DSS 2.0 – Supporting Decision Making with New Technologies
Gloria Phillips-Wren et al. (Eds.)
IOS Press, 2014

doi:10.3233/978-1-61499-399-5-401

Decision Support with Big Data: A Case Study in the Hospitality Industry

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Abstract. The term 'big data' is used to describe data that are beyond the capabilities of an organization to store, analyze and use for accurate and timely decision making. They have alternately been described in terms of characteristics of volume, velocity, variety, veracity. We propose another characteristic of volatility for big data that should be considered in their use for decision making. We utilize a case study approach with a mid-sized company in the hospitality industry to elucidate challenges that an organization faces in developing a big data strategy and highlight research needed in this domain. Challenges identified were *technical* (inconsistent and unstandardized data, implementation and use of new analytics platforms, obtaining a global view of data, visualization of data, integrating mobile data), *organizational* (finding people with the right skills, users' desire for customization), and *strategic management* (finding return on investment in big data, alignment of business and analytics strategies, leadership of analytics initiatives and thought). Decision questions to be addressed in using big data for a marketing decision are illustrated. We demonstrate the use of the decision framework and illustrate challenges identified in the case study with sentiment analysis of Twitter data.

Keywords. big data, analytics, decision support, Twitter, social media, sentiment analysis.

Introduction

While companies are becoming increasingly aware of the competitive advantage that they can gain from using data to make decisions [1], they all struggle with a deluge of data. Data can take a variety of forms from structured data such as transactional data to unstructured data such as customer comments on Facebook, Twitter and other social media. Internal data are often inconsistent and unstandardized, and now firms are faced with even more data flowing from external sources. As data become even more dispersed and from a greater number of sources in the era of 'big data', organizations are struggling to develop a 'big data' strategy. This paper employs a case study approach to investigate the challenges and decision making process faced by a mid-sized firm when considering the use of 'big data' to guide decisions.

The 'big data' wave has captured the imagination of company leaders since it can be directly tied to value generation [2, 3]. Studies show that big data initiatives can

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result in significant value for a company [3]. The McKinsey Global Institute studied big data in five industries in developed sectors in Europe and the US and concluded that a US retailer could increase its operating margin by us to 60%, US healthcare could realize efficiency and quality value of $300 billion, European governments could save more than €100 billion in operational efficiency, and the services sector using personal location data could recover $600 billion [2] with the use of big data analytics.

Big data can provide value to companies in one of three ways: description, prediction and proscription. Description refers to a characterization of the current or past state. Description can be given statistically or using models to explain variability or show relationships. Prediction is the use of data to predict the future state based on the past. Proscription goes one step further and attempts to offer the optimal solution to a problem. For example, a company might describe its supply chain, predict the effect of a new supplier on the supply chain, or optimize the supply chain under a given scenario. Big data permit more variables, with possibly more accurate values, to be incorporated into models, leading to improved fidelity for decision making.

The term 'big data' is so new to the lexicon that almost no academic research papers are available. In fact, a Google Trends 2013 search for the term shows that it is just beginning to be known outside of the technical community. Yet DSS 2.0 will necessarily need to include big data concepts and techniques in order to improve decision making. In this paper we will provide a definition of big data and illustrate a decision making process in order to utilize these data for decision making.

The paper proceeds as follows. We review the definition of big data in section 1. In section 2 we discuss our research design. In section 3 we describe the case study along with technical, organizational and strategic management challenges identified in the case study to develop a big data strategy. Section 4 presents an illustration of decision questions for using big data along with sentiment analysis of social media data from Twitter. Section 5 provides a summary and limitations of the study.

1. Big Data and Decision Making

1.1. Definition of Big Data

Big data are described in general as data that exceed or are beyond the capabilities of the organization to store or analyze for accurate and timely decision making [4]. Davenport and Dyché [3] point out that big companies have been dealing with big data for years as part of their normal analyses, and that mid-sized companies that can improve decisions by including more data in their analysis are the ones currently struggling.

To generalize the definition, the term 'big data' is often described in terms of its characteristics. One of the earliest attempts to do so was provided by Laney [6] who described big data as having three primary characteristics: volume, velocity and variety. These characteristics have been accepted by the community so that definitions describe 'big data' as a dynamic activity: "*Big data technologies describe a new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data, by enabling high-velocity capture, discovery, and/or analysis*" [6].

Volume refers to the sheer quantity of data. A study sponsored by the EMC company indicated that the world's data is doubling every two years, with 1.8

zettabytes in 2011. By 2020 the volume of new data generated is expected to be 50 times that amount [7]. IBM [8] estimates 40 zettabytes (43 trillion gigabytes) of data will be created by 2020, 300 times more than in 2005.

Velocity refers to the speed at which data are generated and analyzed. Sometimes referred to as streaming data, these data come from sources such as sensors in cars and network connections between people. Laney [6] pointed out that companies that can interact with their data quickly have a competitive advantage. For example, real-time Web customer response can be a customer relationship management strategy.

Variety refers to the many forms that data may take, both structured and unstructured, and from sources such as social media, video, audio, and the stock market. Laney [6] suggested that one of the greatest barriers to big data usage would be "the variety of incompatible data formats, non-aligned data structures, and inconsistent data semantics."

A fourth characteristic of **veracity** was added by IBM [8] to refer to the uncertainty surrounding data integrity and lack of trust in the data. When data are used for decision making, accuracy of the data or at least understanding of their variability is needed to properly create data models. Variability in terms of uncertainty can be represented in models with techniques such as fuzzy numbers if the uncertainty can be quantified [9].

We propose a fifth "V" for **volatility** to indicate that data are dynamic and may be time sensitive, even if they are accurate. For example, stock market data are volatile and customer preferences change. Decision makers need to consider the time sensitivity of data when utilizing data for decision making.

1.2 Using Big Data in Decision Making

Compared to DSS 1.0, decision makers face a larger variety of data at a larger volume, questionable veracity, possibly high velocity and potentially highly volatile. Yet case studies of effective use of these data demonstrate that companies can compete on the basis of analytics and achieve competitive advantage using big data in DSS 2.0 [10]. Although big data have been available for several years and leading companies have incorporated them into their decision models, mainstream interest and use has been enabled more recently by affordable storage, access to and development of cloud architectures, data capture technologies, development and placement of sensors for collection of useful information, and innovative and accessible analytic tools for a broader base of users [10]. Companies that are more recent entries into the big data market face an array of issues. In the next section we look at one company, Choice Hotels International, as representative of the challenges and decisions a company faces with the big data deluge.

2. Research Design

We followed a case study approach with a specific company that is expanding [11] and is realizing the potential value in 'big data'. We explored the company's use of data, developing a data-driven culture, and the inclusion of big data in decision making by interviewing managers in the company. Due to confidentiality reasons, we report here only generalized comments that we received from two or more managers.

This research is primarily descriptive, and the case study is exploratory. Following Yin [12] and Stake [13], we developed an initial framework for the study and focused on the case specifically to maximize learning about the human and technical considerations for developing and implementing a 'big data' strategy rather than determining the typicality of the case.

3. Case Study: Choice Hotels International

3.1 Company Description

Choice Hotels International is a hotel franchisor with over 6,500 locations throughout the United States and over 35 other countries [14]. In its portfolio are Comfort Inn/Suites, one of the largest limited-service brands in the US. Quality Inn also serves midscale hotel travelers, while Econo Lodge and Rodeway Inn are offered for budget travelers. Choice Hotels includes the full-service Clarion Inn brand and has added Sleep Inn to its line of hotels. Although Choice Hotels holds 1,160 hotels outside the US, international franchising operations currently account for less than 10% of sales. During the first half of 2012 Choice Hotels opened new international properties in Australia, Brazil, Canada, Czech Republic, France, Germany, Honduras, Italy, New Zealand, and Norway [14]. In 2013, the company consolidated its global headquarters in Rockville, Maryland, in the US.

Companies in the mid-range of cost for accommodations include independent hotels and chains that offer mid-priced hotel/motel rooms or suites, and may include some services such as on-site dining, but do not include gambling casinos. Top companies in this category include Marriott International, Hilton Worldwide Holdings, Dashang Group Company in China, Hyatt Hotels, and InterContinental Hotels Group.

Choice Hotels revenue sources are primarily (more than 90% in fiscal year 2012) from royalty and fees, including marketing and reservations services for its franchisees. Growth in revenue and profit were reported in fiscal year 2012 as the economy improved in its market space with revenue increasing about 8% to $691.5 million compared to 2011 [14]. Thus, data to assist marketing decisions can provide a competitive advantage.

3.2 Challenges to using Big Data for Decision Making

The company's strategy is to offer a mix of brands segmented by consumer types as a franchisor rather than as an operator of hotels. This strategy has helped it expand in a relatively low cost manner, with about 450 hotels in its pipeline of new properties in 2012 as either conversion of existing properties or new development. The company is controlled primarily as a private company with a small number of owners [14]. Competition within the mid-priced hotels group is intense, and many hotel chains have competing loyalty programs. The company spent $79.7 million on advertising in fiscal 2012. Marketing and IT are considered as one department, so about 10% of revenue is spent to increase consumer awareness and drive sales [14]. Although the company regularly utilizes data to make decisions, managers perceive the potential value of big data that can be analyzed to improve the expenditure of marketing dollars. However, the organization faces significant challenges in implementing a big data strategy.

These challenges can be identified as *technical*, *organizational*, and *strategic management*.

Technical Challenge: Inconsistent and unstandardized data.
Recognizing the need for data-driven decision making, marketers within Choice Hotels utilize data that are derived from a variety of sources. Internal data are available from the information technology department, but the loyalty marketing department often does not know the original source of the data, and data are often inconsistent so that veracity is questioned. Marketing has begun to more fully access data directly such as data on email campaigns (e.g. Omniture for revenue and room nights; StrongView [15] for email clicks and opens), or customer stay behavior (Business Objects for loyalty program revenue, member enrollments, and room nights). However, these sources of data are just starting to evolve along with other sources. Data need to be put into formats that are understandable such as dashboards and spreadsheets along with graphs. This variety or diversity of data formats is a challenge for marketing since there is little standardization of data models. Customer data are recorded as customers make inquiries, book rooms, stay in hotels, and give opinions. Since these are intermittent, data may be volatile in the sense that it may need to be utilized quickly in order to be valuable [16].

Organizational Challenge: People with analytics skills to interpret data.
McKinsey [17] estimates that there will be a shortage of 140,000 to 190,000 people with expertise and 1.5 million managers and analysts to fill highly skilled analytics jobs over the next several years. Choice Hotels is facing this shortage of people with sufficient skills to develop and interpret data models to guide decision making by developing people from within and attempting to hire analytics expertise. However, Choice Hotels recognizes that analytics skills alone are not sufficient; domain knowledge is required coupled with analytics to enable insight to make good decisions.

Strategic Management Challenge: Finding the ROI in analytics.
Choice Hotels is in transition from realizing that data are needed to make smart decisions, but "no one is assessing the impacts of IT on the enterprise as a whole …the firm has many good systems,…but a greater percentage of the IT spending each year is required to maintain those systems," and "CIO or IT director works with business unit, product line, or functional leaders to meet their needs, …but delivery is slow" [18]. Although business managers at Choice Hotels are delivering value and utilizing data systems, a direct return on investment (ROI) from this technology has not been established. Many companies are in a similar position of having difficulty quantifying the value of big data [19]. Choice Hotels has difficulty computing the ongoing costs of data-driven initiatives from business units comparing them to the value derived. As a result, the ROI from decisions made on the basis of these data are not known, making it more difficult to gain support for more investment in big data.

Organizational Challenge: Implementing new analytics systems and getting people to use them effectively.
Even when new systems are implemented, getting employees to use them effectively is a challenge. For example, Choice Hotels implemented a new email campaign program focused on analytics, StrongView [15], to complement other sources of data. As with many IT rollouts, little direction was provided to the affected department on how best

to use this new system [20]. As a result, the marketing department debated uses for the system, ways to integrate data from other sources, and metrics that could be used for a monthly newsletter. Research has shown that experience and organizational learning play important roles in successfully implementing and using new information systems [21], and Choice Hotels needs to educate people to utilize new systems to improve decision making.

Organizational Challenge: Desire for customization of analytics systems.
With a COTS (commercial off the shelf) system such as StrongView [15], the marketing department discovered new information that they would like to have from the system, but this customization is expensive. For example, they wanted reporting that could tie specific links in a marketing email to specific market segments to better understand which customers clicked on what article so that they could perform in depth testing with conditional text. However, the department was in the position of requesting investment in customization before showing ROI on the new program or even exploiting existing data in the system effectively. A top-level data strategy is needed.

Strategic Management Challenge: Aligning data-driven decision making with business strategy.
As Choice Hotels moves toward data-driven decision making, the company is bringing on senior managers to lead a culture change toward analytics, process improvement, and customer loyalty outreach. Although the organization has been successful historically, there is room for improvement and growth that leads to new projects and improvement to current processes. Technology is struggling to keep up with requests from the organization as decentralized individual units want access to data for decision making using varied systems and multiple sources.

Technical Challenge: Obtaining a global view of relevant data.
Although all hotel franchises utilize the Choice property management systems, there are data that are not captured. One way to develop a global view of available data is to implement an ERP (enterprise resource planning system) as part of a future strategy. This would be a long term goal for Choice Hotels due to the high cost and the requisite organizational changes of moving to a centralized structure from the current highly decentralized structure. Another approach for small and medium-sized businesses is to outsource data services using cloud and other types of infrastructure.

Technical Challenge: Making data accessible through visualization.
New visualization tools are making data and information accessible to more people for decision making [22]. For example, 'one touch reporting' for marketing is a goal for the marketing department at Choice Hotels to provide a single view of the customer across all channels. Business-relevant analytics embedded into simple tools for managers that need to make decisions enables people to 'think' about the insights that they can gain from data and not just 'do' tasks associated with analytics [23]. Consistent with DSS 2.0, Choice Hotels is developing approaches to personalize the customer experience rather than use a mass marketing approach. Sometimes called digital marketing or automated multichannel campaign management, the goal is to integrate all views of the customer and deliver information to marketers for decision making [24].

Strategic Management Challenge: Leadership of analytics initiatives.
Studies have shown that senior level interest and leadership of IT initiatives is the most important factor in success [19]. Although Choice Hotels has management support and sponsorship of data-driven decision making and analytics, their next step is to define the reporting and information infrastructure and specific reports that are needed to help make smart business decisions. “Surprisingly, clearly defining a reporting and information infrastructure is *no*t a project that is on most enterprise schedules. It should be. Because if you don’t understand the content and direction of your end to end reporting and information infrastructure, you can’t always be sure that you’re identifying the right information to go after-whether it comes from big or traditional data” [25].

Technical Challenge: Keeping up with mobile technologies.
Customers are increasingly accessing information on mobile devices and leaving a widespread digital footprint spread [26]. Choice Hotels was among the first hotel companies to offer a mobile app for reservations, and the loyalty program department has tested allowing hotel guests to join the rewards program on mobile devices. Initial results from signups using a code from a table tent placed in 50 hotel lobbies were not promising, although data from these sources would be useful.

4. Sentiment Analysis of Twitter Data

4.1 Description of Twitter Data

To illustrate the challenges and decisions that Choice Hotels faces to include an external, social media data source (one of the types of big data) in a loyalty marketing campaign, we collected and investigated a sample of data from Twitter and performed a sentiment analysis. First, we provide background on Twitter and sentiment analysis, and then we discuss the decision making process and questions that Choice Hotels would need to address to use this type of big data.

Twitter describes itself as an information network that permits users to send small packets of text or characters of up to 140 characters called ‘tweets’ together with images, videos or links that they can embed [27]. Twitter is used for a variety of purposes including social networking, advertising, delivering news headlines, broadcasting updates on an event or occurrence (such as traffic), retweeting messages, replying to messages, interact with entities such as television programming, and sending messages to specific people. Registered users can identify themselves, build a following of other users, follow other users, and identify specific interests (using hashtag keywords #). Since Twitter is available on mobile platforms such as cell phones as well as the Web, it has become a social networking tool for both businesses and individuals. Twitter’s impact is shown by an erroneous tweet in April 2013 that there were explosions at the White House causing a $134 billion dip in the US stock market [28]. The reaction was swift due, in part, to algorithmic trading and computers that sift through data to determine whether to buy or sell. Twitter has recently launched a successful stock initial public offering (IPO).

Sentiment analysis is a form of social media analytics that ascribes an emotional state to words or phrases. The simplest form of sentiment analysis relies on a dictionary of words that have been given a score such as -5 to +5 to represent the degree of positive or negative emotion based on research. In the case of Twitter, tweets are parsed and keywords are identified and scored, and analyses can reveal correlations between variables. As a recent example, Mitchell et al. [29] investigated how geographic location in the United States correlated with word happiness, with an emphasis on urban areas and their geographic differences. To answer their research question, they used word frequency distributions collected from over 37 million cleaned, geotagged tweets authored in 2011 from over 373 urban locations in the United States providing mobility data and an individual's movement (identified by Twitter user name) to changes in word usage. Individual words were scored for happiness and correlated with city-level survey data. Their analysis showed geographic regions that were happy/unhappy and that happiness increased logarithmically with distance from expected location.

Some researchers point out that context is often lacking in DSS and processing language [30]. Research to understand context was reported by Socher et al. [31] using neural networks and a sentiment treebank to determine the compositional effects of sentiment in language by classifying phrases and sentences. They claim improved accuracy compared to other types of sentiment analysis and an accuracy rate of 80.7%. Inclusion of context is an emerging area of sentiment analysis.

Although Twitter offers consulting and third party support for sentiment analysis and other analytics associated with its data, these services are expensive. We wanted to determine if sentiment analysis could provide useful information for a mid-sized company such as Choice Hotels International. We also wanted to evaluate the ease/difficulty of access to these data and a decision making process that would be followed to determine those big data to include addressing a decision problem.

4.2 Decision Questions for Utilization of Big Data

The decision questions to be addressed in using big data are illustrated with the case study.

1. Variety: What sources of data do we want to consider? (e.g. internal, external, transactional, web, social media)

We determined that, in addition to internal transactional or marketing response data, social media data from Twitter is potentially of interest to the loyalty marketing department since the company has invested in a Twitter feed, @ChoiceHotels. We experimented with several keywords singly and in combination: hotel, hotels, motel, motels, choice hotels, comfort hotel, comfort, suites, inn, quality, Clarion, sleep. Some of the choices yielded primarily advertising data such as tweets from Choice Hotels itself. We chose to use 'hotel, comfort' as the keyword combination for our illustration. We wanted to determine if these two keywords appeared to be related, i.e. do they yield a sample, and whether customers indicated positive or negative sentiment in their tweets.

2. Veracity: How accurate are the data, and can we trust them sufficiently to help us answer the decision question? (e.g. verified, unverified, known variability)

Although demographics are difficult to ascertain, Mitchell et al. [29] claim that about 15% of online adults regularly use Twitter, tweets are denser in urban areas, and 18-29 year olds and minorities are more highly represented on Twitter compared to the general population. In addition, a sample of tweets represent a portion of the population of tweets with no assurance of distribution shape and time of day dependency over which the data are collected. In a rigorous examination of these data, we would need to take sufficiently large samples over sufficiently large time frames to provide confidence in the results. The exceedingly large files required are beyond the scope and storage capability of the current study.

3. Velocity: How fast are the data recorded? (e.g. real-time, daily, monthly)

Data are recorded in real time with Twitter. We can take a sample of those data, obtain the entire data feed, or access historical data for a fee. We decided to use real-time sample of data to determine if the data could be useful in developing a loyalty marketing campaign.

4. Volatility: How much change do we expect in data that we need to answer our decision question, and how quickly must data be utilized in order to provide value (e.g. stable over time, time variant, highly volatile)?

We do not know if these data are stable over time. Once way to determine volatility is to sample data at different times of day to determine if the results vary. In Table 1 we report the results for two time periods, one on a weekend to attempt to include vacation travelers, and one on the following weekday to attempt to include business travelers. We would need to gather data over time to determine if sentiment shifts. Geotagged data are possibly of interest to Choice Hotels in a larger study.

5. Volume: How much data do we want to consider? (e.g. detailed, sampled, summarized)

In this study, we considered detailed data in actual tweets. For illustration purposes, we took a 10 minute sample at different times of day.

4.3 Analysis of Twitter Data

To construct the sample, we created a Twitter account and investigated the structure of a tweet. A tweet contains more information than the 140 characters in a message, including user and geographic information (not available for every tweet). We then wrote a Python program that collected tweets containing the keywords ‘hotel’ and ‘comfort,’ loaded a data dictionary that contained a set of keywords along with their sentiment value ranging from -5 to +5, and wrote a Python program to analyze tweets in our sample and evaluate the data as shown in Table 1. We determined that we do not have sufficient data for location analysis or to ascertain if multiple tweets are coming from the same user. It is possible to analyze the tweets for other characteristics such as word frequency. In this case, word frequency does not appear to add additional insight. In a much larger sample, geographic data could possibly yield insight, and faster processing can be achieved with large data sets by distributing across Hadoop clusters.

Table 1. Sentiment analysis of a sample of Twitter data with keywords ‘hotel’ and ‘comfort.’

	Data from 3:30-3:40 pm EST on Sunday after a holiday weekend	Data from 8:30-8:40 pm EST on the following Monday
Negative words	215	218

Combined Sentiment for negative words	-403	-396
Positive words	646	630
Combined sentiment for positive words	1384	1394
Count of negative tweets	117	112
Count of positive tweets	371	416
Combined sentiment over all tweets	981	998
Most positive tweets	(11) RT @____Active2: Inviting ________ Cozy Comfort ______	(11) #allthatmattersmusicvideo had me like .. A little to close for comfort lol jk It WAS AMAZING AND THE LIGHTS IN THE B…
Most negative tweet	(-8) RT @ZachStroth: If they can build the hotel on Bluemont and Manhattan so quickly, why in the ____ is it taking so ____ long for them to fix…	(-10) The Out Hotel is literally ___ for someone with bad night vision. I've been lost for the last 20 minutes.

Our sample results in Table 1 are illustrative only. Data in the form of 10 minutes of tweets were collected from two different time periods, a holiday weekend when leisure travelers are expected and a weekday when business travelers might be more expected. We find that searching for tweets using the two words ‘comfort’ and ‘hotel’ yields a dataset within our 10 minute window. A visual inspection of these data indicates that the tweets are primarily from individual people rather than tweets from business. Interestingly, the results are similar for both time periods in terms of number of tweets and sentiment, with a combined positive sentiment in both cases. The number of positive tweets is approximately 3-4 times the number of negative tweets. The most positive and most negative tweets have been redacted in the table for possibly inappropriate content.

Based on our study, we find that Twitter data can be analyzed to provide marketing insights, and that social media data can provide more variety and information to integrate with transactional data for Choice Hotels. For example, the results are suggestive that a marketing campaign that stresses comfort of Choice Hotels could yield positive results. The choice of keywords, the time of day of collection, and the size of the dataset needed to be informative requires additional study.

Also of interest to Choice Hotels is the human resources needed to perform the study. We found that a business analyst with some skill in developing computer programs was needed. Twitter provides a description of accessing their data, and tutorials are available to guide users on writing their own programs. However, Choice Hotels would need to invest in human capital to develop the needed skillsets.

5. Summary and Limitations

This study has focused on identifying factors needed to utilize big data in organizational decision making through a case study of one such company actively engaged in implementing a big data strategy. Big data present opportunities and challenges for DSS 2.0 and decision making. Companies are beginning to realize the potential of big data and the need to invest in associated technologies to remain competitive. Yet many companies, especially small and mid-sized firms, are far from effective users of these data.

A case in point is Choice Hotels International, a mid-sized hospitality franchiser with several brands in its portfolio. Choice Hotels has made a commitment to use of big data in combination with its current data and is experiencing the growing pains associated with developing the internal organization and leadership to realize value on a big data investment. Ten challenges for Choice Hotels were identified in managing big data and improving decision making and were characterized as *technical* (inconsistent and unstandardized data, implementation and use of new analytics platforms, obtaining a global view of data, visualization of data, integrating mobile data), *organizational* (finding people with the right skills, users' desire for customization), and *strategic management* (finding return on investment in big data, alignment of business and analytics strategies, leadership of analytics initiatives and thought).

We propose that these challenges are representative of issues faced by companies that are just beginning to address their needs for DSS 2.0. Research in associated technical, organizational and strategic management areas are needed.

We then investigated the potential use of unstructured data in the form of social media data for a loyalty marketing campaign by collecting and analyzing a sample of data with sentiment analysis. We determined that Twitter data is possibly of interest to Choice Hotels, in part because they have a business Twitter feed, and we illustrated the decision making process needed in evaluating data to include. We required specialized skills to access and analyze these data. The limitations to our study include a small sample size, lack of information on demographics of users (not available from Twitter data), and limited keyword search terms. Thus, additional study is needed to generalize the results.

The contributions of this paper to the literature are:

(1) an additional characteristic of big data was identified as volatility to complement volume, variety, velocity and veracity;
(2) technical, organizational, and strategic management challenges in using big data for decision making were identified;
(3) social media data from Twitter were analyzed with sentiment analysis to illustrate a decision making process for using big data.

Evidence is mounting that big data used analytically and strategically can deliver competitive advantage and return on investment for companies. However, the challenges are significant and include lack of human capital, thought leadership and analytics platforms. These challenges provide guidance for future research of big data in organizational decision making.

Acknowledgements

We would like to thank Choice Hotels International for access to their company and providing insights for this paper. We would also like to thank the reviewers for their helpful comments.

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