Twitter and Behavioral Engagement in the Healthcare Sector

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Twitter and Behavioral Engagement in the Healthcare Sector: An Examination of Product and Service Companies.

Abstract

This paper examines Twitter use by product and service companies in the healthcare sector. This four company study aims to identify the type of content posted in Twitter that drives engagement in terms of 'likes', retweets and comments. A sample of 838 tweets were thematically coded as to the perceived tweet function. The tweets were analyzed to determine whether the function was significantly associated with greater or lesser engagement. Linguistic content of tweets was then analyzed using LIWC to determine the type of content associated with greater engagement. Results suggest that company type (product vs. service) and tweet function influence the degree of engagement. Engagement also differed significantly based on the linguistic content of messages, such that word categories associated with greater engagement were identified. Thus, to drive greater engagement with a wider network, the business marketer should consider the nature of the company as well as the function and linguistic content of messages posted to Twitter.

Keywords

Twitter; linguistic analysis; behavioral engagement; products; services

1. Introduction

Markets consist of interactive exchange between multiple actors (Ford, 2011; Fournier, 1998; Vargo & Lusch, 2008a) in which parties have the capacity to affect and be affected by one another. A critical factor both shaping and resulting from such dynamic exchange is the engagement of stakeholders involved. Engagement has been examined in a variety of disciplines, including management. Here, researchers have sought to develop understanding of the contribution of multi-actor engagement to value creation (Chandler & Lusch, 2015), while others, in exploring engagement, have centered on the conduct of specific stakeholders such as employees (e.g., Kahn, 1990; Saks, 2006; Schaufeli & Bakker, 2004) and customers (e.g., Brodie et al., 2011; van Doorn et al., 2010; Gambetti & Graffigna, 2010). Our interest lies in the latter, i.e., customer engagement.

Customer engagement can be explained as a psychological state resulting from specific interactive episodes that a customer experiences with a focal agent or object (Brodie et al., 2011). In developing the concept researchers have elicited three dimensions (Hollebeek., 2011): *emotional* - an individual's degree of positive object-related affect; *cognitive* - an individual's level of object-related thought processing and elaboration; and, *behavioral* - the level of energy, effort and time the individual spends on a particular object. While examination of customer engagement has been undertaken principally in consumer contexts, both the concept and these dimensions have resonance for dynamic, interactive exchange in business markets. We seek, therefore, to expand understanding of customer engagement through its investigation in a business-to-business (B2B) setting.

Dynamic, interactive exchange in business markets can take on different forms (Hakånsson, 1982), but social and informational exchange are especially important in understanding customer engagement. This is particularly so given the changing communications landscape in business markets (Wiersema, 2013) and the capacity of an individual actor's level of engagement to affect and be affected by information exchange episodes (Sashi, 2012). Interpersonal contact (face-to-face or remotely via phone, email or video-conference) has been the mainstay of interactive information exchange in business markets. However, developments in digital communication platforms, such as social media, offer the potential to extend both the scope of this dynamic exchange and the nature of information shared between parties (Ashley & Tuten, 2016; Swani et al., 2014; Swani et al., 2016). These developments would imply that social media channels such as Twitter, LinkedIn and Google+ present the business marketer with a further medium through which to foster customer engagement. Evidence suggests that marketers are using social media platforms to support behavioral engagement (Ashley & Tuten, 2016; Swani et al., 2014; Swani et al., 2016), yet understanding of how to effectively employ such media requires further development (Lacoste, 2016; Siamgaka et al., 2015; Wiersema, 2013).

To improve social media deployment, Swani et al., (2014) call for research that explores its use in different sectors. Our paper responds to this by examining the utilization of Twitter according to the nature of a business marketer's solutions. We distinguish between types of solutions depending on whether they are product or service dominant. While academic and practitioner conceptualizations of solutions have moved away from this neat divide (Vargo &

Lusch, 2008b), the fundamental basis of an organization's expertise is nevertheless rooted in solutions that integrate either predominantly product- or service-based attributes. With regards solutions that are heavily product-based, the business marketer is able to communicate function and performance attributes that a customer can readily evaluate. Contrastingly, the features of predominantly service-based solutions are not only more difficult for the marketer to convey, but can challenge a customer in terms assessing that performance, both in communication messages as well as during and after using such solutions (Ford et al., 1988; Klein, 1998; Nelson, 1970; Norton & Norton, 1988). This is an important point regarding communication, particularly if the business marketer is to maximize the potential of social media. Therefore, the aim of this paper is to examine the extent of variation in Twitter feeds posted by companies with product and service dominant solutions. We scrutinize Twitter content – in both function and language – and the degree of behavioral engagement elicited.

The paper starts by connecting interaction and customer engagement in the B2B context. This is followed by an explanation of the role of social media, specifically Twitter, in the provision of content and the elicitation of behavioral engagement of stakeholders. The method section explains the sampling, method of data collection and the data analysis methods utilized herein. The results examine whether product and service companies differ in their degree of behavioral engagement elicitation overall and by tweet function and use of language. Last, the discussion and conclusion sections examine the key findings in reference to the use of Twitter in B2B contexts, providing managerial implications and suggestions for future research.

2. Literature Review

While engagement has attracted considerable interest in consumer contexts, its associated meanings overlap with understanding of the functioning of business markets and the behavior of actors (organizations and individuals) within them. In this section we synthesize interactive exchange and engagement, and consider how explanations of engagement developed in organizational and consumer settings can be used to understand the concept in business markets. From this we examine the role of social media as an engagement strategy employed by the B2B marketer, before looking at communication as part of this and, more specifically, the use of Twitter as a means to foster behavioral engagement with stakeholders.

2.1 From interactive exchange to engagement in business markets

Irrespective of overarching theoretical framing (such as service dominant logic or actor-network approach) or broad context (for example consumer or business), there is consensus that markets comprise interactive exchange between multiple stakeholders (Ford, 2011; Fournier, 1998; Vargo & Lusch, 2008a). 'Exchange' can be explained simply as the act of giving one thing and receiving another (Oxford Dictionary, 2017). Three critical points relating to exchange have gained wide-spread currency in marketing theory and practice, namely that i). it is interactive - i.e., exchange parties have the capacity to affect and be affected by one another; ii.) it often occurs repeatedly, so that actors' previous interaction experiences inform both present exchanges as well as future events; and, iii.) it can be multidirectional and involve numerous parties (Brodie et al., 2011, Chandler & Lusch, 2015, Ford et al., 2010). Social and information exchange are key in commercial marketplaces (Anderson, 1985; Hakånsson, 1982) and individual managers are central to these dynamic, interaction processes played out both within and between different organizations (Leek et al., 2003; Medlin & Törnroos, 2006; Turnbull, 1990). The role of the individual is pertinent here because exchange with other individuals influences and is also shaped by a manager's engagement in exchange episodes with those other parties.

Engagement has attracted considerable interest as part of efforts to understand human behavior and performance in an organizational setting (e.g., Costa et al., 2014; Kahn, 1990; Saks, 2006; Schaufeli & Bakker, 2004). Saks (2006) argues that an individual's level of engagement varies, and that the cognitive, emotional and behavioral resources that an individual invests in performing their role are contingent on the resources received in return. The dimensions related to individual engagement in an organizational setting and the notion that it is in some way a reciprocal and dynamic phenomenon (Cropanzano & Mitchel, 2005) has resonance in a business market setting. Here, interpersonal contact has long been an essential means for interactive, free-flowing communication in inter-firm relationships (Hakånsson, 1982; Medlin & Törnroos, 2006; Turnbull, 1990). So the psychological state of those individuals with boundary spanning roles will be manifest during and affected by interactions with exchange partners (Dwyer, Schurr & Oh, 1987). In this context, cognitive resource might be evidenced in the degree of mental effort, problem-solving or willingness to participate in intellectually challenging exchanges when interacting with other actors. Emotional resource might be reflected in the individual's – including single network actors - positive (or indeed negative) reactions to dealings with other actors, informed by past and ongoing interaction experience. Finally (and of particular interest to us), the behavioral resource might be related to, for example, an individual manager's extent and frequency of dialogue with representatives of another firm.

Looking from a marketing perspective, Brodie et al. (2011) explain customer engagement as a psychological state (van Doorn et al., 2010) that results from interactive, co-creative experiences with a focal agent/object (e.g., a brand) in a focal service relationship and exists as a dynamic, iterative process. Conceptual development and empirical examination of customer engagement has centered principally on *consumer* experiences with brands and/or services (see for example Brodie et al., 2013; Dessart et al., 2015; Hollebeek et al., 2014; Oh et al., 2016; Wirtz et al., 2013). This development of understanding of consumer engagement can be linked to two factors. First is the shift to viewing consumer behavior as being associated with relational experiences involving multiple parties rather than as transactional, product-focused episodes (Brodie et al., 2011). Second is the facility offered by digital technology and social media in particular. These media enable individual consumers to participate in interactive, information exchange with other parties around a particular brand or service, without such dialogue being connected to a specific commercial exchange with the marketing organization (Dessart et al., 2015; van Doorn et al., 2010; Hollebeek et al,, 2014).

As with understanding in other contexts, consumer engagement is explained as being manifest to varying degrees through cognitive, emotional and behavioral dimensions (Brodie et al., 2011; Dessart et al., 2015; Hollebeek et al., 2014; Hollebeek, 2011). Although engagement might be revealed via these three elements, the behavioral dimension has attracted considerable attention, perhaps, in part, because its manifestation can be readily observed and managed (Oh et al., 2016). As such, behavioral engagement connected to consumer brands/services is evidenced via actions such as sharing, advocating and co-developing (van Doorn et al., 2010; Brodie et al., 2013). Of specific interest to us is how these developments might be used in a B2B setting to foster higher levels of customer engagement behavior via digital technology such as social media.

2.2 Social media: broadening interactive communication for engagement

As we noted previously, interpersonal contact is a central element to interactive, free-flowing communication in business markets. As one of the most used forms of interpersonal contact, face-to-face exchange between company representatives allows the sharing of information, but it is can also shape as well as reveal the individuals' engagement (cognitive, emotional and behavioral). Despite the importance attributed to face-to-face exchange, the growing use of digital technology for interpersonal contact in business relationships has been recognized for some time (e.g., Leek et al., 2003.). The question then is how new forms of digital communications technology such as social media channels might supplement existing interpersonal communication processes and impact the behavioral engagement of those involved.

Digital technology can certainly improve the ease and efficiency of interpersonal contact (Brennan et al., 2014; Leek et al., 2003) and extant research suggests that social media extend the scope for- and use of- interactive communication beyond those traditionally employed. For example, companies as well as individuals can place content and messages on networking sites such as Facebook, Google+ or microblogging facilities such as Twitter. This can serve diverse purposes, from educating participants (Schultz et al., 2012) to enabling customer contribution to research and development activities (Kietzmann et al., 2011). Equally, social media platforms can be used to support sales (Guesalaga, 2016; Michaelidou et al., 2011), facilitate customer management and service provision (Brennan & Croft, 2012; Castronovo & Huang, 2012; Lacoste 2016; Sashi, 2012), relationship management (Quinton & Wilson, 2016) or as part of corporate reputation and brand management (Bruhn et al., 2014; Jussila et al., 2014). Despite these advances, it has been suggested that the full potential of social media interactions remains untapped (Lacoste, 2016; Siamagka et al., 2015). Our research seeks to understand how social media might be used more effectively in business markets and to do this we examine the contribution of Twitter to behavioral engagement.

2.3 Twitter: a platform for engagement

Twitter is a microblogging site with 313 million monthly active users and 1 billion monthly unique visits to sites with embedded tweets (Twitter, 2017). Companies use Twitter accounts to disseminate content (up to 140 characters) to self-selected followers. The messages may contain the “@”symbol which is used to identify a specific account holder and include them in the interaction. The use of a “#” before a word identifies the tweet as contributing to a certain topic of discussion. The “#” also enables Twitter users to search for certain topics, identify relevant discussions and the specific contributors. Such publicly available social media interaction and its adoption by businesses make it an ideal platform to investigate behavioral engagement in a B2B setting.

2.3.1 Creative strategy for engagement: content and messages

For Twitter to support behavioral engagement, it requires that both the content (to which a Twitter feed is connected) and the tweet message itself be designed in such a way that they elicit the appropriate response from followers (Ashley & Tuten, 2016). The facility offered by digital channels through which stakeholders can proactively seek out and action information which is of particular relevance to them has resulted in content marketing becoming an increasingly important communications activity (Pulizzi, 2012). Rather than messages being focused on, for example, commercial sales propositions, effort is directed at creating and making available content that is both relevant and compelling to stakeholders (Holliman & Rowley, 2014; Pulizzi, 2012). Uses and gratification theory (Katz et al., 1973/1974) suggests that individuals will seek out and respond to content which is of personal relevance to them, and that this relevance is based on whether content satisfies an individual’s informational, entertainment, remunerative or relational needs (Dolan et al., 2016; Gao & Feng, 2016).

Given the nature of business markets, it might be expected that content which aligns with an individual’s *informational* requirements is more likely to be viewed as relevant by the business user. Indeed, Leek et al., (2016) show informational content to be integrated into different message functions (e.g., problem solving, sharing informational insight or company specific PR news) employed by the business marketer. Twitter feeds might direct a user to such content via embedded links to the company website, company PDF files or social media sites such as YouTube or LinkedIn (Swani et al., 2014). But in using Twitter for different message functions, the business marketer has to ensure that this informational content is clearly signaled in, and can be readily accessed via the tweet, in order to elicit a behavioral response.

The complexity of engagement with tweets cannot be due to function and shared URLs alone. The language used in such short messages may also play a part in engagement, as the message itself needs to be appealing enough to encourage activity. Specific use of language has been shown to relate to online communication success. Swani et al., (2014) noted that B2B companies use a mix of functional and emotional appeals. Dove et al. (2011) identified linguistic patterns to successful introductions amongst online forum users, and Houghton and Joinson (2012) found linguistic differences in tweets based on the privacy sensitivity of the message. The power of linguistic differences is such that it can be used to identify deception in instant messenger chat (Hancock et al., 2008), and to assess individual differences in personality (Pennebaker & King, 1999). Most notably, Tausczik & Pennebaker (2010) stated that, “language is the most common and reliable way for people to translate their internal thoughts and emotions into a form that others can understand. Words and language, then, are the very stuff of psychology and communication" (p.25). Thus, in identifying the extent to which stakeholders engage with tweets, understanding the linguistic differences in tweets that are more or less related to levels of engagement can help B2B marketers to develop more engaging tweets, strengthening their brand's social media position.

Whatever the function of the tweet and the nature of the message, the aim of the marketer is to elicit a behavioral reaction from followers, i.e., encourage followers to act in some way. Behavioral metrics on Twitter encompass likes, retweeting (i.e., sharing the tweet with others) and commenting on the tweet. In moving from likes, to retweets and comments the effort and content required from the follower increases accordingly, possibly reflecting an increasing degree of engagement (Oh et al., 2016; Wallace et al., 2014). Followers' use of likes suggests that a satisfactory interaction has occurred (Sashi, 2012).

Thus, in summary this paper aims to investigate the different levels of behavioral engagement (likes, retweets and comments) associated with different functions and linguistic styles of tweets for product and services companies. Figure 1 illustrates the scope of the current research, such that the present paper investigates the company type and message properties (black boxes) – Tweet function and linguistic style – to identify any significant relationship between these and the different levels of engagement (gray circles).

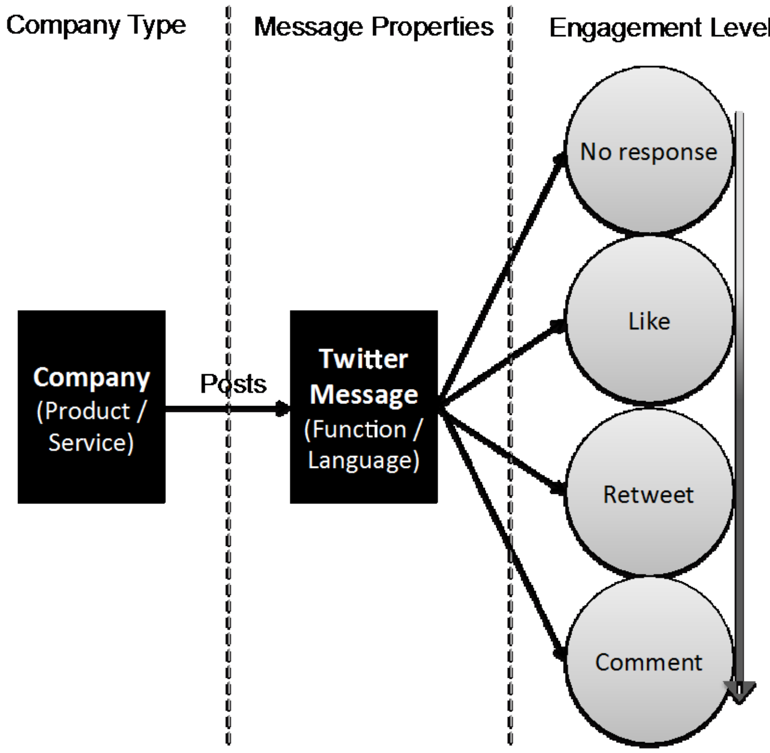

Figure 1: Research scope and focus.

More specifically, the paper seeks to: -

1) Identify whether the level of behavioral engagement with followers, i.e., number of likes, retweets and comments, differs between product and service companies' tweets.

2) Determine whether the level of behavioral engagement, i.e., number of likes, retweets, and comments, differs between product and service companies' tweets for different message functions, i.e., problem solving, information sharing and PR.
3) Determine the differences in linguistic style of tweets associated with differences in stakeholder engagement levels, for product and service companies and different tweet functions.

3. Method

The limit of 140-characters per tweet imposed by Twitter, and the public nature of such tweets, makes Twitter an amenable platform to investigate behavioral engagement. Each tweet can be investigated, or the tweets can be taken collectively, to allow empirical investigation without overload, but providing sufficient data for thorough analysis. Engagement is evident in the 'liking', retweeting and commenting by other Twitter users of/on the company's tweets. Such behavioral engagement practices, the accessibility of data and over 313 million monthly active users (Twitter, 2017) meant Twitter was selected to investigate service and product companies', their customers' and other stakeholders' behavioral engagement. It should be noted, that during the present empirical investigation, Twitter renamed their 'favourites' function to 'likes' (Parkinson, 2015), and the latter term is used herein for consistency.

The nature of interaction between businesses in different sectors meant a single industry sector (healthcare) was selected for analysis to ensure that tweet content and engagement activity were directly comparable, i.e., it was not because of the context that frequency of posts and engagement differed, or aspects of language were conflicting. Although a netnographic approach was not adopted - instead using non-participant observation to avoid affecting the ecological validity of interactions amongst participants (Liu & Maitlis, 2010) - the sampling procedure proposed by Kozinets (2010) guided the selection criteria due to its validity and rigor. Thus, starting with performance data from InterBrand (www.interbrand.com) to identify leading global product and service companies, Twitter accounts were selected for investigation if they were relevant (i.e., were B2B companies), active (posted frequently and were not dormant accounts), interactive (displayed evidence of behavioral engagement through 'likes' and retweets), substantial, heterogeneous (with an array of different followers) and data rich (contained tweets with various different URLs and post content for a meaningful analytical interpretation).

Table 1: Summary details of product and service companies.

Company	**Business Activity**	**Headquarters**	**Turnover € (billion)**	**Employees (million)**
A	Healthcare systems	Amsterdam, Netherlands	21,39	1,05
B	Electrical engineering and electronics	Berlin/Munich, Germany	71,92	3,57
C	Consulting and	Dublin, Ireland	29,67	3,84

	professional services			
D	Consulting and professional services	London, United Kingdom	28,26	2,1

To ensure an equal balance between product and service companies in this investigation of engagement in the B2B healthcare sector, two product companies and two service companies were selected (see Table 1 for details). Tweet Archivist Desktop was used to conduct live scraping from these four companies. Live scraping is the collection of tweets by observing the real-time behavior of Twitter users according to specific text search criteria. The software program remained active for a period of 16 days, which enabled the collection of substantial, content rich tweets that met our sampling criteria (see above). The software searched for tweets every 30 minutes and saved the data to a local file, used subsequently for analysis. Specifically, the scraping used Twitter's search Application Programming Interface (API), and whilst this is limited to the previous 100 tweets or past one week's worth of tweets (whichever is met first), scraping once every 30 minutes ensures that every tweet is collected from the companies selected. Tweets will only be missed if more than 100 tweets are posted every 30 minutes, which in checking the companies' Twitter accounts on twitter.com, was not the case for our sample. Herein, the API was searched for tweets *from* each company account (from:AccountTwitterHandle), i.e., those posted or retweeted by the companies of interest.

Thus, a total of 838 tweets from four Twitter accounts were collected, with 490 tweets from the two product companies (Company A, n=339; Company B, n=151) and 348 tweets from the two service companies (Company C n=63; Company D n=285). No tweets were eliminated, making the sample a census of company posts for the 16-day period. For each tweet, Tweet Archivist Desktop collected the following data fields: from whom the message originated, the date and time of the message, the message itself, the numbers of likes, retweets and comments the tweet received, and any associated URLs, hashtags and links to media.

All tweets collected were then coded using an iterative thematic analysis for their function (i.e., purpose of the tweet message) by classifying the message content. Although themes were identified in the data, the analysis performed herein was not true grounded theory such that the patterns identified were without prior theorizing. In this ilk, Braun and Clarke (2006, p. 81) argue "that a 'named and claimed' thematic analysis means researchers need not subscribe to the implicit theoretical commitments of grounded theory if they do not wish to produce a fully worked-up grounded-theory analysis", but later note that "it is important that the theoretical position of a thematic analysis is made clear, as this is all too often left unspoken" (p. 81). Thus, it is critical to acknowledge that a first pass of the data was made to identify the core themes of the data, but that this first pass is mired in prior knowledge of business communication functions, and sought to categorize the data more broadly for three main communication purposes. Namely, the purposes of information sharing, problem solving and public relations. A second stage of coding then further scrutinized these categories to find specific functions of each of the three purposes, which was a more inductive pass of the data within these broad themes.

Information sharing was selected as a broad category for investigation as "content in the form of social networks and blogs that enable individuals to create, share, and recommend information is extending the spheres of marketing influence, and a wide variety of social media platforms are providing the tools necessary for these influential and meaningful firm-customer exchange" (Hanna et al., 2011, p. 266). Thus, both the functions of social media, and the desire to instigate meaningful firm-customer exchange, facilitate the generation and sharing of information. In a similar vein, Sashi (2012) suggests social media interaction "allows sellers to share and exchange information with their customers but also allows customers to share and exchange information with one another as well" (p. 255), making information sharing a necessary component in our iterative approach to data categorization. Second, social media have been suggested to help facilitate firm-customer interaction to solve specific customer or industry wide problems. Indeed, Sashi (2012) states, "Using social media, organizations can forge relationships with existing as well as new customers and form communities that interactively collaborate to identify and understand problems and develop solutions" (p. 255). Thus, we look to identify instances of problem solving in company tweets that can facilitate the development of solutions for business customers. However, our iterative approach and the use of thematic analysis allows a "flexible method for qualitative research" (Braun & Clarke, 2006, p. 77). Last, public relations forms the basis of a theme whereby communication about the company is made in an attempt to attract and build relationships, with Saffer et al. (2013) noting, "Twitter provides organizations the ability to engage in contingency interactivity with publics – providing the kind of relationship-building communication that has been missing from websites. Lovejoy et al. (2012) suggested that Twitter's potentially contingent interactive messages like replies and mentions can assist organizations in communicating with other users" (p. 213).

As such, our thematic identification is driven by the data in the tweets, but also by preconceptions of the first identified, broader categories. Table 2 shows the categories, description of the categories and verbatim tweets to evidence the category differentiation as well as interconnection. It can be seen further, that the broader categories of Information Sharing, Problem Solving and PR have a relationship of a parent-child node, such that the sub-categories belong to these three, but have further distinction from one another. More broadly, the three main categories are evidently related, such that a PR tweet for the purpose of relationship building, could in some cases contain information sharing, but differs in that the function was interpreted as being primarily about relationship building.

In beginning this coding, a sample of the tweets (n=32) were coded by three researchers to agree upon the aforementioned coding template before each researcher coded the remaining tweets in isolation. Only slight agreement was reached in initial coding (Light's Kappa = .156, fully-crossed design; see Hallgren, 2012), therefore coding continued until 100% agreement was established.

Table 2: Identified tweet classification, definition and example verbatim.

Initial Code	Secondary Code (Tweet Function)	Definition	Example Verbatim
Information Sharing (n=931)	*Information Sharing – Customer (n=144)*	Messages designed to share information about customers in general.	Top 10 #digitalhealth trends: See what made the list in 2014. #hcsm [URL]
	Information Sharing – Events (n=318)	Messages designed to share information about an upcoming or past event.	Lung cancer: A women's health issue. Hear from Dr. Andrea McKee: [URL] #RSNA14
	Information Sharing – Product (n=133)	Messages detailing information about a particular product.	AlluraClarity's interventional X-ray suites are tailored to Neurology, Oncology, and the Hybrid OR. Explore: [URL] #RSNA14
	Information Sharing – Sales Subscription (n=10)	Messages about subscribing to be sent information from the company, e.g., a newsletter.	Happy holidays! The Dec/Jan edition #TNVHealth has been released. Read it and sign up here [URL]
	Information Sharing – Opinion (n=42)	Messages voicing an opinion on a particular topic.	We believe it's a new world #BeyondTheImage...a world where consumers want to get more engaged in their health journey. Frans van Houten
	Information Sharing – Industry (n=284)	Messages that share information about the wider industry.	Will the #healthcare industry move closer to #interoperability in 2015? [URL] #CHSBlog
Problem Solving (n=144)	*Problem Solving – Generic (n=122)*	Messages suggesting how more general problems in the industry might be solved.	Facing an increase in elderly, chronic patients & costs? #Health #analytics can help. [URL]
	Problem Solving – Specific Customer (n=15)	Messages relating to the company’s having solved a problem for a specific customer.	Video: See How the NHS’ Airedale improved care quality and efficiency. #patientengagement [URL]
	Problem Solving – Specific Problem (n=7)	Messages relating to the company’s having solved a specific problem within the industry.	#EMR access outweighs privacy concerns for #UK chronic patients. [URL]
Public Relations (PR)(n=108)	*N/A*	Messages that provide positive company information, e.g., recognition at	We're creating a more relaxing experience for patients during #MRI scans w/Ambient Experience. [URL] #RSNA14

		industry awards.	

N.B. Tweets can belong to more than one category

In addressing RQ1, to determine any significant differences in the level of behavioral engagement obtained on Twitter between product and service companies, inferential statistical analyses were conducted. As the dependent variables (number of 'likes', number of retweets, number of comments) are count data, thus have a Poisson distribution, three negative binomial regressions with log-link – a form of Poisson regression for over-dispersed data were conducted (for full details see Gardner, Mulvey & Shaw, 1995). A binomial IV of company type (product or service tweets) was entered into each regression with the three DVs, consecutively. Similar analyses have been conducted with other count based DVs including breast cancer incidence (Yost et al., 2001), the severity of state-sponsored mass murder (Krain, 1997) and daily customer mistreatment by employees (Wang et al., 2011), each of which adopt appropriately the method used herein.

In addressing our second research question, analyses were then conducted to determine if there were any differences in 'likes', retweets or comments (behavioral engagement measures) between product and service companies for each tweet function (*Information sharing – customer, Information sharing – events, information sharing – product, information sharing – sales subscription, information sharing – industry, problem solving – generic, problem solving – specific customer, problem solving – specific problem,* and *PR*). Thus, the number of 'likes', retweets and comments were entered as DVs in separate regressions, with company type (product/service) as the IV (binomial) and cases selected for each of the tweet functions in turn. This meant that for each tweet function, e.g., *PR*, data were selected that related only to tweets coded as PR tweets, and the number of 'likes', retweets and comments were regressed on company type.

On the principal that not only the perceived intention of the tweet could lead to differences in behavioral engagement, but also the language of the tweet, linguistic analyses were conducted for tweet functions where significant differences in behavioral engagement were found. Linguistic analysis will identify any differences in the language used between tweets with higher or lower engagement levels, and any language differences between product and service tweets. As such, it can be ascertained whether the way in which tweets are written has any significant relationship with stakeholder engagement levels for product and service companies. Those tweet functions that have no significant engagement differences between product and service tweets will also be investigated linguistically, however the analysis will be conducted on product and service tweets together. Where there are no differences in engagement with tweets between products and services, any potential differences in language associated with engagement levels overall can be determined. Collectively, these analyses address our third research aim.

To determine linguistic differences in a large dataset, and conduct inferential statistical tests to ascertain significant differences, a computational linguistic approach was adopted. Specifically, the 2015 Linguistic Inquiry and Word Count (LIWC) dictionary and software was used. LIWC was developed to assess psychologically meaningful differences in text passages in social science research (for details on the development of LIWC see Tausczik & Pennebaker, 2010), which in the present context identifies the percentage of words in each tweet that belong to one of the predefined linguistic categories of LIWC. LIWC "reads files word by word, matching each word against a dictionary of words that are defined for different types […] It outputs 80 distinct measures varying from general descriptors (e.g., total word count) to linguistic elements (e.g., auxiliary verbs) to psychological constructs (e.g., cognitive words) (Hewett et al., 2016, p.6). LIWC has been verified across multiple corpus in a variety of contexts (see Pennebaker et al., 2015), including identification of college student success (Pennebaker et al., 2014), predicting electoral outcomes from Tweets (Tumasjan, et al., 2011), identifying the sensitivity of tweets posted (Houghton & Joinson, 2012), the success of interpersonal introductions in online fora (Dove et al., 2011), the use of normative and regulatory structures in the legitimation of markets (Humphreys, 2010), and brand buzz in social media (Hewett et al., 2016).

Linguistic categories were selected for their relevance to the present study. For example, the number of commas and punctuation more generally were not of interest to the present study, as well as the overall word count and words per sentence (which are rather limited in 140 character tweets). The remaining, more meaningful word categories (i.e., not grammar and punctuation, but those relating to cognitive, social and psychological processes, as well as more developed linguistic patterns, such as the use of first person singular, or third person) were chosen to identify linguistic differences beyond a surface or purely grammatical perspective. Thus, those assessed and entered for statistical analyses included 37 word categories: *affect, positive emotion, negative emotion, anxiety, anger, sadness, family, friend, female, male, insight, cause, discrepancies, tentativeness, certainty, differentiation, see, hear, feel, biological, affiliation, achievement, power, reward, risk, past focus, present focus, future, focus, motion, space, time, work, leisure, home, money, death* and *informal*. The results from the LIWC were entered alongside the tweet data to conduct inferential analyses, as described above.

4. Results

Overall the results of our four-company study show that the level of behavioral engagement is low. When investigating "likes" and comments it is evident that tweets with high and low likes or comments are distinguished by factors including different tweet functions, company type (product or service) and linguistic word categories. In particular, when "likes" are investigated with reference to linguistic style, tweet functions can be significantly contrasted between product and service companies. With regards comments whilst the number differs across company type and tweet function, linguistic categories only differentiate between tweets with low and high comments. The number of retweets was not influenced by type of company or tweet function and the linguistic categories only differentiated between tweets with a high and low number of comments. The following sections examine these findings in greater detail.

4.1 Stakeholder engagement for product and service tweets

The mean level of engagement with the tweets is low. Service tweets received more likes and comments than product tweets, however, no significant differences were found between product and service tweets for number of retweets. Details of the negative binomial regressions with loglink for each engagement type can be seen in Table 3.

Table 3: A comparison of service and product companies types of engagement.

	Service	**Product**	**Omnibus Chi-Sq (model effects)**	**Goodness of Fit (value/df)**
Mean(±SD) Number of Likes per tweet	3.74(±12.771); n=339	2.82(±7.414); n=481	12.162, $p<.001$	1.426
Mean(±SD) Number of Comments per tweet	0.28(±1.073); n=338	0.19(±0.612); n=481	5.896, $p<.05$	0.717
Mean(±SD) Number of Retweets per tweet	5.09(±14.062); n=339	4.65(±5.176); n=481	1.297, $p>.05$	0.961

4.2 Stakeholder engagement levels for product and service tweets according to each tweet function

Further analysis sought to determine whether there were differences in engagement for product and service tweets for each tweet function identified earlier. As shown in Table 3, no significant differences were evident between products and services for retweets, thus further investigation continued for likes and comments only (retweet engagement will be investigated for linguistic differences across product and service companies and across tweet functions - see section 4.5).

Two sets of ten negative binomial regressions with loglink were conducted. One set for each engagement type (Likes DV1;Comments DV2), to compare product and service company tweets (categorical IV), for each of the ten tweet functions identified in Table 2; thus determining whether engagement varied by the function of the tweet for product and service companies. Results for each test can be found in Tables 4 and 5, engagement by likes and comments respectively.

Table 4: The number of likes for service and product company tweets with different functions.

Function of Tweet	**Mean(±SD) Number of Likes**		**Omnibus Chi-Sq (model effects)**	**Goodness of Fit (value/df)**
	Service	**Product**		
Problem solving – generic	2.62±2.256; n=13	2.87±5.4; n=108	0.072, *p*>.05	1.087
Problem solving - specific customer	2.50±1.517; n=6	3.11±2.205; n=9	0.125, *p*>.05	0.347
Problem solving - specific problem	1.75±2.217; n=4	5.00±6.254; n=3	1.414, *p*>.05	1.628
Information sharing – customer	7.31±22.845; n=94	1.68±3.408; n=44	40.750, *p*<.001	2.072
Information sharing – events	1.48±1.327; n=25	3.19±9.203; n=289	7.734, *p*<.01	1.345
Information sharing – product	1.00±1.732; n=3	2.61±11.857; n=130	1.310, *p*>.05	1.638
Information sharing - sales subscription	1.50±0.926; n=8	1.00±1.414; n=2	0.136, *p*>.05	0.547
Information sharing – opinion	2.41±1.873; n=17	2.48±4.088; n=23	0.005, *p*>.05	0.969
Information sharing – industry	2.57±4.941; n=197	3.29±4.858; n=84	2.686, *p*>.05	1.102
PR	32.77±53.160 ; n=13	2.96±4.741;n= 93	94.170, *p*<.001	1.584

As can be observed in Table 4, product and service company tweets did not differ in terms of their number of likes for seven tweet functions. Only *Information Sharing – Customer* (Omnibus Chi-Sq = 40.750, *p*<.001), *Information Sharing – Events* (Omnibus Chi-Sq = 7.734, *p*<.01), and *PR* (Omnibus Chi-Sq = 94.170, *p*<.001) demonstrated a significant difference in number of likes for product and service company tweets. The mean values show service companies have more likes for *Information Sharing – Customer* tweets (7.31±22.845) than product companies (1.68±3.408), fewer likes for *Information Sharing – Event* tweets (1.48±1.327) than product companies (3.19±9.203), and more *PR* tweets (32.77±53.160) than product companies (2.96±4.741).

Table 5: The number of comments for service and product company tweets with different functions.

Function of Tweet	**Mean(±SD) Number of Comments**		**Omnibus Chi-Sq (model effects)**	**Goodness of Fit (value/df)**
	Service	**Product**		
Problem solving – generic	0.23±0.439; n=13	0.14±0.502; n=108	0.491, *p*>.05	0.543
Problem solving - specific customer	0.17±0.408; n=6	0.00±00; n=9	1.740, *p*>.05	0.228
Problem solving - specific problem	0.00±0.000; n=4	0.33±0.577; n=3	1.530, *p*>.05	0.345
Information sharing – customer	0.60±1.891; n=94	0.11±0.321; n=44	14.780, *p*<.001	1.033
Information sharing – events	0.00±0.000; n=25	0.18±0.627; n=289	8.101, *p*<.01	0.583
Information sharing – product	0.00±0.000; n=3	0.17±0.637; n=130	0.928, *p*>.05	0.603
Information sharing - sales subscription	0.29±0.756; n=7	0.00±0.000; n=2	0.896, *p*>.05	0.817
Information sharing – opinion	0.12±0.332; n=17	0.30±0.635; n=23	1.355, *p*>.05	0.628
Information sharing – industry	0.18±0.437; n=197	0.23±0.665; n=84	0.460, *p*>.05	0.593
PR	2.62±4.369; n=13	0.32±0.824;n=92	33.584, *p*<.001	1.025

As can be observed from Table 5, seven of the ten tweet functions showed no significant differences in the number of comments between product and service companies. However, *Information Sharing – Customer* (Omnibus Chi-Sq = 14.780, *p*<.001), *Information Sharing – Events* (Omnibus Chi-Sq = 8.101, *p*<.01), and *PR* (Omnibus Chi-Sq = 33.584, *p*<.001) demonstrated a significant difference in the number of comments for product and service company tweets. Mean values show service companies receive more comments for *Information sharing – Customer* tweets (0.60±1.891) than product companies (0.11±0.321), fewer comments for *Information Sharing – Event* tweets (0.00±0.000) than product companies (0.18±0.627) and more comments for *PR* tweets (2.62±4.369) than product companies (0.32±0.824).

4.3 LIWC analysis for number of likes by tweet function

A negative binomial regression was conducted for each of the ten tweet functions, with Number of Likes as the DV, and each of the outputs from the 37 LIWC categories as IVs. For tweet functions with significantly different likes (*Information Sharing – Customer, Information Sharing – Events*, and *PR*; see Table 4), linguistic analysis was conducted to identify the interaction between product or service and the word categories used in the tweets for each respective function. For the remaining seven tweet functions, no significant differences were found between product and service tweets, suggesting no association between company type and tweet engagement. Thus, linguistic analysis was conducted across product and service companies' tweets to examine language differences in relation to the number of likes tweets received overall, allowing suggestions for companies as to the most effective language to drive the number of likes. Results and parameter estimates are shown in Tables 6a, 6b and 6c.

Table 6a: Linguistic word categories associated with number of likes for significant models of Information Sharing.

		Info Sharing - Product	**Info Sharing - Industry**	**Info Sharing - Customer**	**Info Sharing - Events**
Affect (Beta^{sig})	Product		-1278.516***		
	Service				14673.01***
Positive Emotion (Beta^{sig})	Product		1278.493***		
	Service				-21921.698***
Tentativeness (Beta^{sig})	Product				
	Service				10667.228***
Certainty (Beta^{sig})	Product				-0.116*
	Service				
Reward (Beta^{sig})	Product	0.179***			0.073*
	Service				3390.685***
Present Focus (Beta^{sig})	Product				
	Service				21422.289***
Biological (Beta^{sig})	Product	0.103**			0.077***
	Service				-7105.675***
Space (Beta^{sig})	Product				-0.038*
	Service				3573.559***
Informal (Beta^{sig})	Product		0.089**		0.092***
	Service				
Insight (Beta^{sig})	Product		-0.06*		
	Service				-24913.933***
Cause (Beta^{sig})	Product				
	Service				-42831.799***
See (Beta^{sig})	Product				
	Service				-14453.293***
Hear (Beta^{sig})	Product				
	Service				49780.889***
Achieve (Beta^{sig})	Product				
	Service				7242.824***
Power (Beta^{sig})	Product				
	Service			0.243**	-7019.489***
Past Focus (Beta^{sig})	Product				
	Service				-7340.936***
Money (Beta^{sig})	Product			-1.424*	
	Service				
Affiliation (Beta^{sig})	Product				
	Service			-0.171*	-21409.95***
Risk (Beta^{sig})	Product			-0.537*	
	Service				-18199.985***
Work (Beta^{sig})	Product				
	Service			-0.143*	
Anxiety (Beta^{sig})	Product				
	Service				13655.426***
Sad (Beta^{sig})	Product				
	Service				-85673.959***
Friend (Beta^{sig})	Product				
	Service				21384.445***
Motion (Beta^{sig})	Product				
	Service				17782.685***
Time (Beta^{sig})	Product				
	Service				-24948.735***
Omnibus Chi-Sq (model effects)		111.586***	57.582*	246.385***	137.940***
Goodness of Fit (value/df)		1.064	1.035	1.015	1.139

± Non-Significant * p<.05 **p<.01 ***p<.001

Table 6b: Linguistic word categories associated with number of likes for significant models of Problem Solving.

		Problem Solving - Generic
Affect ($Beta^{sig}$)	Product	307.653*
	Service	
Positive Emotion ($Beta^{sig}$)	Product	-307.59*
	Service	
Negative Emotion ($Beta^{sig}$)	Product	-307.235*
	Service	
Tentativeness ($Beta^{sig}$)	Product	-0.265*
	Service	
Certainty ($Beta^{sig}$)	Product	-0.204*
	Service	
Reward ($Beta^{sig}$)	Product	0.152*
	Service	
Present Focus ($Beta^{sig}$)	Product	-0.057*
	Service	
Omnibus Chi-Sq (model effects)		54.967*
Goodness of Fit (value/df)		0.876

± Non-Significant * p<.05 ** p<.01 *** p<.001

Table 6c: Linguistic word categories associated with number of likes for PR.

		PR
Affect (Beta^{sig})	Product	
	Service	-13.471***
Positive Emotion (Beta^{sig})	Product	
	Service	
Negative Emotion (Beta^{sig})	Product	
	Service	
Tentativeness (Beta^{sig})	Product	
	Service	11.663***
Certainty (Beta^{sig})	Product	
	Service	
Reward (Beta^{sig})	Product	
	Service	27.175***
Present Focus (Beta^{sig})	Product	
	Service	
Biological (Beta^{sig})	Product	
	Service	50.707***
Space (Beta^{sig})	Product	
	Service	
Informal (Beta^{sig})	Product	
	Service	
Insight (Beta^{sig})	Product	
	Service	-49.41***
Cause (Beta^{sig})	Product	
	Service	11.577***
Differ (Beta^{sig})	Product	0.465**
	Service	50.537***
See (Beta^{sig})	Product	-0.199*
	Service	14.867***
Hear (Beta^{sig})	Product	-0.244*
	Service	
Achieve (Beta^{sig})	Product	
	Service	12.271***
Power (Beta^{sig})	Product	
	Service	-11.915***
Past Focus (Beta^{sig})	Product	
	Service	-13.195***
Money (Beta^{sig})	Product	0.157*
	Service	
Omnibus Chi-Sq (model effects)		197.335***
Goodness of Fit (value/df)		0.999

± Non-Significant * *p*<.05 ***p*<.01 ****p*<.001

The results show that for *Information Sharing – Product* (Table 6a) a significant model was found, with an increase in Reward and Biological words being associated with an increase in the number of likes. An increase in words relating to a reward is useful in increasing likes. However, for this particular context – the healthcare sector - the increase in Biological words is expected, as the products and services discussed in the tweets are related to biological functions.

For *Information Sharing – Industry* tweets (Table 6a), a decrease in the use of overall Affect words is associated with an increase in the number of likes although Positive Emotion is significantly related to an increase in the number of likes. An increase in the use of Informal words and a decrease in the use of Insight words are also significantly related to the number of likes that tweets receive.

For *Problem Solving – Generic* tweets (Table 6b) an increase in the use of Affect and Reward words was significantly related to increases in the number of likes. This suggests that regardless of the company type, the use of emotion more generally and words that suggest reward are associated with an increase in engagement through tweets being liked. Alongside this, a decrease in the use of Positive Emotion, Negative Emotion, Tentativeness, Certainty, and Present Focus words was significantly related to an increase in number of likes. This suggests that although more emotion words in general are useful, not being particularly positive or negative is related to increases in likes. Similarly, being less tentative or certain is also associated with increases in likes, as well as writing tweets with a focus on the present.

For *PR, Information Sharing – Customer,* and *Information Sharing – Events,* tweets are analyzed for product and service companies, rather than across the two. For *PR* (Table 6c), an increase in the use of Tentativeness, Reward, Biological, Cause, Differ, See and Achieve words was significantly associated with an increase in the number of likes for service companies, whereas a decrease in Affect, Insight, Power and Past Focus words is significantly related to an increase in the number of likes for service companies. For product companies and the function of *PR*, an increase in the use of Differ, See and Money words was related to an increase in the number of likes. The decrease in the use of Hear words was significantly related to an increase in the number of likes.

For *Information Sharing – Customer* (Table 6a), an increase in the use of Power words is related to an increase in the number of likes for service companies. The decrease in the use of Affiliation and Work words is associated with an increase in the number of likes for service companies. For product companies, a decrease in the use of Money and Risk words is related to an increase in the number of likes.

For *Information Sharing – Events* (Table 6a), for service companies, an increase in the use of Affect, Tentativeness, Reward, Present Focus, Space, Hear, Achieve, Anxiety, Friend and Motion words is related to an increase in the number of likes. A decrease in the number of Positive Emotion, Biological, Insight, Cause, See, Power, Past Focus, Affiliation, Risk, Sad and Time words is also related to an increase in likes. For product companies, an increase in the use of Reward, Biological and Informal words is associated with an increase in likes; whereas fewer Certainty and Space words are associated with more likes.

4.4 LIWC analysis for number of comments by tweet function

As with the number of likes, ten negative binomial regressions with loglink were conducted with number of comments as the DV and the 37 word LIWC categories as IVs. Similar to the analysis for the number of likes, for the three tweet functions that were significantly different for product and service companies (Table 4), analysis was conducted to investigate the linguistic style for each of the two company types. The remaining seven tweet functions were conducted without distinction between product and service tweets. Results and parameter estimates are shown in Table 7.

Table 7: Linguistic word categories associated with number of comments for each tweet function.

	Tweet Function									
	Problem Solving - Generic	**Problem Solving - Specific Customer**	**Problem Solving - Specific Problem**	**Info Sharing - Product**	**Info Sharing - Sales Subscription**	**Info Sharing - Opinion**	**Info Sharing - Industry**	**PR**	**Info Sharing - Customer**	**Info Sharing - Events**
Omnibus Chi-Sq (model effects)	38.786±	4.709±	3.256±	37.919±	6.612±	25.237±	67.837***	42.285±	±±	56.954±
Goodness of Fit (value/df)	N/A	N/A	N/A	N/A	N/A	N/A	0.402	N/A	N/A	N/A

± Non-Significant * p<.05 **p<.01 ***p<.001

As no significant results were found for linguistic differences across product and service companies' tweets for each tweet function, a negative binomial regression with loglink was conducted across tweet functions and across company type, with *Number of Comments* as the DV and the 37 word categories as IVs. This allowed meaningful investigation into the linguistic differences in tweets that received different numbers of comments, and thus identifying which word categories business to business companies can use to help increase the number of comments they receive (see Table 8 for results).

Table 8: Linguistic word categories associated with number of comments made on both product and service companies' tweets.

Mean(±SD) Number of Comments per Tweet	**Omnibus Chi-Sq (model effects)**	**Goodness of Fit (value/df)**	**LIWC Word Category**	**Beta^{sig}**
0.23±0.835; n=819	116.363 ***	0.608	Friend	0.346***
			Informal	0.105***
			Leisure	0.124*
			Power	0.094***
			Work	-0.083***
			Hear	-0.130*
			Differ	-0.301*

The findings show that although the mean number of comments per tweet is low (0.23±0.835), the negative binomial regression with loglink found a significant model for the different word categories related to tweets with greater, or fewer, comments. Specifically, the greater use of Friend, Informal, Leisure and Power words is significantly related to an increase in the number of comments, whereas fewer Work, Hear and Differ words are significantly related to receiving more comments for each tweet.

4.5 Retweets

As demonstrated earlier, the number of retweets companies' tweets received did not differ by product or service companies. As such, further investigation into the differences between product and service tweets was not conducted. However, by collapsing product and service tweets into one category of tweets, linguistic analysis can be conducted to identify meaningful differences in language that are associated with the number of retweets such messages receive. Thus, LIWC was conducted with *Number of Retweets* as the DV, and the

37 word categories as the IVs. Table 9 shows the significant word categories associated with the *Number of Retweets* companies' messages receive.

Table 9: Linguistic word categories associated with number of retweets made on both product and service companies' tweets.

Mean(±SD) Number of Retweets per Tweet	**Omnibus Chi-Sq (model effects)**	**Goodness of Fit (value/df)**	**LIWC Word Category**	**Beta^{sig}**
4.83±9.867; n=820	149.005***	0.816	Insight	-0.024*
			Informal	0.088***
			Tentativeness	-0.044*
			Work	-0.033***
			Biological	0.025*
			Achieve	0.037**
			Power	0.043***
			Past Focus	0.044*

As with number of comments, the negative binomial regression with loglink for the number of retweets by the different LIWC word categories showed a significant model. Specifically, an increase in the use of Informal, Biological, Achieve, Power and Past Focus words, was significantly related to an increase in the number of retweets a tweet received. However, the use of *fewer* Insight, Tentativeness and Work words was related to an increase in retweets.

5.0 Discussion

The discussion starts by firstly examining the overall level of behavioral engagement i.e., likes, comments and retweets for product and service tweets. It then examines how the tweet function and linguistic qualities influence behavioral engagement for product and service companies. Differences between product and service tweets are examined followed by the similarities. Table 10 summarizes the findings to be discussed.

Table 10: Summary of linguistic findings eliciting greater engagement.

Comparison of Product and Service Companies Behavioral Engagement	**Comparison of Product and Service Behavioral Engagement by Tweet Function**	**SERVICES**	**PRODUCTS**

		LIKES **increase with**			
Services received more likes	*Information sharing – customer* Services received more likes	*More* Power	*Less* Affiliation, Work		*Less* Money, Risk
	PR Services received more likes	*More* Achieve, Biological, Cause, Differ, Reward, See, Tentative	*Less* Affect, Insight, Past, Power	*More* Differ, Money, See	*Less* Hear
	Information sharing – events Products receive more likes	*More* Achieve, Affect, Anxiety, Friend, Hear, Motion, Present, Reward, Space, Tentativeness	*Less* Affiliation, Biological, Cause, Insight, Past, Positive, Emotion, Power, Risk, Sad, Time	*More* Biological, Informal, Reward	*Less* Certainty, Space
	Problem solving-generic No difference				
	Information sharing – product No difference				
	Information sharing - industry No difference				
		COMMENTS **increase with**			
Services received more comments		*More* Friend, Informal, Leisure, Power		*Less* Work, Hear Differ	
	Information sharing – customer Services received more comments				
	PR Services received more comments				
	Information sharing - events Products received more comments				
		RETWEETS **increase with**			
Number of retweets did not differ between service and product		*More* Informal, Biological, Achieve, Power		*Less* Insight, Tentativeness, Work	

5.1 Overall behavioral engagement

Overall the degree of behavioral engagement with B2B tweets is relatively low. Many stakeholders involved with the company may exchange information and express opinions predominantly through other communication channels such as face-to-face and therefore have less need to interact with the company through Twitter. Contrastingly, stakeholders who are considering becoming involved with the company or who have a vested interest e.g., competitors may be inclined to interact via Twitter.

Previous research (Oh et al., 2016, Wallace et al., 2014) suggested that behavioral engagement varies according to the effort required, and that this effort increases from likes to retweets to comments. Our expectation that the number of likes would be greatest as they require the least amount of effort, followed by retweets, and then finally by comments is not evident in our results however with overall behavioral engagement being highest for retweets, followed by likes then comments.

Besides effort, Oh et al. (2016) and Wallace et al. (2014), suggest that behavioral engagement can also be explained by audience. Likes and comments, whilst public and generally accessible to a broad stakeholder audience, will be directed predominantly at the company because these actions are undertaken on the company's Twitter platform. These may be used to maintain a connection, with followers using these forms of engagement to convey the nature of their affiliation with the company and to signal their perceived usefulness of information received via Twitter feeds. Likes indicate that the information tweeted has been seen by followers and positively received. Comments also acknowledge that the tweet has been seen and has evoked a reaction whether positive or negative from the follower. Behavioral engagement is highest for retweets. The audience for retweets is the follower's network of followers and a primary concern of these communications is for the follower to convey information about themselves

5.2 Behavioral engagement elicited by service and product companies

As we noted previously, Swani et al. (2014) called for research that investigates social media use in different sectors and our study involving four companies indeed shows that behavioral engagement on Twitter differs between product and service businesses. Service companies elicited greater behavioral engagement (likes and comments) than product companies. With services, stakeholders may feel it necessary to interact to a greater degree and acquire a substantial amount of information about the company prior to using or supplying them. They may gather information from formal, official sources e.g., brochures websites, but as a less formal medium, Twitter enables the collection of both unedited feedback from other users and official information through links embedded in the tweets (Swani et al., 2014). Customers purchasing from service companies may have a greater need to obtain substantial knowledge to reduce perceived risk and affirm their choice through liking or commenting as they are often difficult to evaluate even after use (Katz et al., 1973/74). Product company customers may focus more on obtaining technical information from official, formal sources such as websites, relying less on sources such as Twitter. Once the product is purchased customers can more readily evaluate product performance and may have less need to confirm their purchase through a medium such as Twitter. In addition to information exchange, social exchange is important in B2B markets (Anderson, 1985; Hakånsson, 1982) and followers may use Twitter to interact with the company, this enabling them to evaluate the speed and nature of their response - qualities which may be especially pertinent when evaluating service companies.

5.2.1 *Differences* in behavioral engagement and the associated linguistic characteristics according to tweet function

Service and product companies differed in the level of behavioral engagement elicited for certain tweet functions. Whilst service companies received more likes and comments than product companies for tweets sharing information about customers and PR, product companies received more for sharing information about events; these are examined more closely below.

Service company tweets summarized information about various customer issues relevant to a wide range of stakeholders such as the uptake of health insurance, and the use of new technology. They often utilized a top ten format to concisely convey this information for example,

"Top 10 quotes from #healthcare leaders on #PatientEngagement. [URL]".

The brevity enables followers to quickly obtain a succinct overview or update. This type of tweet educates followers and was found to be an important purpose of social media by Schultz et al. (2012). Service companies use Power words e.g., top, leaders, to convey their expertise and capabilities regarding selected issues, thus increasing behavioral engagement (likes). Product company tweets in this category tended to focus on various groups of diseases, prevention and diagnosis and are again educational. Engagement in the form of likes was increased by avoiding Risk related words; it might be inferred that stakeholders do not want negative information in relation to these issues. Audiences may interpret such negative words as indicating a company's lack of capability and competence. Our analysis suggests that both service and product companies balance functional and emotional appeals in the tweets to encourage engagement (Swani et al., 2014).

PR tweets were related to the service companies' latest research or accolades, demonstrating company knowledge and expertise, e.g.,

"Explore how #MnA can help #medicaltechnology companies overcome growth challenges & capitalize on opportunities:[URL]".

Followers appreciate the tangible evidence of the companies' capabilities and competences when considering or already doing business with the company and these elicited more behavioral engagement (likes and comments). Linguistically the service companies' PR tweets use Reward (advance, approach, goal, benefits) and Achieve (success, better) words to generate more likes, reinforce their capabilities and competence and signal to customers the benefits of engaging with them. Simultaneously, services' PR tweets contained more

Tentative words (nearly, possible), perhaps due to the fact that services are difficult to evaluate and companies may not want to over promise on what they can deliver.

Product companies elicited more behavioral engagement (likes and comments) for their tweets about events. The limited time of the events means there are many companies competing for attention so tweets need to highlight the companies' solutions. For example,

"Excited to showcase our full range of advanced #radiology technologies this week at #RSN A14. Have you stopped by booth 6742yet?".

The tweets encouraged followers to learn more about specific issues or company or product capabilities at the trade event. Tweets were also used to keep attendees up to date with what was happening at the event. During a trade show customers and other stakeholders may be actively searching for, and especially receptive to, relevant information from various media including Twitter, and maybe more inclined to like or comment on such tweets. Product companies using more Biological words (e.g., health, MRI, dose, diagnostic, clinical) and more Reward words (e.g., best, take, accessible) in their tweets evoked more likes by conveying a strong functional appeal and reflecting company capabilities. Similarly, service companies' event tweets used more Reward (e.g., gain, better) words and more Achieve words (e.g., success, challenge) to evoke more likes and convey the benefits of dealing with them. However, they were simultaneously more tentative, possibly due to their less concrete offering being more difficult to evaluate. Services' event tweets used Hear words, inviting followers to listen to what they have to say at these events. Interestingly, the service companies used more Anxiety words (e.g., worried), acknowledging potential concerns of followers in order to highlight how their company can alleviate them. The service companies actively avoided using Risk, Sad and Power words as they may want to avoid negative associations with their service which is intangible and difficult to evaluate.

5.2.2 ***Similarities*** **in behavioral engagement and the associated linguistic characteristics by tweet function**

For the majority of tweet functions service and product companies were similar in the level of engagement (likes and comments). Practitioner research (Anon, 2015) highlighted the importance of obtaining information regarding general problem solving for buyers. This type of information was equally useful for both product and service companies' stakeholders as there was no difference between them in the level of behavioral engagement. Both service and product companies need to demonstrate that they are capable of resolving various types of issues. Consequently the tweets encompassed their ability to resolve problems in general as well as industry and customer-specific problems. This reinforces practitioner research which found that customers require industry information from experts (Anon, 2015). Both product and service organization tweets performed this function and evoked similar levels of behavioral engagement from their customers and stakeholders. Service and product company tweets that shared information about products, sales subscription, opinion and the industry evoked similar levels of engagement. Again, this reinforces practitioner research which found these types of information were useful for B2B customers (Anon, 2015).

Product and service companies were similar in the level of behavioral engagement i.e., likes and comments, for a number of tweet functions but the tweet functions i.e., problem solving generic, information sharing product and information sharing industry differed in the linguistic characteristics that evoked more likes. The tweets that sought to signal general problem solving capabilities (company or product) emphasized the rewards and benefits to stakeholders from engaging with the firms. These tweets incorporated more Affect and Reward words. For example

"How to increase safety, efficiency, and patient outcomes in #electrophysiology procedures? [URL]".

The problem solving tweets, whilst emphasizing the rewards, were neutral in the emotional tone and neither certain nor tentative in their statements. This suggests that the companies want to ensure they can deliver on their promises, rather than fail to deliver or under sell themselves. As found in previous research (Turley & Kelly, 1997) tweets sharing product information emphasized functional capabilities. For example,

"What are the benefits of CT imaging using the SOMATOM Force? Learn about contrast me dia & motion artifacts from #RSNA [URL]".

The tweets contained more Reward words to ensure stakeholders were aware of the positive aspects of using the product.

Tweets sharing information about the industry used more Positive Emotion words, e.g.,

"1/14 learn best practices involving the Primary Care Medical Home model for integrating c are and monitoringresults:[URL]".

Interestingly, the linguistic characteristics which evoked more comments did not vary with either the nature of the organization (product or service) or the individual tweet function. Comments were increased by the use of Power words (top, help, manage, leader) e.g.,

"Top 10 quotes from #healthcare leaders on #PatientEngagement. [URL]".

These types of tweets may appeal to followers seeking to convey their own opinions by engaging with such tweets.

Behavioral engagement was highest for retweeting, and followers of both product and service companies were equally likely to retweet. Retweeting is fundamentally different from liking and commenting as the retweet will appear on the follower's Twitter account and in the twitter feed of their followers. Contrastingly, a follower's likes and comments will not appear on their Twitter account or the Twitter feed. Retweets are a reflection of the follower's knowledge, expertise, beliefs and values and can indicate self-esteem and affiliations (Katz et al., 1973/74). The tweets which tend to be retweeted have more Biological words reflecting a follower's knowledge and expertise in the sector. They also contain more Achievement and Power words which emphasize the desire of wanting to be perceived as successful, capable and competent within the specific area. Such tweets cannot be tentative as this may negatively impact the perception of the follower as an expert in the field. Followers will carefully select the tweets they retweet in order to portray a specific, positive image of themselves. This controlling and editing of self-image may be especially important in a business context as the follower will want to be perceived positively by others with whom they do business and those they might wish to do business with. It is also possible that the follower's expertise is further enhanced by being discerning and retweeting a tweet from an authoritative company within the sector.

6.0 Conclusion

Based on a study of four companies, this paper has identified how the tweets of service and product businesses differ in the level of behavioral engagement. This was undertaken in two stages. First, the differential engagement of product and service tweets was determined. Second, the linguistic characteristics of the message functions were examined to establish differing types and levels of engagement. Thus, the findings herein contribute to the knowledge of B2B engagement in social media; specifically, that tweet functions and the language used in the content of messages interacts with company type to affect behavioral engagement in terms of likes, tweets and comments. As a theoretical step, this contribution develops understanding of behavioral engagement by showing that tweet function and linguistic style can impact the reception of company messages. Managerially, we suggest ways that companies can frame their Twitter messages to greater behavioral effect.

Although overall behavioral engagement is relatively low, this investigation provides insights into how the level of behavioral engagement may be influenced by the intended tweet function and linguistic style. Likes provide an indication of the type of tweet that is preferred by followers, while comments may provide insight as to why a tweet is engaging. Service companies elicit more likes and comments for tweets sharing customer information and PR whereas product companies elicit more for sharing information about events. There are linguistic differences for these tweet functions which result in more likes. For many tweet functions service and product companies do not differ in their engagement. However, linguistically some of the functions have characteristics which evoke greater behavioral engagement i.e., likes. Whilst no systematic linguistic characteristics of tweets were found to evoke more comments for either service or product companies, across the various tweet functions certain linguistic characteristics generally increased comments. Followers' likes and comments are predominantly aimed at the company and may be used by the company to indicate how communications can be refined. Retweets had the highest level of behavioral engagement. These messages will appear on the followers' Twitter accounts and appear in their followers' twitter feeds, whereby followers will be discerning in what they retweet in terms of both the content and the source as it will reflect their self-image (Hollenbeck & Kaikati, 2012). Followers will want to convey positive qualities such as their level of knowledge and expertise in the sector and are prepared to put some effort in to developing and maintaining their self–image.

6.1 Managerial Implications

Managers want customers and various other stakeholders to engage with their Twitter content and freely exchange information. Previous research has found social media to serve a number of purposes, including educating customers (Schultz et al., 2012), contributing to R&D (Kietzmann et al., 2011), supporting sales (Guesalaga, 2016; Michaelidou et al., 2011), relationship management (Quinton & Wilson, 2016) and corporate and brand management (Bruhn et al., 2014; Jussila et al, 2014). However, these functions might not be necessarily relevant to stakeholders and some can be quite broad. This study has identified various tweet functions which account for the needs of different followers and which are more focused e.g., information sharing – events. The identification of specific tweet functions enables the company to carefully construct a tweet to suit the stakeholders' requirements – this resonates with previous research which argues that content has to be relevant and compelling (Holliman & Rowley, 2014; Pulizzi.2012).

Behavioral engagement i.e., likes and comments, is predominantly directed towards the company. It allows the company to identify the nature of content evoking a reaction from followers and determine its valence. Through these types of behavioral engagement, the company can determine what information is well received, thus assisting the firm in the development of tweet content and the management of customers' knowledge (Chua & Bannerjee, 2013). Twitter may also generate information from potential customers (as well as from other stakeholders), thus helping the firm. Interactions from Twitter provide insights into potential customers which may be used to determine whether to initiate relationships with them via other means of communication and information exchange (Clarke, 2015).

It is clear from the research results that stakeholders of service companies and product companies engage differentially depending on the function of the tweet. Service company tweets that shared customer information or PR elicited more behavioral engagement, whilst product companies tweets' that shared information about events elicited more behavioral engagement. The language used in the tweets needs to be adapted specifically to its function to encourage the followers' likes. Companies need to be conscious of the fact that the language used to elicit more comments does not vary for these functions, although it does differ to that used to elicit likes.

There are a number of tweet functions related to problem solving and information sharing for service and product companies where the level of behavioral engagement is similar. Companies need to bear in mind that for some functions (problem solving-specific customer, or -specific problem or information sharing -sales subscription) there were no linguistic characteristics that would encourage likes in particular. Certain linguistic adaptations for other functions (problem solving – generic, information sharing – product and –industry) were apparent that could be used to encourage likes. Companies, again, need to be mindful of the fact that the language required for eliciting comments for these functions differs from that which elicits likes. The need to make linguistic adaptations according to tweet function and the type of behavioral engagement sought adds complexity for managers.

For companies, retweeting, is extremely useful as a means to disseminate information to stakeholders who are potentially outside of their own network. In order to utilize this effectively, knowledge and understanding regarding what is retweeted would help companies refine their communication content on Twitter to maximize its distribution. As this information is to be conveyed to the follower's network, the company needs to utilize tweets which will enhance the identity of their follower, such as being an expert, or having up-to-date knowledge on current issues. This can be reflected in the linguistic characteristics which evoke more comments; companies need to use words which signal Achievement and Power alongside others which are industry specific. So for example, in this study of the healthcare sector such words were Biological related.

In summary, when composing tweets, companies should consider three aspects. First, the function of a tweet, i.e., its intended purpose. Second, the language used in framing the message, as specific word categories can collectively alter the interpretation beyond the overall message itself. Finally, the type of behavioral engagement sought – likes, retweets or comments to fulfil their strategic purpose.

6.2 Limitations and Future Research

This investigation has identified similarities and differences in behavioral engagement between four product and service companies in the healthcare sector. The current study examined the level of different types of behavioral engagement for service and product companies' followers. Research could be carried out to examine the characteristics of the tweet and the nature of the retweets, as well as the comments that were evoked. It is vital for companies to understand the initial tweet characteristics which elicit a positive, neutral or negative reaction. This information would better equip service and product companies to produce tweets to elicit positive rather than negative reactions to enhance their reputation rather than damage it. Other studies should draw from a larger number of companies to establish if findings from this investigation are consistent amongst businesses involved in the healthcare sector. Furthermore, research needs to be conducted across different sectors to determine whether the functions of tweets, the linguistic characteristics and the pattern of behavioral engagement elicited for service and product companies is the same as in the healthcare sector or whether differences systematically occur across sectors. Such supplementary investigations would allow generalizable conclusions to be drawn which would enable managers to more readily develop communications that obtain the desired results.

This study focused on behavioral engagement and the way in which it is influenced by the nature of the company, the tweet function and the linguistic characteristics. Research could be performed to understand how tweet functions influence followers' motivations to perform each type of behavioral engagement. This would enable the cognitive and emotional elements of the followers to be examined and related to behavioral engagement. In turn this would permit companies to better tailor their communications to their followers' needs and to elicit greater cognitive, emotional and behavioral engagement.

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