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Big data analytics sentiment: US-China reaction to data collection by business and government

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ABSTRACT

As society continues its rapid change to a digitized individual, corporate, and government environment it is prudent for researchers to investigate the zeitgeist of the global citizenry. The technological changes brought about by big data analytics are changing the way we gather and view data. This big data analytics sentiment research examines how Chinese and American respondents may view big data collection and analytics differently. The paper follows with an analysis of reported attitudes toward possible viewpoints from each country on various big data analytics topics ranging from individual to business and governmental foci. Hofstede's cultural dimensions are used to inform and frame our research hypotheses. Findings suggest that Chinese and American perspectives differ on individual data values, with the Chinese being more open to data collection and analytic techniques targeted toward individuals. Furthermore, support is found that US respondents have a more favorable view of businesses' use of data analytics. Finally, there is a strong difference in the attitudes toward governmental use of data, where US respondents do not favor governmental big data analytics usage and the Chinese respondents indicated a greater acceptance of governmental data usage. These findings are helpful in better understanding appropriate technological change and adoption from a societal perspective. Specifically, this research provides insights for corporate business and government entities suggesting how they might adjust their approach to big data collection and management in order to better support and sustain their organization's services and products.

1. Introduction

The collection and management of “big data” has become a charged topic not only within the information technology (IT) field, but more broadly in society, including the corporate and government arenas (Chen et al., 2012; Wang et al., 2016). First perceived as just another technology used for forecasting, to better target customers and to increase corporate growth, its use, and misuse, has propagated into other societal realms. Big data can provide benefits such as more focused advertising and marketing of products and services – leading to higher prosperity and more adoptable and sustainable products and services. However, there is also the concern of privacy and intrusion into one's personal life (van de Pas and van Bussel, 2015). There is tension between a corporation's desire for economic growth and the consumers' desire for privacy. Do personalized advertisements increase sales by focusing on an individual's specific needs and wants or do they create frustration by demonstrating to an individual that some entity knows a lot more about them then they would like others to know? Continuously convincing an individual of new products they “need” (assuming the analytics produce an accurate calculation of the “need”) is a great business model for creating profit for the corporation, but may have the opposite effect on societal and environmental progress toward lack of privacy and sustainability. While technology can contributes toward environmentally unfriendly practices (i.e. planned obsolescence of computing and mobile devices), it can be used toward environmentally sustainable practices such as reducing waste. For example, enabling mailings to go to individuals who more likely have an interest or need for a particular service or product—rather than to everyone, thus saving on mail delivery, ink toner and paper product usage.

While there is no grand theory for “big data” at this time there is no doubt that this phenomenon is taking the research world by storm. Abbasi et al. (2016) provide a research framework that spans disciplines and research methodologies arguing the impact big data will have on research. At its heart big data differs from traditional data when you consider the big V's of Big Data (Buhl et al., 2013; McAfee and Brynjolfsson, 2012), namely volume, variety, velocity, and

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veracity. Volume in terms of gigabytes to petabytes (and beyond) of data to analyze requiring new hardware and software solutions to handle this size. Variety considers that all data is not just text and numbers but rather more complex objects such as documents, images, sound, and video that could be analyzed for additional insights. Velocity reflects the incoming pace of new data. Consider a smart city solution that tracks people and automobile traffic through its intersections. Finally, veracity, one of the major underlying themes of this research, deals with the privacy, confidentiality, integrity, trustworthiness, and availability of big data. Chen et al. (2012) and Wang et al. (2016) discuss how the advances in business intelligence, analytics, and big data technologies are reaching into the political and governmental arenas ranging from healthcare to transportation and national infrastructure. It is in this spirit, with an eye toward business and governmental usage of big data that we conducted this research, to gauge the concerns of respondents from the two largest economies in the world.

As corporations and governments use technology to better identify and track their customers and citizens, it is important to determine appropriate, acceptable, and sustainable limits. Otherwise customers and citizens may complain and rebel—even leading to the organization's demise and downfall. This paper examines perceptions of the use of new technologies to collect and analyze big data by respondents from China and the United States. We analyze how these new big data and data analytics technologies impact consumer behavior in adopting new products and services, often with serious concerns of privacy—within two quite different countries and cultures. Chinese and US respondents report on their attitudes toward the collection and use of personal data, big data, data mining, and data warehousing usage by business and government. Finally, this work provides insights for corporate business and government entities suggesting how they might adjust their approach to big data collection and management in order to better support and sustain their organization's services and products.

2. Background

Examining some general country metrics show that the United States of America (US) and the People's Republic of China (China) share many similarities. Both countries cover approximately the same total area and land area; the US has a total area of 9,629,090 km^2 and covers a land area of 9,158,960 km^2; China has a total area of 9,596,961 km^2 and covers a land area of 9,327,420 (United Nations, 2006). The US and China are the two largest economies by gross domestic product (GDP) by an order of magnitude with 17.4 trillion USD and 10.4 trillion USD total GDP respectively in 2015 (World Bank, 2016). These two countries are also the world's leaders in CO_2 emissions (World Bank, 2016) and are above the world average in life expectancy and total fertility rate. (World Bank, 2016). However, not all of the macro country data are similar, most notably population size, GDP growth, internet users, land use, and percent of GDP spending on public education, (United Nations, 2006). These macro country metric differences likely have an impact on the public perception of Big Data (BD) and Information Systems (IS) and technologies.

Differences in the perception of BD and IS between the US and China may also stem from a combination of cultural history contexts, political philosophy and ideology, and population demographics. The US is the product of Western European colonialism combined with free market and democratic ideologies, whereas China is the product of imperial dynasties and eventually communist authoritarian ideologies. Although authoritarian communist and democratic ideologies are quite different, some of the root beliefs overlap but with different solutions to social and civic issues. For example, China handles the Internet much differently than the US, employing heavy censorship and control of what content is available to people within the country via what has become known as the Great Firewall of China (Eko et al., 2011).

3. Research framework

This big data analytics sentiment research gathers data on perceptions of individuals toward big data collection and analysis – especially as they relate to data collected by corporate business and government. In order to decipher the differences and similarities between the US and China in how their citizens view big data collection, analytics and technology usage, and how they may perceive them in the future, a theoretical framework can be useful in framing our data analysis. There have emerged a few multinational cultural frameworks to draw from. Two of the most well know frameworks include Hofstede's Cultural Dimensions framework (Hofstede, 1983, 2011) and the GLOBE project (House et al., 1999, 2002). Both frameworks have their supporters (Bauer, 2015; Capece et al., 2013; Ngoc, 2016) and their critics (Graen, 2006; Martinsons and Ma, 2009; Orr and Hauser, 2008). However, in the end for this research we followed the likes of Li and Persons (2011) and Villatoro et al. (2014) and utilized Hofstede's framework to guide this research examining user sentiment on big data usage and analytics from US and Chinese populations. Li and Persons (2011) work used Hofstede's cultural dimensions to frame their study on business ethics between US and Chinese students, in a similar manner as our study. Villatoro et al. (2014) also employed Hofstede's framework (in addition to using Forsyth's (1980) ethics position theory) when studying ethics and values from subjects in China, Mexico, and the US.

3.1. Hofstede framework

The Hofstede framework examines countries, organizations, institutions and societies on six cultural dimensions. These include power distance, uncertainty avoidance, individualism versus collectivism, masculinity versus femininity, long term versus short term orientation, and indulgence versus restraint (Hofstede, 2011). Table 1 below provides a brief description of each of these dimensions.

Fig. 1 below displays the six dimensions of both China and the US as measured by Hofstede's research. On the dimension of masculinity both China and the US are quite close. There is some difference in the uncertainty avoidance dimension between the two countries. However, it is worthy to note that across the remaining four dimensions (power distance, individualism, long term orientation, and indulgence) there is quite a significant difference.

Hofstede metrics on the US and China from a cultural perspective are used to help inform the development of the research hypotheses in

Table 1
Hofstede's national culture dimensions.

National culture dimension	Description
Power distance	The degree of acceptance by the less powerful that there are inequities in power distribution within an organization, institution or society.
Uncertainty avoidance	The level of stress within a society when outcomes are unknown or unknowable.
Individualism versus collectivism	The degree to which members of society identify as individuals or as a group.
Masculinity versus femininity	The measure of the division of emotional roles of males and females within a society.
Long term versus short term orientation	The measure of the range of focus for members of a society's efforts, whether they are far sighted or short sighted.
Indulgence versus restraint	The measure of how much people in a society try to control immediate gratification

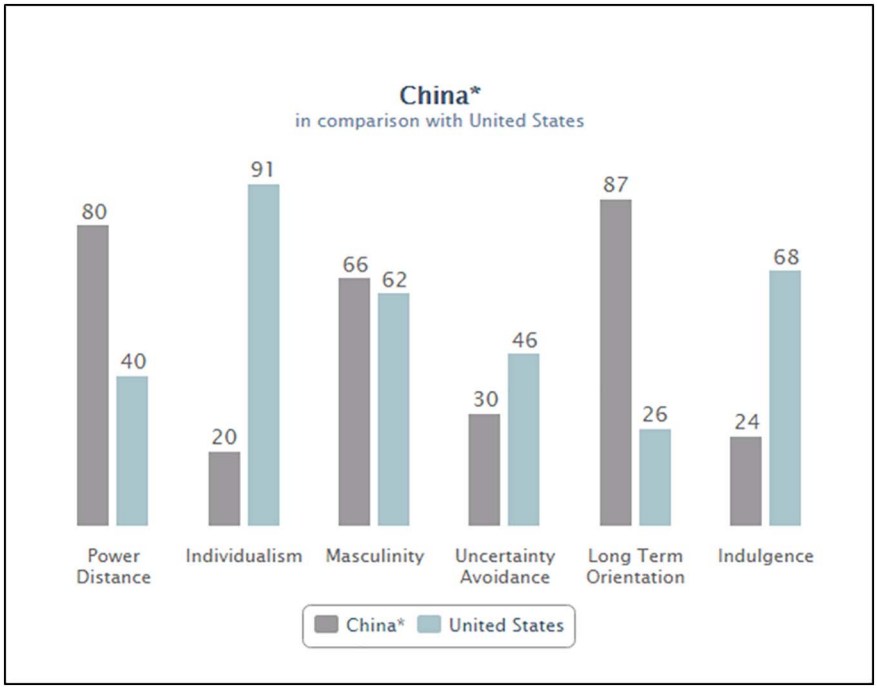

Fig. 1. China & US Cultural Dimensions (adapted from http://geert-hofstede.com/china.html).

this project. In the development of our hypotheses Hofstede's cultural dimensions potentially predicts differences in sentiment between respondents reacting to the use of big data analytics.

4. Method/model

In this survey research we seek insights on individual sentiment toward big data usage by business and government. Propositional statements are provided for respondents to reflect on and judge. In this study we extend the survey instrument utilized in LaBrie et al. (2014). Foundations for our current study can be found in Cazier and LaBrie (2007) where seven myth – counter-myth pairs (what we refer to in this research as propositions) on data mining/warehousing usage were proposed and categorized into three distinct foci: individual consumer myths (proposition pairs 1–3 in this study, see Table 2 below), business myths (proposition pairs 3 and 4 in this study), and societal myths (proposition pairs 6 and 7 in this study). Each of the myth – counter-myth pairs were structured so as to not show bias from the authors. Supporting arguments and evidence was given for both alternatives of the myth scenarios, allowing the survey respondents to come to their own conclusion on the value of the myth statements (what we call propositions in this work). In fact, respondents could agree with both the myth and the counter-myth argument, in which case a third question was asked of the respondents that sought their judgement on which side was more likely to be the case. This 2007 research surveyed respondents only in the US. Findings suggested that the consumer-oriented myths were largely viewed in a negative light (Merging data decreased value – Myth 1b, Profiling decreased value – Myth 2b, Pervasive marketing was soundly rejected as being for the benefit of the consumer with Myth 3a having strong disagree from respondents, whereas Myth 3b was strongly supported. When asked which was more likely Myth 3b was preferred). In addition, the 2007 findings suggested views on business usage of data was generally slightly positive (DW improves productivity – Myth 4a, but both Myth 5a and 5b came out statistically significant on whether DW improves or hurts an organization's image). Finally, their 2007 findings suggested that from a societal standpoint that while using data warehousing technologies is seen as helping the environment (Myth 6a supported), that government usage of data warehousing technologies was strongly opposed (both Myth 7a was rejected soundly, while Myth 7b was supported enthusiastically).

Table 2
Nine big data proposition/counter-propositions.

Analysis level	Proposition	Counter-proposition
Individual focused propositions	1a) The merging of current customer data with secondary sources ultimately increases value for the consumer.	1b) The merging of current customer data with secondary sources ultimately hurts the consumer.
	2a) Customer profiling leads to more customized service and thus creates consumer value.	2b) Customer profiling, with not enough data, may lead to more customized service that actually reduces consumer value.
	3a) Using persuasive marketing techniques increases consumer value.	3b) Using persuasive marketing techniques reduces consumer value.
Business focused propositions	4a) Data collection improves organizational productivity.	4b) Data collection reduces organizational productivity.
	5a) Data warehousing/"big data" project improves your organizational image.	5b) Data warehousing/"big data" projects hurts your organizational image.
	6a) Data warehousing/"big data" projects reduces waste and helps the environment.	6b) Data warehousing/"big data" projects increases waste and harms the environment.
Government focused propositions	7a) Governmental use of data warehousing/"big data" projects are good for society.	7b) Governmental use of data warehousing/"big data" projects are not good for society.
	8a) Governmental use of cameras and drones are good for society.	8b) Governmental cameras and drones are not good for society.
	9a) Metadata that accompanies pictures, Internet searches, and social media posts is helpful for businesses and government to cater to the consumer.	9b) Metadata that accompanies pictures, Internet searches, and social media posts can be harmful for consumers if it's used by businesses and government.

The LaBrie et al. (2014) research was a longitudinal study, that replicated Cazier and LaBrie (2007) with updated language around big data and the conversion to proposition language. The term proposition was preferred to myth, as these were statements the respondents were to judge. Respondent data, again all US, was collected a decade apart and revealed some key insights of sentiment change toward the usage of big data technologies. From the consumer perspective, findings suggested that individuals were more comfortable with sharing their data and having their data used to market to them. No change in attitudes toward business usage of big data technologies were found over the 10-year period. Finally, and perhaps most surprising from the 2014 study, no statistically significant change was measured in attitudes toward government usage of data.

Following LaBrie et al. (2014) this study extends that research by adding two additional proposition counter-proposition question pairs that address technological advances in big data collection from drones, cameras, and metadata captured by digital photos and videos. Additionally, this study gathered data from Chinese and US respondents, whereas the previous study only focused on US respondents. Furthermore, the previous work of LaBrie et al. (2014) classified their propositions (myths in their original language of the 2007 survey) in three categories consisting of three consumer myths, two business myths, and two societal myths. This research reclassifies the existing and new propositions in a balanced fashion in the following three major foci: Individual, Business, and Government. In this research each category has three proposition – counter-proposition pairs. We continue their survey structure in not only presenting a proposition with a counter-proposition argument, but also including a question on which of the pair of propositions is more likely to be the case. This continues to help in the analysis of when a respondent agrees (or disagrees) with both proposition and counter-proposition alternatives by providing insight to which one the respondent believes is more likely. Table 2 below lists the nine proposition and counter-proposition pairs used in this research.

The following sections provide additional, updated discussion that these propositions – counter-propositions are still open for debate. Propositions eight and nine are newly developed for this research and are discussed in more detail below. Following the discussions of each grouping of individual, business, and government propositional statements, a hypothesis is presented for testing.

4.1. Individual focused propositions & hypothesis

4.1.1. Individual proposition 1 – merging data and secondary sources

Proposition 1 concerns itself with the mass proliferation of personal data. It is no longer sufficient for organizations to rely solely on the data that they collect on an individual. To better “serve” the customer many organizations are involved with acquiring additional data on their consumers from outside the firm, referred to as secondary source data. Hofacker et al. (2016) discuss a new data culture in marketing to consumers where the use of secondary sources is becoming more widely practiced and accepted (2016). Libaque-Saenz et al. (2016) investigate, when consumers are given a choice to authorize secondary use of personal data, what benefits may occur. Furthermore, Martin (2015) frames the use of secondary data in terms of a big data industry supply chain.

4.1.2. Individual proposition 2 – consumer profiling

Consumer profiling is a common data analytics and marketing strategy used by organizations to better target customers for future sales. Blanco-Justicia and Domingo-Ferrer (2016) continue to investigate the individual privacy versus consumer profiling debate by suggesting that at least in loyalty programs there may be a way to provide a new form of anonymous profiling. This mechanism then gives more power to the consumer/individual of how much of their profile they want to release to a vendor. Another recent study by Johar et al. (2014) investigates the optimized tuning of web based personalization systems in e-tailing. They suggest a balanced-optimized approach of items where an immediate sale might take place versus offering items to learn more about the consumer's preference.

4.1.3. Individual proposition 3 – persuasive marketing

Persuasive marketing techniques commonly practiced by business repeatedly target consumers in a more focused and increasingly recurring manner. Su Jung et al. (2015) investigate mobile marketing techniques and that a brand app can be used as a persuasive marketing tool. They find that “sticky” apps, those downloaded and consistently used, increase sales of the brand's products, whereas, those apps that are downloaded, used seldom and are abandoned, could actually hurt the brand. While many are calling for the manipulative and persuasive marketing techniques to be abandoned, Miles (2015) suggests ways in which therapeutic/hypnotic theory may be used as a reconciliatory medium for more negotiative, dialogical approach to marketing.

4.1.4. Individual focused hypothesis

It is generally believed that there is American cultural value emphasizing personal privacy. Wang et al. (2011) found that in social media usage the US users tended to be the most privacy concerned over their Chinese and Indian counterparts. Camp (1999), Liu and Arnett (2002), and MacDermott and Smith (2013) each discussion American views of privacy as it relates to the web. Dinev et al. (2006) posited that the US had a higher regard to privacy as compared with their Italian counterparts hypothesized in large part based on the Hofstede Cultural Dimensions scores of Italy relative to the US scores, especially in the case of the individualism-collectivism score. Fischer (2009) provides a valuable discussion on whether or not we can even evaluate a country's culture from individual response and how a multilevel framework is needed. Given its strong sense of individualism (vs collectivism) from Hofstede's national cultural dimensions, where the US scores 91 as opposed to the Chinese score of 20 and its relationship to a strong sense of personal privacy the following hypothesis is offered:

H1. US respondents will have a less favorable view on data usage targeted at individuals (merging data/secondary sources, profiling, persuasive techniques) than their Chinese counterparts.

4.2. Business focused propositions & hypothesis

4.2.1. Business proposition 4 – organizational productivity

Organizations use technology to become more efficient and productive. If an organization is recognized as a leader in data collection and/or usage it might be perceived as being more productive. Philip-Chen and Zhang (2014) investigate a new data paradigm – data-intensive scientific discovery (DISD) where the shear vastness of big data might cause organizational challenges. The Tambe (2014) study on firm productivity finds big data projects involving modern technologies (Hadoop, MapReduce, and Apache Pig) result in a 3% faster productivity growth, but the findings come with some caveats, largely around a firm's data management maturity level.

4.2.2. Business proposition 5 – organizational image

Business must pay attention to their image to stay competitive. Major technology mistakes can reduce a firm's value in the eyes of shareholders and customers. Hirsch (2013) gives some guidelines for corporate reputation management in this age of data transparency or in his term “nudity”. Navetta (2014) warns, if precautions are not taken, big data can cause big trouble for an organization's reputation. This warning is primarily focused on the proper management of private data.

4.2.3. Business proposition 6 – data and the environment

In recent years more and more organizations have looked inwardly in how they may improve their processes in support of being better

stewards of the environment. Corporate Social Responsibility (CSR) initiatives, specifically along the lines of the environment and "Greening IT" are expected by many consumers to earn their patronage. Often technology can be utilized to support these initiatives (Lacey, 2014). However, organizations must be careful not to "Cloud wash" – a new term introduced by Moorthy et al. (2015) combining the use of big data/cloud computing technology solutions and greenwashing. There are even calls to reduce the amount of data (van Bussel et al., 2015) via a digital archiving in order to reduce technology and energy usage.

4.2.4. Business focused hypothesis

It is generally recognized that there is a significant relationship between the US economy and Wall Street (Holmes and Maghrebi, 2016; Laopodis and Sawhney, 2002; Sawhney et al., 2006). Given the short term approach of demand to meet expectations for each quarterly report, American CEO's have bemoaned the fact they often have to make short term decision and trade-offs over long term strategy in order to satisfy Wall Street (Hamm, 2006). This short term focus spills over to many facets of American life, and is congruent with Hofstede cultural dimension of short versus long term orientation scores related to the US vs China. The US rating of 26 as compared to China's rating of 87 shows a significant gap between these two countries' approach to long term orientation. Furthermore, the historically pro-business perspective (DeLuca, 1994; McCarthy, 2015) and innovation culture (Segal, 2011) of the United States also partly manifests itself in Hofstede's cultural dimension of indulgence (Coelho, 2011) where the US scores higher relative to China (68 vs 24). Furthermore, as a wealthy nation, the US citizens often indulge themselves in pet causes. Over the past few decades it has become increasing important for many Americans to focus on the environment (Cohen, 2014). This manifests itself in buying low/no emissions cars, investing in personal solar power, and supporting large tax increases for mass transit solutions (Ansolabehere and Konisky, 2014). As such, based upon the American short term, pro-business, innovative, and indulgence culture the following hypothesis is offered:

H2. US respondents will have a more favorable view on data usage by businesses (collection, projects, environmental considerations) than their Chinese counterparts.

4.3. Government focused propositions & hypothesis

4.3.1. Government proposition 7 – government big data projects

Governments are one of the few institutions that can manage very large programs. They generally have the capacity, in terms of monetary, human, and technological resources, to tackle big data projects. Furthermore, most governments are expert data collectors, having long histories of data collection that predate the information age (Amankwah-Amoah, 2015). Very few would argue that when the government participates in big data projects where the primary focus is on scientific research, health, crime, or minimizing government waste (Gómez, 2015; Huffine, 2015; Lu et al., 2012) this directly benefits the society in which they are operating in. However, there are also many out there that might conclude that government is overstepping its mandate with big data projects that might start out as well-meaning: such as fighting terrorism but then expand to citizen surveillance (Calo, 2016) or controlling religion (Candia et al., 2011).

4.3.2. Government proposition 8 – cameras and drones

This new proposition and its associated counter-proposition is intended to investigate whether the data collection via the use of cameras and drones is seen as good for society and for corporations or whether cameras and drones have too many serious personal privacy and freedom implications. Closed-circuit television (CCTV) cameras seem to be in every major city around the world, providing "fast, cost-efficient and automated method of identifying people as well as behavioral-pattern recognition" (Weber and Staiger, 2015). According to Aggarwal (2015) the government is collecting data from sources such as traffic cameras and sensors which include data, time, license plate number, color and even speed—to be analyzed by Real-Time Analytics (RTA). In addition, there are also a growing number of commercial operators using satellites orbiting hundreds of miles above earth to gather data and images (remote sensing) which are sold to companies and even governments for commercial and non-commercial uses (Lewis and Caplan, 2015).

A 60 by 60 cm drone evaded White House radar and landed inside the White House complex in Washington D.C. — highlighting the fact that managing this technology is a huge problem (Simpson, 2015). In the US, divergent Unmanned Aerial Vehicles (UAVs) or drones restrictive legislation has been proposed in Congress—due to the multiple interests, concerns about diminishing privacy, and perhaps a fear of the unknown (Blitz et al., 2016). One step in the transfer of military drone technology to civilian and corporate applications is the emergence of the "public order" drone which encompasses both firefighting and law enforcement (Blitz et al., 2016). In Europe, article 8 of the European Convention on Human Rights (ECHR) seems to suggest that the state is required not only to abstain from interfering but also to take positive steps in adopting measures to secure respect for private life. Weber and Staiger (2015) conclude that recent case law seems apply this article to drones as well. A study by Jansen (2015) found that privacy concerns relating to behavioral privacy, privacy of location and space, privacy of association, privacy of property and privacy of data and image are of very high societal importance. Behavioral privacy is especially important because it contributes to a "chilling effect" on society in outdoor space and thereby implies serious harms to freedom, autonomy and democracy.

The extended survey thus asks the respondents to consider the following proposition and counter-proposition given the following brief scenarios.

Proposition 8a. Governmental use of cameras and drones are good for society.

Video feeds are a relatively new form of massive data collection. Everything from speeding to red-light running cameras have purported to increase safety (less speeding – safer roads, and where red-light cameras have been installed, less fatalities at those intersections). Drones are being used for border patrol, and many discussions are taking place in order to find the right fit for drone usage for the protection and monitoring of large crowds, parades, sports venues, etc.

Proposition 8b. Governmental cameras and drones are not good for society.

Many argue that the trade-offs of cameras and drones amount to a trade-off of personal freedom and unreasonable invasion of privacy. Cameras everywhere and unmanned drones flying overhead amount to a "big brother" society, which can lead to individuals being targeted for any number of reasons beyond criminal activity (i.e. political, religious, or other reasons).

4.3.3. Government proposition 9 – metadata usage

This new proposition and its associated counter-proposition is intended to investigate whether or not metadata that is embedded in Internet website usage, digital photos and videos, as well as most modern documents, for example Microsoft Office documents, is a concern of the populace. For the purposes of this study metadata is defined in the most general of terms as data about data (Moen, 2001). More specifically, Foshay et al. (2007, 2014) define metadata more dimensionally as information about the meaning, quality, location, and lineage of decision support data. Rousidis et al. (2014) focus on the usage of metadata for big data and the importance of the data quality.

More and more businesses and government agencies are using metadata for decision making. We see this in the field of Business

Table 3
Means and significance tests per country.

Propositions	US respondents		China respondents	
	Mean	Significance (2-tailed)	Mean	Significance (2-tailed)
Proposition 1a	3.594	0.000	3.609	0.000
Proposition 1b	3.236	0.001	3.651	0.000
Proposition 1aOR1b	2.882	0.081	2.970	0.613
Proposition 2a	3.633	0.000	3.852	0.000
Proposition 2b	3.701	0.000	3.836	0.000
Proposition 2aOR2b	3.032	0.665	2.861	0.036
Proposition 3a	2.777	0.001	3.463	0.000
Proposition 3b	3.436	0.000	3.141	0.066
Proposition 3aOR3b	3.3	0.000	2.891	0.158
Proposition 4a	3.832	0.000	3.824	0.000
Proposition 4b	2.877	0.064	3.045	0.501
Proposition 4aOR4b	2.461	0.000	2.577	0.000
Proposition 5a	3.784	0.000	3.477	0.000
Proposition 5b	3.466	0.000	3.627	0.000
Proposition 5aOR5b	2.909	0.182	3.024	0.723
Proposition 6a	3.748	0.000	3.661	0.000
Proposition 6b	2.899	0.133	3.113	0.136
Proposition 6aOR6b	2.535	0.000	2.677	0.000
Proposition 7a	2.844	0.056	3.469	0.000
Proposition 7b	3.638	0.000	3.243	0.002
Proposition 7aOR7b	3.252	0.002	2.897	0.176
Prob8a	3.032	0.684	3.768	0.000
Prob8b	3.509	0.000	2.859	0.035
Proposition 8aOR8b	3.183	0.019	2.485	0.000
Proposition 9a	3.329	0.000	3.266	0.001
Proposition 9b	3.443	0.000	3.842	0.000
Proposition 9aOR9b	3.032	0.668	3.213	0.003

Intelligence (Foshay et al., 2014; Shankaranarayanan and Even, 2004; Watson et al., 2006), as well government usage (Christian, 2001) and surveillance (Donohoe, 2014; Tzanou, 2013). As technological solutions automate more and more of this type of data collection and analysis we ask the respondents to consider the following proposition and counter-proposition given the following brief scenarios.

Proposition 9a. Metadata that accompanies pictures, Internet searches, and social media posts is helpful for businesses and government to cater to the consumer.

When you take a digital picture or 'tweet' or make a Facebook post from a smartphone (or any mobile device) there is a lot of accompanying data that is stored along with that photo/tweet/post, including time/date stamps and GPS location. Over a period of time businesses such as Google, Apple, AT & T, and Verizon can gather maps and trends of where you were/are/might be going. This will allow for better target marketing. For example, on your way home, you may be prompted with a happy hour advertisement to a Chinese restaurant you pass every day, rather than some advertisement from a restaurant miles away from your current route.

Proposition 9b. Metadata that accompanies pictures, Internet searches, and social media posts can be harmful for consumers if it's used by businesses and government.

If we are truly creatures of habit, is it right for businesses or governmental agencies to capitalize on knowing where we were, are, or where we are going to be? If business/government did collect this data for their employees – perhaps they would take action if the employee was at a competitor's location. Or if business/government collected this data on you, they may try to use it to verify your presence at work. And if such data was obtained (hacked) by criminals wanting to do you harm, this causes more risk to the consumer.

4.3.4. Government focused hypothesis

Given the Chinese historically strong pro-government cultural value (Bell, 2015; Wan, 2013) we look for which of Hofstede's cultural dimensions would support this Chinese pro-government value. The Individualism dimension plays a role since it refers to how members of society identify as individuals as opposed to as a group. With China's score of 20 in this category it signifies that China is a highly collectivist culture where people act more according to the interests of the group –

and this group may be the government. Hofstede's long-term orientation refers to how a society maintains links to its past while dealing with the present. With a score of 87 China can be seen as a pragmatic culture, with support of the past environment—which may translate into support of a stable government and their actions. Also, the impact of e-government to citizens' technology has brought about more government transparency and public participation in China (Zhao et al., 2015). The Indulgence dimension, where China has a score of 24, indicates an acceptance of restraints by the social norms of one's society, instead of a focus one one's own individual gratification. While Dai and Chen (2015) find that location tracking significantly impacts Chinese users' privacy concerns, it seems there is an acquiescence of the government's role in this data collection. In the US, perhaps due to the revelations of Snowden and others on the data collection by the NSA (Preibusch, 2016) trust in government data collection practices has fallen. The court battles between the FBI and Apple, with the FBI asking Apple for the password of an iPhone (Hack, 2016) also raised questions as to the broad reach of government surveillance. Based on these values from Hofstede's national cultural findings the following hypothesis is offered:

H3. Chinese respondents will have a more favorable view on data usage by government (big data projects, cameras/drones, metadata usage) than their US counterparts.

5. Results and discussion

A total of 398 people were surveyed, consisting of 221 that attended two universities in the US and 177 who attended a university in Beijing, China. One US university is a private university on the West Coast while the other US university is a public university on the East Coast. In both China and the US both undergraduate and graduate students were surveyed. The first test performed on the data was to make sure we could reject the null hypothesis that survey respondents had an opinion (something other than 'neither agree nor disagree' for the proposition pairs and something other than 'both equally' for the "which proposition was more preferred" question). In all cases, for each proposition and counter-proposition individually as well as which proposition was more preferred, it was found that the null hypothesis can be rejected for the sample set as a whole (N = 398) as well as for each country's data set (US N = 221, China N = 177) at p-value of 0.000 suggesting the respondents did have some form of opinion, agreeable or disagreeable for each proposition.

Table 3 below shows the means (and one sample t-test for significance) for both US and Chinese based responses. A five point Likert scale ranged from 1 – Strongly Disagree to 5 – Strongly Agree, with 3 signifying 'Neither Agree nor Disagree' was employed. For the which proposition is more preferred questions another five point Likert scale that ranged from 1 – Definitely Proposition A to 5 – Definitely Proposition B, with 3 signifying 'Both Are Equally Likely'. While there is some discussion on what statistical method is proper for Likert scale analysis (Jamieson, 2004), during our analysis we ran both the more commonly used Independent Sample t-tests and ANOVA as well as the less commonly used, but perhaps more appropriate non-parametric Mann-Whitney U asymptotic test for significance. In all of our tests the significance levels of the results came out the same, thus we report here only the more commonly used t-test results.

For guidance in interpreting our results in Table 3 below, darker shaded rows show propositions that were statistically significant for both countries. That is that the respondents believed that particular propositional statement was something other than neutral. It could have been positive sentiment – means above 3.0, or a negative sentiment – means below 3.0. Lighter shaded cells show statistical significance for a single country (US or China), and white cells indicate no statistical significance.

Table 4 below shows the results of the independent sample t-test for significant differences between groups. Here we are testing if the US responses are statistically significantly different from the China responses. Country means, differences between the means (with asterisks indicating significance level), and interpretation columns are provided.

5.1. Results of the hypothesis testing

Hypothesis H1 generally finds confirming support.

For those individual propositions with statistical significances between groups (Propositions, 1b, 2a, 3a, 3b) US respondents were less agreeable with the individual data analytic technique (2a – individual profiling, 3a and 3b – persuasive techniques). The only statistically significant finding that was opposite to the predicted value was Proposition 1b, where based on H1, we would have predicted a higher value of US respondents over their Chinese counterparts. Furthermore, when it came to predicting which proposition is more preferred, the only statistically significant result occurred between proposition 3a and 3b, and as predicted, the US respondents supported the more negative side (3b) whereas the Chinese respondents support the more positive proposition (3a).

Hypothesis H2 is confirmed.

Directionally the data from all propositions and counter-propositions support the hypothesis that the US respondents have a more favorable view on business data usage. From a statistically significant standpoint only two propositions (5a and 6b) were significant. In both cases the data showed support for the hypothesis.

Hypothesis H3 is strongly confirmed.

Concerning governmental use of big data analytic technologies (7a and 7b) there was overwhelming statistically significant evidence that the Chinese respondents supported this where the US respondents believed this would have negative effects. This was further demonstrated by the opposite statistically significant opinions on which propositions should win (7aOR7b) where the Chinese respondents supported the positive proposition (7a) and the US respondents supported the negative proposition (7b). Furthermore, we find the same exact results when it comes to government use of drones and cameras (Proposition 8). Here we find the same statistically significant pattern Chinese respondents supported this (8a) where the US respondents believed cameras and drones would have negative effects (8b). Parallel to which proposition is more preferred (7aOR7b) above, again we find opposite statistically significant opinions on which propositions is more preferred (8aOR8b) where the Chinese respondents supported the positive form of the proposition on the use of cameras and drones (8a) and the US respondents supported the negative form of the proposition (8b) when considering camera and drone usage.

Like the collection of individual propositions where there was one (1b) statistically significant proposition that did not fall in the hypothesized direction, this happened once in the governmental collection of propositions. Proposition 9b, if supporting the hypothesis, should have resulted in a higher mean score for the US respondents compared to their Chinese counterparts. In our analysis of this anomaly we believe that the proposition counter-proposition pair may have been worded poorly. In the wording we refer to consumer (individual), business, and government. Depending on how the respondents focused on the question, they could have thinking about business usage versus government usage. In that case had this pair of propositions been grouped with the business propositions the results would have been congruent with the predicted business hypothesis.

5.2. Discussion of big data analytics sentiment data with Hofstede

In order to decipher the differences and similarities between the US and China in how their citizens view big data collection, analytics and technology and their impact on individuals, business, and government, theoretical frameworks can be employed. We considered the well-known Hofstede framework and its six dimensions for guidance in

Table 4
Between group (US & China) analysis.

Proposition	US mean	US interpretation	China mean	China interpretation	Mean difference	US-China interpretation
Proposition 1a	3.5936	Agreed	3.6092	Agreed	− 0.0156	Both agreed equally
Proposition 1b***	3.2364	Agreed	3.6514	Agreed	− 0.4151***	Both agreed, Chinese agreed more
Proposition 1aORb	2.8818	More positive	2.9697	Neutral	− 0.0879	Chinese neutral, US more positive (1a)
Proposition 2a**	3.6335	Agreed	3.8523	Agreed	− 0.2188**	Both agreed, Chinese agreed more
Proposition 2b	3.7014	Agreed	3.8362	Agreed	− 0.1348	Both agreed, Chinese agreed more
Proposition 2aOR2b	3.0318	Neutral	2.8614	More positive	0.1704	US neutral, Chinese more positive (2a)
Proposition 3a***	2.7773	Disagreed	3.4633	Agreed	− 0.6860***	OPPOSITE: US disagreed, Chinese agreed
Proposition 3b**	3.4364	Agreed	3.1412	Agreed	0.2951**	Both agreed, US agreed more
Proposition 3aOR3b***	3.3000	More negative	2.8909	More positive	0.4091***	OPPOSITE: US more negative (3b), Chinese more positive (3a)
Proposition 4a	3.8318	Agreed	3.8239	Agreed	0.0080	Both agreed equally
Proposition 4b	2.8767	Disagreed	3.0452	Neutral	− 0.1685	Chinese neutral, US disagreed
Proposition 4aOR4b	2.4612	More positive	2.5774	More positive	− 0.1162	Both positive (4a), US more positive
Proposition 5a***	3.7844	Agreed	3.4773	Agreed	0.3071***	Both agreed, US agreed more
Proposition 5b	3.4658	Agreed	3.6271	Agreed	− 0.1614	Both agreed, Chinese agreed more
Proposition 5aOR5b	2.9087	More positive	3.0238	Neutral	− 0.1151	US more positive (5a), Chinese neutral
Proposition 6a	3.7477	Agreed	3.6610	Agreed	0.0867	Both agreed, US agreed more
Proposition 6b*	2.8991	Disagreed	3.1130	Agreed	− 0.2139*	OPPOSITE: US disagreed, Chinese agreed
Proposition 6aOR6b	2.5346	More positive	2.6766	More positive	− 0.1421	Both more positive (6a)
Proposition 7a***	2.8440	Disagreed	3.4689	Agreed	− 0.6249***	OPPOSITE: US disagreed, Chinese agreed
Proposition 7b***	3.6376	Agreed	3.2429	Agreed	0.3947***	Both agreed, US agreed more
Proposition 7aOR7b***	3.2523	More negative	2.8970	More positive	0.3553***	OPPOSITE: US more negative (7b), Chinese more positive (7a)
Proposition 8a***	3.0321	Neutral	3.7684	Agreed	− 0.7363***	US neutral, Chinese agreed more
Proposition 8b***	3.5092	Agreed	2.8588	Disagreed	0.6504***	OPPOSITE: US agreed, Chinese disagreed
Proposition 8aOR8b***	3.1835	More negative	2.4850	More positive	0.6985***	OPPOSITE: US more negative (8b), Chinese more positive (8a)
Proposition 9a	3.3288	Agreed	3.2655	Agreed	0.0632	Both agreed equally
Proposition 9b***	3.4429	Agreed	3.8418	Agreed	− 0.3989***	Both agreed, Chinese agreed more
Proposition 9aOR9b	3.0323	Neutral	3.2130	More negative	− 0.1808	US neutral, Chinese more negative (9b)

*** $p = 0.001$.
** $p = 0.01$.
* $p = 0.05$.

framing the hypotheses. The Hofstede framework examines countries, organizations, institutions and societies on six cultural dimensions. These include power distance, uncertainty avoidance, individualism versus collectivism, masculinity versus femininity, long term versus short term orientation, and indulgence versus restraint (Hofstede, 2011). We found similarities to our propositions on the dimensions of individualism versus collectivism, long term versus short term orientation, and indulgence versus restraint.

Individualism versus collectivism refers to the degree to which members of society identify as individuals or as a group. The main issue addressed by this dimension is the degree of interdependence a society maintains among its members. It has to do with whether people's self-image is defined in terms of “I” or “We”. In individualist societies people tend to look after themselves and their direct family only. In collectivist societies people belong to ‘in groups’ that take care of them in exchange for loyalty. With a Hofstede score of 20 China is a highly collectivist culture where people act more according to the interests of the group and not necessarily of themselves. Relationships with colleagues are cooperative for in-groups, but are cold or even hostile to out-groups. The US score of 91 is very high on the individualism side with the focus on “I”.

Our first three propositions focus on increasing value for the individual consumer by merging of current and secondary customer data, individual customer profiling, and using persuasive marketing techniques. The Hofstede interpretation of the US as high on the individualist side would cause us to predict that US respondents would be more supportive of these first three propositions. China as a collectivist culture would lead us to predict that the focus on our first three propositions would be on the negative side for the Chinese respondents. But this is not the case: Both agreed equally on proposition 1A, the Chinese agreed a bit more on proposition 2A, and the Chinese agreed on proposition 3A whereas the US disagreed with this proposition.

Hofstede's long term versus short term orientation is the measure of the range of focus for members of a society's efforts, whether they are far sighted or short sighted. “This dimension describes how every society has to maintain some links with its own past while dealing with the challenges of the present and future, and societies prioritize these two existential goals differently. Normative societies which score low on this dimension, for example, prefer to maintain time-honored traditions and norms while viewing societal change with suspicion. Those with a culture which scores high, on the other hand, take a more pragmatic approach: they encourage thrift and efforts in modern education as a way to prepare for the future.” (Hofstede, 2011).

China has a score of 87 in this dimension—a high score. This view of China as a pragmatic culture with an easy ability to adapt traditions would imply that the Chinese people would more readily adapt to new technologies and increased data collection and analytics, whereas the United States, with only a score of 26 in this category, views new technologies with more suspicion. This is supported by our data.

Hofstede's indulgence versus restraint is the measure of how much people in a society try to control immediate gratification or the extent to which people try to control their desires and impulses. China's low score of 24 indicates that it is a restrained society which does not put much emphasis on leisure time and they seek to control the gratification of their desires. “People with this orientation have the perception that their actions are restrained by social norms and feel that indulging themselves is somewhat wrong.” (Hofstede, 2011).

The United States with a score of 68 is on the high side and would be called an indulgent society which puts more weight on leisure time and personal gratification. Proposition 3 asks whether persuasive marketing increases or reduces consumer value. One would think that the Chinese, who do not focus as much on “gratification of their desires” according to the Hofstede model would indicate a higher disdain for persuasive marketing, since their focus is not on pleasing themselves or wanting others to persuade them to focus on themselves. Yet our analysis of Proposition 3A data indicates that Chinese agree that “persuasive marketing techniques increases consumer value” whereas the US disagreed.

6. Conclusion and future research

Technological change continues to happen – Moore's law assures us of that. More and more of an organization's (business or governmental) value is being placed on how it manages and sustains its use of big data. This research provides key insights on how respondents from the two largest economies of the world, namely China and the US, think about how individuals, businesses, and governments employ big data collection and analytics. Three of our findings suggest that:

1) Chinese respondents tend to be more open to big data efforts targeted at the individual (merging of secondary source data, profiling, and persuasive marketing techniques).
2) US respondents are generally more supportive of business usage of big data projects, especially when related to sustainable environmental concerns.
3) Chinese respondents strongly support governmental usage of big data projects, whereas their US counterparts strongly oppose the usage of these technologies.

The first and third findings align with Hofstede's long term orientation dimension where China has a value of 87 versus the US with a value of 26 (Fig. 1) supporting the view that China is a very pragmatic culture with an ability to more easily adapt to changes in traditions. Our findings also indicate that Chinese respondents seem to more readily adapt and accept new technologies and increased data collection and analytics, whereas the United States respondents tend to view these new big data technologies with more suspicion.

These findings have practical implications for business and government in terms of sustainability efforts when it comes to the use of technology. As cities become “smart” and implement technology to manage more efficiently transportation, logistics, and energy consumption, attention needs to be taken in their data gathering, management, and usage techniques (Etzion and Aragon-Correa, 2016). While big data initiatives are necessary in order to gain more of the benefits for business and society, misuse of this data is also a real possibility. Something like gathered traffic data can also lead to identification of individual commuter habits and locations, inhibiting reasonable personal privacy. As “smart” utilities are implemented for sustainable practices, either in the home, business, or cities, data breaches could disrupt entire systems leaving the individual, business, or government at risk (Martin, 2015; Moorthy et al., 2015).

6.1. Limitations

Like any survey administered to university students, some generalizability issues may arise. We have attempted to mitigate some of these factors by collecting data from both undergraduate and graduate student populations. Graduate students tend to be a lot more diverse, and representative of the general population (Compeau et al., 2012). Furthermore, we recognize there is not a clean fit between the nine propositions, counter-proposition pairs and Hofstede's six dimensions of national culture. We have attempted, rather than focus on each one, to employ the specific dimensions where the US and China differ the most. Finally, our classification of the propositions into Individual, Business, and Government foci may not be the ideal groupings. For example, Business Proposition 6, related to big data and the environment, could be viewed as business related, but also could be viewed from a governmental focus. In addition, Governmental Proposition 9, related to metadata, had both business and government labels in the proposition, potentially confusing the respondents. Further data collection and additional statistical methods (i.e. factor analysis) could potentially confirm or suggest alternative groupings.

6.2. Future research

Applying Hofstede's framework to our hypotheses development proved fruitful. While we did see some alignment, it really is just a beginning. We see value in additional research focusing on an alternative global theoretical framework, namely the GLOBE framework. The Global Leadership and Organizational Effectiveness (GLOBE) framework is intended to examine the interconnections of social and organizational culture as well as organizational leadership. This is done by measuring nine culture dimensions on two levels each, actions and values. The culture dimensions include: uncertainty avoidance, power distance, social collectivism, in-group collectivism, gender egalitarianism, assertiveness, future orientation, performance orientation, and humane orientation (House et al., 2002; Shi and Wang, 2011). These dimensions provide further opportunity to measure and analyze the sustainability implications of big data collection and analysis.

This research focused on the US and China, primarily because they are the two largest economies in the world and that, given their histories, political systems, and wide variations along many of the dimensions in Hofstede's framework, we would easily find differences. We intend to extend this research to additional countries, utilizing the GLOBE framework where additional insights may emerge. It may also be the case that these differences are not dependent on country and culture, but also be dependent on factors such as age, education, work experience, etc.

The authors believe we are on the verge of a fourth generation of big data usage and surveillance. Tavani (2016) discusses how society has moved from a first generation view of “Big Brother” surveillance where it was the government monitoring citizens to a third generation where individuals can now play the role of big brother. Technological advancements have moved us though a second generation in which business is considered the big brother, considering the personal data that organizations such as Google, Baidu, Apple, and others hold on individuals. Given the ubiquity of social media (Facebook, RenRen, Twitter, Weibo, and the like), the third generation of surveillance enables individuals to monitor other individuals. In addition, in this third generation of surveillance, the citizenry might now also monitor government and business like never before. The technological changes that big data collection and analytics bring will likely force corporations and governments to greater transparency and accountability. Given the global emphasis on sustainability efforts, there is no doubt that technology focusing on the big data activities of business and government will have impact on individuals throughout the world.

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