 9 for *other*, including hashtags only with no URL.

Within the RT corpus, 46 tweets (47.9%) were text-only compared to 39 tweets (40.6%) in the OC corpus. The OC corpus had 14 link-only tweets (14.6%), compared to six (6.3%) found in the RT corpus. Combining text and links, the OC corpus had 30 tweets (31.3%) that had a link and at least two words that were not hashtags, compared to 27 (28.1%) in the RT corpus. There were

17 tweets (17.7%) in the RT corpus and 13 (13.5%) in the OC corpus that were classified as *other*, meaning that the tweets were either hashtags only, or were in languages other than English.

Analysis of the Textual Elements Found in RT and OC Subcorpora

		RT Subcorpus		OC Subcorpus	
Code	Category/Description	Total	%	Total	%
1	Text Only	46	47.9%	39	40.6%
2	Link Only	6	6.3%	14	14.6%
3	Text and Link	27	28.1%	30	31.3%
9	Other	17	17.7%	13	13.5%

Table 7: *Results of manual hand-coding: Unit of Analysis*

These findings are interesting because they suggest that the levels of interactivity between participants were quite high. Upon further analysis, 30 of the text-only retweets were direct retweets of Nike content, which for the most part did not contain any URLs. Within the OC corpus, most of the text-only content were statuses, thoughts, and opinions (categorized as *status* and *phatic* structures). Most of the text-and-link combinations in the OC corpus had a general/unrelated theme (code 6 in Table 8: Topics/Themes, next page) with links to images that were not related to Nike.

Figure 9: *Example of a text-and-link (code 3) combination in the OC corpus*

5.2. RQ2: Emerging Conversations

5.2.1. Hand-Coding for Topics and Themes.

Tweets were analyzed individually and assigned a code based on its overall topic. Using this qualitative approach, seven categories were identified, namely: (1) Nike+ Related, (2) Nike – Fitness Related, (3) Nike – General and Other Products, (4) Fitness non-Nike, (5) Motivation non-Nike, (6) General – Unrelated, and (7) Other/Junk. The aim of this categorization scheme was to assess how well the content in each tweet related to Nike's overall mission or goal.

Analysis of the Topics and Themes Found in RT and OC Subcorpora

		RT Subcorpus		OC Subcorpus	
Code	Category/Description	Total	%	Total	%
1	Nike+ related	0	0.0%	3	3.1%
2	Nike - Fitness related	27	28.1%	8	8.3%
3	Nike - General & Other Products	23	24.0%	10	10.4%
4	Fitness related, non-Nike	5	5.2%	14	14.6%
5	Motivation, non-related	2	2.1%	15	15.6%
6	General - Unrelated	16	16.7%	31	32.3%
9	Other/Junk	23	24.0%	15	15.6%

Table 8: *Results of manual hand-coding: Topics and Themes*

The RT corpus saw the greatest number of Nike-related topics, with 27 tweets (28.1%) related to Nike and Fitness, and 23 tweets (24%) related to Nike in general (e.g., quotes, products). Only seven tweets were not related to Nike, though five tweets were still fitness related and two were motivational in general. A total of 39 retweets (40.6%) were not related to Nike, fitness, or motivation; 23 retweets were identified as *junk* for either having an insufficient amount of context, or because of language.

Within the OC corpus, 46 tweets were not related to Nike, fitness, or motivation; 15 out of the 46 tweets (15.6%) were categorized as *junk*. The OC corpus had 21 tweets that were directly related to Nike, including eight that were related to Nike and fitness, and three that were related to

Nike+. The OC corpus also had 14 fitness related tweets that were not affiliated with Nike, and 15 tweets that were generally motivational with no ties to Nike.

Descriptions and Examples of the Topics and Themes within the RT and OC Subcorpora

	Topics/Themes	Description	Example
1	Nike+ related	Directly related to fuelpoints, Nike+	#nikefuel #nikerunning #JustDoIt I won 30 and 30, a 30.00mi Challenge using Nike+. http://t.co/KWXZniTbD5 #nikeplus
2	Nike - Fitness related	Nike and fitness related strings. Can include fitness-related quotes	358m done! First time ever. #JustDoIt (@ SSC Swimming Pool) http://t.co/kxwzg7jjsr
3	Nike - General & Other Products	Can mention other Nike products, but not directly related to fitness. Can include generic quotes	Love my new @Nike tees. #nike #JustDoIt #reupload #betterphoto #lovethem http://t.co/jV3Uc2PMQ3
4	Fitness related, non-Nike	Fitness related, but not Nike	I went hard in the gym today. #justdoit
5	Motivation, non-Nike	motivational, but not Nike	Goals.... Dreams with deadlines #justdoit
6	General - Unrelated	Not related to Nike, fitness, or motivation	#illustration #marker #drawing #night #JustDoIt #art #draw http://t.co/6NQ6rHsHQZ
9	Other/Junk	Junk/Foreign Languages/ insufficient context	Ja ik moet echt! @loopmaatjes #JustDoIt #lazybastard

Table 9: *Categories for Topics and Themes*

5.2.2. Identifying Emerging Conversations using Corpus Linguistics.

In order to gain a better understanding of what users are saying within the #JustDoIt conversation, the texts within the tweets were analyzed using the AntConc Corpus Toolkit. The RT and OC subcorpora were analyzed separately through AntConc’s keyword, collocation, and cluster analysis tools. Within the RT corpus, a total of 154 keywords were found that were repeated at least 225 times within the corpus; the OC corpus had 156 keywords. Due to space restrictions, Table 10 (next page) provides only the top 10 list of keywords per corpus.

Keyness Score by Keywords Found in the RT and OC Subcorpus

Keywords - RT Subcorpus		Keywords - OC Subcorpus	
Word	Keyness Score	Word	Keyness Score
Time	11,965.38	Nike	21,548.39
Nike	8,256.38	run	6,078.61
finish	6,647.23	day	4,570.31
Run	6,346.15	workout	4,570.31
Line	6,115.24	nikeplus	4,312.55
start	5,841.33	fitness	4,140.71
season	4,673.29	time	3,808.01
moving	4,499.00	today	3,659.95
Quit	4,315.66	running	3,402.22
Day	4,252.28	motivation	3,182.88

Table 10: *Top 10 keywords by subcorpus*

Terms like *time, Nike, run,* and *day* were common among both top 10 lists, though all words from either list could be found in the other. The difference between both lists were the keyness scores attributed to each word by AntConc, which is due to a combination of frequency of appearance when compared to the reference corpus, and the corpora size (see: Baker, 2006).

Research Question 2 seeks to provide an understanding of the conversations that took place within the #JustDoIt conversation. The keyword analysis revealed the significant keywords found in each subcorpora, and it was determined that there were indeed some overlap between the RT and OC subcorpora. At the most basic level, identifying some of the keywords within each subcorpus provided some insight into what the conversations were about. To provide a greater depth of understanding, AntConc was once again used to analyze the contents of the tweets. AntConc's collocation analysis and cluster analysis tools were used to identify some of the contexts in which the keywords that were found. Results of these analyses will be discussed in the following sections.

5.2.3. Collocation – words that co-occur and non-occur.

Using a keyword, such as *Nike*, the collocation tool crawls the text files and identifies words that frequently occur around the search term based on the tool's settings. The tool then provides the frequency and statistical significance of the words that were found. Each word that is identified by the collocation analysis is called the *collocate*.

The tool was configured based on the standard settings of 4-words to the left (4L) and 4-words to the right (4R) of the search term. The statistical measure used in calculating collocations was the principle of *mutual information* (MI). Generally, words that usually occur more often closer to the search term than it does without (e.g., non-occurrence), the greater the chance that collocate represents the context in which the search term was used (Baker, 2006). Thus, the collocation analysis provides insight into what users are "talking about" when referring to *Nike*. Table 11 (below) summarizes the top 10 collocates for *Nike*.

Top 10 Collocates within the RT and OC Subcorpora for the "Nike" Keyword

	RT Subcorpus			OC Subcorpus		
Rank	Word/Collocate	Frequency	Stat	Word/Collocate	Frequency	Stat
1	hypervenoms	13	7.30007	gymwanker	5	6.29619
2	knightsnation	27	7.23904	niallc	9	6.14419
3	sponsoring	96	7.18459	purchases	7	5.78162
4	nikelondon	22	7.18459	obrigado	5	5.71123
5	barbarian	96	7.18459	lunars	5	5.71123
6	hypervenom	16	7.01466	idr	5	5.71123
7	sandals	61	6.98604	winnerstays	6	5.55922
8	lunar	24	6.86266	pigalle	6	5.55922
9	sepatumurah	14	6.82202	mercurialvapor	6	5.55922
10	nikefreerun	15	6.76955	Apc	6	5.55922

Table 11: *Top 10 collocates for Nike by subcorpus*

Much of the collocates had very similar MI scores, suggesting that the conversations shared a common theme. For example, it was found that most of the collocates in the RT corpus for the term *Nike* were actually Nike product lines (5/10 collocates). Within the OC corpus, only two collocates for *Nike* were actual product names, though most of the content was *about* Nike purchases. One outlier was “gymwanker” – which is actually a hashtag on Instagram that functions much like a Twitter hashtag in that it indexes posts under the tag. Tables 15 and 16 in Appendices C and D provide some of the results from the collocation analyses. Due to the scope of this MRP, only a handful the results were summarized.[12]

Though the collocation tool was configured to identify the most common words that occur 4-words to the left and to the right of *Nike* (the search term), further analysis is required to fully understand the context in which the keyword was used. The cluster tool allows for this detail.

5.2.4. Cluster Analysis.

The cluster analysis tool was used to identify the context. AntConc’s cluster analysis tool was configured to show a maximum cluster size of five, meaning that the tool would identify the five words surrounding the collocate. Table 17 (Appendix E) summarizes the results of the cluster analyses performed on the top five keywords in each subcorpora. Within the OC corpus, results from the cluster analyses that analyzed keywords (*Nike, run, day, workout, nikeplus*) found that a majority of the themes were related to Nike products or quotes. Collocates that most strongly related to fitness and motivation were *run*, *day*, and *workout*. Nike branding and product placements were most visible within the *Nike* and *nikeplus* collocates (clusters found “join Nike…” and “Nike family” co-occurrences). Within the *Nike* keyword, one interesting topic that emerged was promoting the boycotting of Nike; the cluster analysis found that these tweets asked users to boycott Nike products.

The analysis also found similar topics within the RT corpus. Collocates for the *Nike* keyword relating to the boycotting of Nike were *sponsoring*, and *barbarians*. Product placements and branding collocates included *hypervenoms*, and *knightsnation* – both of which were used as subsequent hashtags within the tweet.

One difference observed between the RT and OC corpora was that the RT corpus had much less fitness and motivational phrases. Most of the clusters were categorized as *other*, as they contained parts of quotes from Nike. Even still, some of these quotes – such as “the starting line proves just as much as the finish line” – were too vague to infer a relation to fitness and motivation.

On a comparative level, tweets in the OC corpus had a stronger relation to fitness, motivation, and Nike related themes. Evidenced through the frequency of each literary item, tweets observed in the RT corpus were mostly quotes retweeted by multiple users. Based on the content alone, some tweets were difficult to interpret as having a relationship with Nike (e.g., quotes such as “Don’t let your luck run out” were vague and seemed unrelated to Nike or fitness). The cluster analysis also detected a topic of boycotting Nike by providing samples of how keywords such as *sponsoring*, and *barbarian* were used directly from the corpora; the collocation analysis would have provided insufficient context to detect such contexts.

5.3. RQ3: Meta-Analysis: Comparing topics in user @DarkeyTJ and @NikeFuel

Two prominent nodes that were identified using Netlytic’s Name Network Analysis were @DarkeyTJ and @NikeFuel. Both nodes showed a high *total-degree* centrality, suggestive that the two profiles published as well as received a lot of tweets within the #*JustDoIt* hashtag. A meta-analysis to compare the topics discussed in both nodes seemed appropriate at this point to provide greater insight into the conversations that took place; the @DarkeyTJ group represents user-initiated interaction, while the @NikeFuel node could be reflective of Nike’s overall strategy. Tweets from both nodes were extracted from the main corpus into the @DarkeyTJ and @NikeFuel subcorpora. The tweets were then analyzed using keyword, collocation, cluster analysis;

qualitative hand-coding was not performed on the new subcorpora because the goal was to simply identify topics and themes within the side conversations. Additionally, the new subcorpora were incomparable in size: the @NikeFuel corpus had 784% more tweets than the @DarkeyTJ corpus.

The @DarkeyTJ corpus had 131 entries, 120 of which were posts published by @DarkeyTJ. On the other hand, the @NikeFuel corpus had 1,028 tweets, 455 of which were published from the @NikeFuel profile (44.2%). While the size of both corpora may seem insignificant relative to the main corpus, and insufficient to generalize what other users may be talking about within the #JustDoIt hashtag, the name network visualization's total-degree centrality suggests that the nodes may have been two of the most active conversations; other users may have participated in the #JustDoIt hashtag much less.

Collocation analyses were performed on the top five keywords in each subcorpus, and an additional analysis was performed on the word *Nike* to determine if and how the brand was mentioned. Cluster analyses helped to identify the contexts in which the words and collocates were used, thus providing a holistic view of the conversations transpired within each corpus.

The top five keywords extracted from the @DarkeyTJ include *mi, pace, nikeplus, great*, and *ran*, while in the @NikeFuel corpus, *NikeFuel work, hard, day,* and *foolproof* were the top keywords (see: Table 18 and Table 19 in Appendices F and G). Again, due to the relative sizes of the corpora, the keyness scores found in these corpora were considerably lower than those found in the RT and OC subcorpora.

Results such as *ran*, *Nike*, *sustaining*, *trail*, *mnths* [sic], and *fuelband* were found to be collocates of the keywords found in the @DarkeyTJ corpus. Using the cluster analysis to contextualize these words, it was found that all of them related to Nike+ activities. Interestingly, words such as *tina, wigan, nick,* and *truth*, also collocates of the keywords, were found to be usernames which @DarkeyTJ had mentioned. These tweets were messages of encouragement directed toward the users for their accomplishments in their physical activities. These tweets read:

@truth863 incredible pace. I could only dream of moving that fast..... #justdoit

@Chuck_Boyer great work sustaining your pace.... #justdoit

At the outset, these tweets represent user-to-user interaction in that the "@" character directed @DarkeyTJ's tweet toward specific users. In referencing @DarkeyTJ's corpora, it was found that user @truth863 acknowledged @DarkeyTJ's encouragement by retweeting the message, showing that users were aware of one another (Himelboim, McCreery, & Smith, 2013). This interaction is quite interesting in terms of the imagined audience; the acknowledgement of each other signifies the transition from being a member of one another's imagined audience to their actual audience. In other words, by responding to @truth863's tweet, @DarkeyTJ identified himself as an actual viewer of the tweet. Conversely, by retweeting @DarkeyTJ's response, @truth863 identified himself as a member of @DarkeyTJ's actual audience. The same concept can be observed in the interaction between @DarkeyTJ and @Chuck_Boyer in the second tweet.

Evidence of ambient affiliation was found in the interaction between @DarkeyTJ and @Chuck_Boyer; @Chuck_Boyer's original tweet was not tagged with #JustDoIt, nor was it addressed to @DarkeyTJ.[13] Presumably a member of @Chuck_Boyer's imagined audience, @DarkeyTJ acted on the tweet by responding, and tagging the tweet as relevant to the #JustDoIt conversation. As a result, the conversation was made immediately searchable through searching the #JustDoIt hashtag—thus "affiliating ambiently" (Zappavigna, 2011, p. 803), both @Chuck_Boyer and the interaction.

The @NikeFuel profile had starkly different results. Collocates of the keywords found in the @NikeFuel corpus such as *yea, winfromwithin, Jordan, justdoit, and NikeFuel* were subsequent hashtags that were included in the tweet. This means that the messages were classified as being a part of multiple threads, although no significant interactions among the @NikeFuel profile and other users were found. In fact, most of the contexts found in the @NikeFuel corpus were largely quotations; collocates such as *work, bank, foolproof,* and *earned* were words found within various quotes. Compared to the @DarkeyTJ corpus, the @NikeFuel corpus recorded higher instances of the same literary items occurring (e.g., multiple instances of the same line), suggesting that most of the content within the @NikeFuel were retweets. These scores of repeated content ultimately flooded the #JustDoIt thread, construing heteroglossia by constantly defining and steering the topic of the conversation toward fitness and motivational themes. These tweets can also leverage ambient affiliation by exposing content to more audiences with every retweet. If the @NikeFuel corpus is to be representative of other Nike affiliated profiles, then these results may indicate retweeting as part of a larger operational strategy. For @DarkeyTJ, however, the originality of each tweet (i.e., lack of repetition) could suggest that the posts and comments were seeking a more comprehensive way to engage with other users.

Findings from the @DarkeyTJ and @NikeFuel subcorpora suggest a starkly different approach to engaging participants in the #JustDoIt hashtag. While Nike affiliated accounts engaged by posting quotes and retweeting mentions of the profile, active users such as @DarkeyTJ tend to engage with others by tweeting words of encouragement. In either case, ambient affiliation can be observed with each retweeted message or unsolicited response (e.g., not directed). Moreover, by tagging motivational quotes and tweets of encouragement, both @DarkeyTJ and @NikeFuel are construing heteroglossia by negotiating the meaning or purpose of the hashtag. Future research should continue to use the comparative approach to examine a much broader range of profiles, including comparing Nike affiliated-to- Nike affiliated and user-to-user nodes.

6. Discussion

6.1. Conceptualizing User Interaction: Ambient Affiliation

The results of the study clearly depict the notion of ambient affiliation among participants of the #JustDoIt conversation in multiple ways. First, these user-to-user connections were essentially drawn using Netlytic's Name Network tool, which visualized a total of 59,772 nodes, containing 99,973 users. The discrepancy between the number of nodes and the volume of users suggests that there are different types of affiliations among users. Indeed, Gruzd and Roy (2014) observed that nodes that were more connected – denser in the visualization – had users that were more likely to engage in discussions with others, whereas less connected nodes suggested that users were less likely to engage (p. 33). The outer edges of the visualization depicted users that were simply mentioned in a tweet, but no reply was given or recorded[14] (see Figure 11, below). These users were affiliated by virtue of being mentioned, but were not an active participant themselves – thus being ambient or unaware.

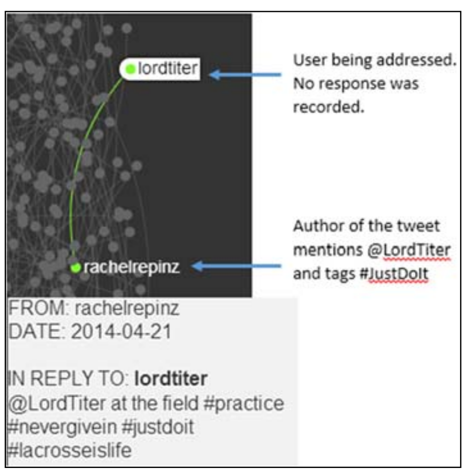

Figure 10: *Example of ambient affiliation in isolated nodes*

Second, other instances of ambient affiliation were also observed in Nike's, NikeFuel's, and DarkeyTJ's interactions with other users. These profiles responded to and tagged tweets that were not originally embedded with #JustDoIt, and by doing so, they ultimately classified the tweets as having the same purpose or topics associated with the overall tag. The owners of the original tweet were thus affiliated with the overall conversation. More interestingly, the observed responses abandoned the hashtags that were originally assigned (e.g., #nikeplus), almost as if they were re-classifying or re-assigning the tweet to the #JustDoIt topic. This reclassification epitomizes the notion of heteroglossia, explained earlier.

Non-tagged Tweets with Responses Tagged with #JustDoIt

Profile	Original Tweet	Response
@Nike	@hellodayblog Mar 31: *Warm up run before #ntcfit workout. #monday I just ran 2.50 mi with Nike+. #nikeplus*	@Nike: *@hellodayblog Monday Funday.* ***#justdoit***
@DarkeyTJ	@melaniac Apr 27: *I just ran 15.1 km with Nike+. go.nike.com/jpc7hi #nikeplus*	@DarkeyTJ: *@melaniac gr8 work!* ***#justdoit***
@NikeFuel	@MatthieuNOLA Mar 28: *I achieved the Great 8 trophy with my Nike+ FuelBand. #nikeplus http://go.nike.com/72k64us pic.twitter.com/BOoEz2vU7L*	@NikeFuel: *@MatthieuNOLA Believe, achieve, repeat. Keep moving, keep earning, keep balling.* ***#justdoit***

Table 12: *Example of users being affiliated with #JustDoIt via responses*

Third, it should also be noted from the samples above that the original tweets were not addressed to another user. This furthers the notion of ambient affiliation in that the responders are either following the original tweeter, or searching for topics other than #JustDoIt to follow. Given @Nike and @NikeFuel are corporate Nike accounts, the latter scenario may seem more likely (Nike only follows 200 profiles, but has over 3 million followers). If this were the case, then it suggests that ambient affiliation occurred in the other topics (#ntcfit, #Monday, and #nikeplus in the first tweet, for example), which @Nike and @NikeFuel felt compelled to respond. With @DarkeyTJ's example, ambient affiliation was evidenced when @DarkeyTJ responded to the original user's tweet, which reflected what previous Twitter content studies would suggest as having a status or self-promoting structure rather than the conversational style (Dann, 2010; Naaman et al., 2010). This is rather interesting since it challenges the observations of other studies: Naaman et al. (2010) found that the most interesting and follow-worthy content were *informers* rather than *meformers*. Informers were those that posted interesting content and attracted more followers, while meformers focused on the self (p. 192). Not only did the original tweet that @DarkeyTJ responded to reflect the meformer classification, but so did all of the quotes published by @Nike. This suggests that the followers of the #JustDoIt hashtag were not necessarily following the conversation for newsworthy content; instead, they were more interested in retweeting others' status updates and accomplishments.

6.2. Heteroglossia and the Shifting Conversations

The keyword, collocation, and cluster analyses performed on the RT and OC subcorpora provided evidence that Nike's iconic "Just Do It" message was used in multiple ways. The observed topics included brand communication, fitness and motivational themes, and other, non-brand related messages from users. By definition, then, Nike's slogan-turned-campaign handle indeed experienced heteroglossia by having multiple meanings among participants.

While Nike originally intended that the message serves as a channel for users to inspire and motivate one another, the collocation and cluster analysis revealed that in at least one conversation, participants have used the tag to support a boycott of Nike products. The cluster analysis revealed keywords such as *barbarian*, and *sponsor* in the phrase:

> "WHY is Nike sponsoring this BARBARIAN? "@DogRescueTweets: #Boycott #Nike #justdoit #animalabuse #dogfighting pic.twitter.com/RpVkHuKpTE

In this case, the #JustDoIt hashtag could have been used as a classifier, a process, or both. Zappavigna (2011) explains that classifiers identify a subject to which the content belongs, whereas a process “construes an action in the world” (p. 792). In the aforementioned example, #JustDoIt was used to classify the tweet as Nike-related (e.g., using Nike’s own term as ammunition against the organization). Consequently, all followers of the #JustDoIt hashtag would eventually be able to search for and view the tweet. As a process, the #JustDoIt line of text in the tweet above could have been used as a part of a broader message, such as saying “boycott Nike – just do it.” So how does this relate to the concept of heteroglossia? Androutsopoulos (2011) claims that “heteroglossia does not occur… but is *made* [emphasis placed by the original author]; it is fabricated by social actors who have woven voices of society into their discourses, contrasting these voices and the social viewpoints they stand for” (p. 282). In other words, participants in the boycott subtopic have taken the original slogan and reframed it as a form of action—to boycott Nike. Coupled with ambient affiliation, the group’s message has thus been amplified and therefore promoted and exposed to all followers of the conversation. In this case, Bruns and Moe (2014) state that “many voices may compete to make themselves heard, and their ability to do so above the fray depends largely on those around them taking up the message and passing it on—on Twitter, by retweeting” (p. 19). The process of defining the term #JustDoIt was also seen in the meta-analysis of @NikeFuel’s conversation. Much like the subtopic of boycotting Nike products, @NikeFuel published messages that were widely retweeted by its followers. In both cases, users were competing to steer the topic of the hashtag toward a particular meaning of “Just Do It” by gaining more retweets, thus leveraging ambient affiliation among the imagined audience to construe heteroglossia. Heteroglossia was essentially present within the hashtag because of the mix of voices, all of which used Nike’s “Just Do It” message to their own ends.

6.3. Nike and the Imagined Audience

Numerous conversations took place within the #JustDoIt conversation. Nike's observed role was not only to produce content, evidenced by the scores of RT @Nike's within the RT corpus, but also to invite users who have shared their Nike+ and NikeFuel accomplishments by responding to his or her tweet. Ultimately, the publishing of content reflects the notion of the imagined audience when followers of @Nike retweet the brand's messages, exposing the tweet to even more networks. Despite the fact that the quotes published by Nike reflected a meformer orientation rather than the informer, conversational orientation, Naaman et al. (2010) hypothesize that meformer tweets "may play an important role in helping users maintain relationships with strong and weak ties" (p. 192). Indeed, Nike may have pushed its agreeable quotes to its followers, anticipating that the message would reach its imagined audience. Moreover, Nike effectively reassigned content from the spheres of #nikeplus to #JustDoIt. In essence, Nike used Twitter to redirect users who have posted fitness and motivational content to the #JustDoIt thread, and they did so by recruiting audiences elsewhere.

Strong evidence was derived from the quantitative analysis that suggests users were in fact discussing Nike, fitness, motivation, or a combination of the three. Statistical measures using mutual information (for collocation analysis) and log-likelihood (keyword lists) calculations, for example, produced notable results indicating product-related topics were taking place. From the qualitative perspective, 52% of the sample RTs were related to Nike, while only 18.8% of the OC tweets were. Revisiting the image of competing voices (Bruns & Moe, 2014, p. 204), it is clear that participants who post original content are trying to adapt the #JustDoIt keyword for non-Nike related purposes. By recruiting users from other conversations, however, Nike is determined to reserve the meaning of #JustDoIt for fitness or brand-related content.

6.4. Limitations and Future Study

The Nike corpus that was constructed for this MRP was not representative of all interactions and discussions that users were having about Nike. This study was limited solely to the discussions that took place within the #JustDoIt hashtag, and more specifically, from March 1, 2014 – April 31, 2014. Replies and other content that may be relevant to the campaign could have been missed if the campaign hashtag was not embedded. Furthermore, the study was confined to Nike, thus the results and discussions may not apply to all corporations that are engaging with users on Twitter. As such, opportunities to further this work include:

- **Scope –** Future research should broaden the scope of this work to consider other companies and their Twitter campaigns. Results would either validate or challenge the observations made, thus expanding the knowledge of B2C communication on Twitter.
- **Heteroglossia and Social Business –** Research should also investigate the relationship between shifting topics and its impact on financial revenue. Previous work has already acknowledged the importance of electronic word-of-mouth, but there still exists a gap in knowledge that ties user-to-user influence on Twitter to financial returns. In other words, Nike's objectives as mentioned in this MRP may be too broad to form a connection between Twitter usage and corporate goals. More specific goals, such as a percentage increase in product sales or in Twitter followers, along with analytical data from Twitter, should be used to better explain how Twitter helps corporations run social businesses. Moreover, having specific goals would help identify the potential role and value virtual communities bring to corporate brands.
- **Temporal Analysis –** It was not in the scope of this MRP to analyze conversations through time. Zappavigna (2011) suggests that "communities shift as hashtags shift, and different

couplings of ideational and interpersonal meaning are established depending on what people are talking about at a given time” (p. 803). Thus, studies that track conversations through time may seem appropriate in furthering work in ambient affiliation and heteroglossia.

Moreover, the MRP focused specifically on the interactions that took place between Nike and the virtual audience. A more in-depth study of the B2C relationship may be appropriate in order to fully understand how social media affects relationships offline. This area of study may provide greater insight into contemporary business practices, perhaps even accumulating evidence to support key trends about social media adoption, moderation methods, and content strategies.

Lastly, it should be acknowledged that the propensity to tweet, let alone tagging content with a specific hashtag, should be considered an area of interest for future studies. Especially for marketing professionals, identifying factors that motivate users to post content and engage with brands in the virtual world could be beneficial in developing strategies that seek, for example, to build brand loyalty or to achieve virality. While these concepts and ideas were not alluded to in this MRP, the methods and results from this study helps to better understand consumer behaviour, and more specifically consumer behaviour on Twitter.

7. Conclusion

The purpose of this MRP was to examine the levels and forms of interaction that took place within Nike's #JustDoIt hashtag on Twitter. Using a mixed-methods approach of CAQDAS, corpus linguistics, and hand-coded analyses, this MRP successfully framed B2C interactions observed in the hashtag using Mikhail Bakhtin's (1981) concept of heteroglossia and the notion of the imagined audience (Litt, 2012; Zappavigna, 2011). The study addressed the gap in knowledge about how brand communication on Twitter relates to consumer engagement by investigating ways in which Twitter can mediate B2C relationships.

The MRP discussed how participants of the #JustDoIt conversation used and interpreted the hashtag, which reflects what Bakhtin (1981) refers to as "openendedness" (p. 7) within heteroglossia. This work also showed how audiences within Twitter's imagined audience can discover one another through their own interpretation and uses of the hashtag. Relating these findings to Rajagopal's (2013) concept of social business, this MRP explained how Nike leveraged ambient affiliation—which was evidenced through retweets, username mentions, and re-tagging of tweets—to manage and stimulate conversations and branded-content within the #JustDoIt tag.

The analyses found that participants of the #JustDoIt conversation tweeted original content more than they retweeted, although the majority of Nike-related content were in the form of retweets. This revealed that users were actively following and endorsing Nike's messages, further suggesting that the role of Nike and its affiliated accounts were to produce retweet-worthy content. Strong evidence was also produced using the keyword, collocation, and cluster analyses that suggests that the overall topic of the #JustDoIt tag was related to Nike. At least one conversation was found to challenge Nike's brand and reputation. However, the scores of users retweeting Nike messages dominated the crowd of voices that were competing to define how #JustDoIt should be used. This further suggests that retweets were a valuable form of interaction for the organization.

The study merely showed that heteroglossia existed within Nike's #JustDoIt Twitter hashtag. Future studies should track hashtags through a longer period of time so as to identify how heteroglossia manifests among the audiences. This work can also be expanded upon by introducing a model to measure eWOM, thus mapping how B2C (and consumer-to-consumer) interactions on Twitter translates to financial revenue. Future work can also focus on other aspects of the B2C relationship, aiming for example, to understand how online B2C interaction transfers over to the offline world. Lastly, within the umbrella of consumer behaviour, future studies can extend the findings on the patterns of behaviour found in this MRP and investigate the consumers' motivation to engage with products and brands virtually. For the scope of this MRP, these ideas were not fully explored and discussed.

Nonetheless, this MRP provided a basis for studying in detail, B2C interactions within a Twitter hashtag. In sum, the concepts of heteroglossia and the imagined audience as observed in this MRP can inform organizations on how to navigate through the sea of voices that make up Twitter.

8. Appendices

Appendix A List of Previous Studies in Twitter Content Classification

	Java et al (2007)	Jansen et al (2009)	Pear Analytics (2009)	Honeycutt and Herring (2009)	Naaman et al (2010)
Conversational	“Conversations”	Information Seeking	Conversational	Addressivity/ About addressee/ Exhort/ Solicit Information	Question to followers
Pass Along	“Information or URL sharing”	Information providing	Pass-along/ value/ Self-promotion	Information for others	Information sharing/ Self-promotion
News	“news reporting”	Information providing	News	Self-experience/ Announce/ Advertise/ Opinion	
Status	“Daily chatter”	Comment/ Sentiment	Pointless babble	Self-experience/ Exhort/ Information for self/ Metacommentary/ Media use/ Other	Opinions/ Complaints/ Me NOW/ Anecdote (me)/ Self-promotion
Phatic	“Daily chatter”	Comment/ Sentiment	Pointless babble		
Spam			Spam		

Table 13: *Twitter Content Categories (Dann, S., 2010)*

Appendix B Results of Qualitative Analyses Performed - RT and OC Subcorpora

		RT Subcorpus		OC Subcorpus	
AUTHOR		**Total**	**%**	**Total**	**%**
1	@User - Individual/Consumer	96	100.0%	92	95.8%
2	@Nike - Organization	0	0.0%	0	0.0%
3	@Nike - Affiliate	0	0.0%	4	4.2%
9	Other	0	0.0%	0	0.0%
FORM OF INTERACTION					
1	Original Tweet - Direct mention	0	0.0%	6	6.3%
2	Original Tweet - Indirect mention	0	0.0%	15	15.6%
3	Original Tweet - No mention	0	0.0%	75	78.1%
4	Retweet - Direct mention	3	3.1%	0	0.0%
5	Retweet - Nike Direct	54	56.3%	0	0.0%
6	Retweet- Indirect mention	8	8.3%	0	0.0%
7	Retweet - No mention	31	29.2%	0	0.0%
9	N/A - Spam/Junk Data	0	0.0%	0	0.0%
CONTENT STRUCTURE					
1	Conversational	19	19.8%	27	28.1%
2	Pass along	52	54.2%	15	15.6%
3	News	3	3.1%	1	1.0%
4	Status	3	3.1%	22	22.9%
5	Phatic	3	3.1%	15	15.6%
9	Spam	16	16.7%	16	16.7%
SOURCE DEVICE					
1	Twitter on mobile device	72	75.0%	52	54.2%
2	Twitter on the web	11	11.5%	6	6.3%
3	Twitter application	1	1.0%	16	16.7%
4	Nike / related application	0	0.0%	1	1.0%
5	Other Social Media	0	0.0%	21	21.9%
9	Other	12	12.5%	0	0.0%
TOPICS/THEMES					
1	Nike+ related	0	0.0%	3	3.1%
2	Nike - Fitness related	27	28.1%	8	8.3%
3	Nike - General & Other Products	23	24.0%	10	10.4%
4	Fitness related, non-Nike	5	5.2%	14	14.6%
5	Motivation, non-related	2	2.1%	15	15.6%
6	General - Unrelated	16	16.7%	31	32.3%
9	Other/Junk	23	24.0%	15	15.6%
UNIT OF ANALYSIS					
1	Text Only	46	47.9%	39	40.6%
2	Link Only	6	6.3%	14	14.6%
3	Text and Link	27	28.1%	30	31.3%
9	Other	17	17.7%	13	13.5%

Table 14: *Results from Qualitative Analysis*

Appendix C Results from keyword, collocation, and cluster analyses on RT Corpus

Keyword	Collocates	Cluster	Themes
Time	have	nike: you don't have time	Nike - general
		time to not have time. #justdoit	Other
	every	time to spare. make every run	Fitness / Motivation
		conquer a new trail every time	Fitness / Motivation
	same	@cmihelic1 same time tomorrow? #justdoit	Other
Nike	hypervenoms	imobsessed #hypervenoms #justdoit #nike @mokshabrooklin	Nike - general
		carlitosssx7 #imobsessed #hypervenoms #justdoit #nike	Nike - general
	knightsnation	justdoit @nmfootball: #knightsnation2014 #nike #justdoit	Nike - general
		knightsnation2014 #nike #justdoit @Nike: @mgandonie	Nike - general
	sponsoring	nike sponsoring this barbarian? \@dogrescuetweets	Nike- general
	barbarian	sponsoring this barbarian? \@dogrescuetweets: #boycott	Nike- general
Finish	tale	a fairy tale finish. #justdoit	Other
		deserves a fairy tale finish	Other
	strong	to be cut. finish strong	Other
	masters	masters has a finish line	Other
	storybook	finish. #justdoit a storybook season	Other
Run	out	tricks. @cristiano is out of	Other
		out of this world. #justdoit	Other
	luck	out. #justdoit @nike: don\'t	Nike - general
		your luck run out. #justdoit	Other
	every	nikegolf: accept every challenge. #justdoit	Nike / Motivation
		every run your best run	Fitness / Motivation
Line	proves	starting line proves just as	Other
	starting	the starting line proves just	Other
		getting to the starting line	Other
	masters	masters has a finish line	Other
	determination	the starting line. determination will	Other
	finish	to the finish line. #justdoit	Other
		at the finish line. #justdoit	Other

Table 15: *Summary of Analyses on RT Corpus*

Appendix D Results of Keyword, Collocation, and Cluster analysis on OC Corpus

Keyword	Collocates	Cluster	Themes
Nike	boycott	wleemoore76 please boycott nike &	Other
		justdoit please boycott nike &	Other
	join	join nike for the ultimate	Nike - general
		nike for the ultimate experience	Nike - general
	justdoit	nike #justdoit i just ran	Nike / Fitness
		nike #justdoit wishing, start doing	Nike - general
	family	to the nike family!! #justdoit	Nike - general
		the nike family!! #justdoit #striveforgreatness	Nike - general
Run	mi	mi run with a pace	Fitness / Motivation
		crushed a 2.0mi run with	Fitness / Motivation
	luck	your luck run out. #justdoit	Other
Day	runthedistance	day for #training #runthedistance #freeyourrun	Fitness / Motivation
		beautiful day for #training #runthedistance	Fitness / Motivation
	workoutfriday	day! #friday #workoutfriday #fridayfun #workout	Fitness / Motivation
	lifts	lifts. others dedicate their day	Fitness / Motivation
	energyefficiency	today is world day #energyefficiency	Other
Workout	motivation	fitness #workout #motivation #stayfit #justdoit	Fitness / Motivation
		motivation #inspiration #goals #workout #getitdone	Motivation
	daily	missed your daily workout? don	Fitness / Motivation
	fitness	fitness #motivation #inspiration #goals	Fitness / Motivation
		health #fitness #workout #motivation #stayfit	Fitness / Motivation
Nikeplus	mi	mi pace with nike+. #nikeplus	Nike / Fitness
	pledging	i\'m pledging my #nikeplus	Nike - general
		justdoit pledging my #nikeplus km	Nike - general
	gps	with nike+ sportwatch gps. #nikeplus	Nike - general
	nikefree	night running.#nike #nikefree #nikeplus	Nike - general
		nike #nikefree #nikeplus #nikerunning	Nike - general
	running	nikeplus #nikerunning #noexcuses #justdoit	Nike - general
		nikeplus #nikerunning #nikefuelbandse #justdoit	Nike - general

Table 16: *Summary of Analyses on OC Corpus*

Appendix E Summary of Results for Cluster Analyses

RT Corpus	OC Corpus
Nike	Nike
to the **nike** family!! #justdoit	mi pace with **nike**+. #nikeplus
nike sponsoring this barbarian? \ #boycott	km pace with **nike**+. #nikeplus
fuel the machine !!! #**nike** #ntc	join **nike** for the ultimate
support with **nike**+ by tagging	**nike** for the ultimate experience
onemomile #JustDoIt #mofarah #**nike** #london	boycott **nike** & michael vick
Finish	Day
a fairy tale **finish**. #justdoit	a beautiful **day** for #training
finish. #JustDoIt a storybook season	today is world **day** #energyefficiency
finish line. your running never	no beautiful **day** for #training
has a **finish** line. your	beautiful **day** #training #runthedistance #freeyourrun
get you to the **finish**	one **day** at a time
Line	Nikeplus
getting to the starting **line**	mi pace with nike+. #**nikeplus**
getting to the finish **line**	km pace with nike+. #**nikeplus**
line proves just as much	pledging my #**nikeplus** km for
starting **line**. determination will get	with nike+ sportwatch gps. #**nikeplus**
at the starting **line** today	nike+ sportwatch gps. #**nikeplus** #nikerunning
Run	Run
let your **run** do the [talking]	**run** with a pace of
make every **run** your best	let your luck **run** out
if i can **run**. i	morning **run**. #nikerunning #nikeplus #justdoit
run. i can jump #justdoit	crushed a 7.0km **run** with
we’re stronger every **run**	crushed a 2.0mi **run** with
Time	Workout
don\'t have **time** to	counts! missed your daily **workout**
to not have **time**. #justdoit	motivation #healthy #strong #change #**workout**
take on two next **time**	healthy #strong #change #**workout** #qualitytime
one stride at a **time**	fitness #motivation #inspiration #goals #**workout**
a new trail every **time**	justdoit #**workout** #goforit #relaxing #night

Table 17: Top 5 clusters for the top 5 keywords by subcorpus

Appendix F Keyword, Collocation, and Cluster Analysis on @DarkeyTJ corpus

Keyword	Collocates	Cluster	Themes
mi	ran	mi pace with nike+. #nikeplus	Nike - general
		pace with nike+. #nikeplus well	Nike – general
	pace	mi pace with nike+. #nikeplus	Nike – general
		a 7\'53\/mi pace with nike	Nike – general
	mi	mi pace with nike+. #nikeplus	Nike – general
	nike	mi pace with nike+. #nikeplus	Nike – general
		a 7\'53\/mi pace with nike	Nike – general
pace	uninspiring	an uninspiring pace but at	Other
		cheers nick.... an uninspiring pace	Other
	truth	truth863 incredible pace. i could	Fitness / Motivation
		catch @djrussc #justdoit @darkeytj: @truth	Other
	tina	an awesome pace, tina. well	Fitness / Motivation
		awesome pace, tina. well done	Fitness / Motivation
	sustaining	great work sustaining your pace	Fitness / Motivation
		work sustaining your pace.... #justdoit	Fitness / Motivation
nikeplus	wigan	my ... #nikeplus @wigan10k well	Nike – general
		nikeplus @wigan10k well done	Fitness / Motivation
	trail	a biking and running trail	Fitness / Motivation
		and running trail. excellent! #justdoit	Exercise
	nick	cheers nick.... an uninspiring pace	Exercise
		nabrookes cheers nick.... an uninspiring	Exercise
	mnths	mnths, -30 lbs, 1 mara, 6 hlf maras	Fitness
		nike+. #nikeplus mnths, -30 lbs, 1 mara	Nike / Fitness
great	sustaining	great work sustaining your pace	Fitness / Motivation
		work sustaining your pace.... #justdoit	Fitness / Motivation
	stomping	and old stomping grounds! great	Other
		hometown and old stomping grounds	Other
	sj	sj good luck with the	Motivation
		sj great work! what marathon	Fitness / Motivation
nike	mnths	mnths, -30 lbs, 1 mara, 6 hlf maras	Fitness
		nike+. #nikeplus mnths, -30 lbs, 1 mara	Fitness
	lbs	lbs, 1 mara, 6 hlf maras, now	Fitness
		mnths, -30 lbs, 1 mara, 6 hlf maras	Fitness
	gorgeous	gorgeous day to #justdoit! i	Other
		nike+. #nikeplus gorgeous day to	Nike – general
	fuelband	fuelband. #nikeplus had a great	Nike – general
		my nike+ fuelband. #nikeplus had	Nike – general

Table 18: *Summary of Analyses on @DarkeyTJ Corpus*

Appendix G Keyword, Collocation, and Cluster analysis on @NikeFuel corpus

Keyword	Collocates	Cluster	Themes
nikefuel	yeah	fleetfeetchgo yeah!!!! “@nikefuel: @mattkjacobson nice	Nike - general
		justdoit @nikechicago @nikefuel @fleetfeetchgo yeah	Nike - general
	winfromwithin	begins @nikefuel #winfromwithin #justdoit @nikefuel	Nike - general
		hunt begins @nikefuel #winfromwithin #justdoit	Nike - general
	jordan	jumpman23 #nike #jordan #justdoit #23 #snow	Nike - general
		nike #jordan #justdoit #23 #snow @nikefuel	Nike - general
	hurting	hurting... #ntc @nike @nikefuel #sweatit	Nike / Fitness
		justdoit hurting... #ntc @nike @nikefuel	Nike / Fitness
foolproof	justdoit	hard work is foolproof. #justdoit	Nike - general
work	foolproof	hard work is foolproof. #justdoit	Nike - general
		rt hard work is foolproof	Nike - general
	hard	rt @nikefuel: hard work is foolproof. #justdoit	Nike - general
		hard work is foolproof. #justdoit” @davidihughes @sinner	Nike - general
	green	just wear green. work for it. #justdoit	Other
	wear	nikefuel: wear your resolution on your wrist	Nike - general
		just wear green. work for it. #justdoit	Nike - general
hard	work	rt @nikefuel: hard work is foolproof. #justdoit	Nike - general
	nikefuel	rt @nikefuel: hard work is foolproof. #justdoit	Nike - general
		nikefuel: wear your resolution on your wrist	Other
	part	hard part, the rest is easy. #justdoit	Nike - general
day	everyday	rt @nikefuel: every day, not everyday. #justdoit	Other
	bank	nikefuel: 30 days in the bank starts with	Nike - general
		the bank starts with 1 day earned. #justdoit	Nike - general
	starts	finish to the week, tomorrow it starts	Other
	earned	the bank starts with 1 day earned. #justdoit	Other
		earned your spot along multi-millionaires row	Other
	today	what movement will today’s chapter hold	Other
		why don’t you make today a 5k day? #justdoit	Fitness / Motivation
nike	nikefuel	nikefuel: don\'t just wear green. work for it	Nike - general
		nikefuel: 30 days in the bank starts with 1 day earned	Nike - general
	justdoit	hard work is foolproof. #justdoit	Other
		green. work for it. #justdoit	Other
	fuelband	justdoit #cardio #fuelbandse #fuelband @nikefuel	Nike - general
		got my #nike #fuelband. so	Nike - general
	nikerunning	justdoit @nikenyc @nikerunning @nikefuel @teamrunnyc	Nike - general
		nikenyc @nikerunning @nikefuel @teamrunnyc #fuelcheck	Nike - general

Table 19: *Summary of Analyses on @NIKEFuel Corpus*

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NOTES

[1] The official campaign period was August 20, 2013 – September 13, 2014 (NIKE Inc., 2013a).

[2] The NikeFuel system awards points to users based on the activities that they do.

[3] Nike Community Forums: www.nike.com/community

[4] Heteroglossia is a term that describes the different interpretations of a word or utterance (Bakhtin, The Dialogic Imagination: Four Essays, 1981).

[5] CAQDAS stands for Computer-Assisted Qualitative Data Analysis Software

[6] Some profiles were made private since the data collection, thus restricting the content to the user's own network.

[7] The AntConc Corpus Toolkit is a non-proprietary software program for corpus analysis. It can be downloaded here: http://www.antlab.sci.waseda.ac.jp/software.html. See also, Anthony (2005) for more details on the tools available on the program.

[8] www.randomizer.org

[9] http://www.surveysystem.com/sscalc.htm

[10] http://help.sentiment140.com/for-students

[11] Some of the tweets that were collected within the main corpus were in a language other than English. This did not affect most of the results in the study. Within the hand-coded results, tweets in foreign languages were classified as spam/junk. On AntConc, foreign words were either added to the program's stop list, or ignored within the keyword, collocation, and cluster analyses. It was decided to keep these tweets within the main and sample corpora as it contributes to the overall accuracy of any given hashtag corpus; removing these tweets may affect the corpus' overall representativeness of actual conversations on Twitter.

[12] Studies using corpus linguistics also infer relationships from only a few words using concordance tools; common words such as *the* and *we* for example, are usually disregarded.

[13] It was difficult to detect ambient affiliation between @DarkeyTJ and @truth863 in the analysis phase because user @truth863's profile has been made private. The tweet and its potential threads are no longer visible to the public.

[14] This MRP only collected tweets with the #JustDoIt hashtag.