Chapter 2:

Big Data Analytics and Ethnography: Together for the Greater Good

Vincent Charles[1] and Tatiana Gherman[2]

[1] Buckingham Business School, University of Buckingham, Buckingham, UK

v.charles@buckingham.ac.uk

[2] School of Business and Economics, Loughborough University, Loughborough, UK

t.i.gherman@lboro.ac.uk

Abstract *Ethnography* is generally positioned as an approach that provides deep insights into human behaviour, producing 'thick data' from small datasets, whereas *big data analytics* is considered to be an approach that offers 'broad accounts' based on large datasets. Although perceived as antagonistic, ethnography and big data analytics have in many ways, a shared purpose; in this sense, this chapter explores the intersection of the two approaches to analysing data, with the aim of highlighting both their similarities and complementary nature. Ultimately, this chapter advances that ethnography and big data analytics can work together to provide a more comprehensive picture of big data, and can thus, generate more societal value together than each approach on its own.

Key words: analytics, big data, ethnography, thick data.

1 Introduction

For thousands of years and across many civilizations, people have been craving for knowing the future. From asking the Oracle to consulting the crystal ball to reading the tarot cards, these activities stand as examples that show how people have always sought any help that could tell them what the future held, information that would aid them make better decisions in the present. Today, the craving for such knowledge is still alive and the means to meet it is big data and big data analytics. From traffic congestion to natural disasters, from disease outbursts to terrorist attacks, from game results to human behaviour, the general view is that there is nothing that big data analytics cannot predict. Indeed, the analysis of huge datasets has proven to have invaluable applications.

Big data analytics is one of today's most famous technological breakthroughs (Fichman, Dos Santos, & Zheng, 2014) that can enable organizations to analyse fast-growing immense volumes of varied datasets across a wide range of settings, in order to support evidence-based decision-making (Watson, 2014). Over the past few years, the number of studies that have been dedicated to assessing the potential value of big data and big data analytics has been steadily increasing, which also reflects the increasing interest in the field. Organizations worldwide have come to realize that in order to remain competitive or gain a competitive advantage over their counterparts, they need to be actively mining their datasets for newer and more powerful insights.

Big data can, thus, mean big money. But there seems to be at least one problem. A 2013 survey by the big data firm Infochimps, who looked at the responses from over 300 IT department staffers, indicated that 55% of big data projects do not get completed, with many others falling short of their objectives. According to another study published by Capgemini and Informatica (2016), who surveyed 210 executives from five developed countries (France, Germany, Italy, the Netherlands, and the UK) to assess the business value and benefits that enterprises are realizing from big data, only 27% of big data projects were reported as profitable, whereas 45% reached their equilibrium, and 12% actually lost money. Further, in 2015, Gartner predicted that through 2017, 60% of big data projects will fail to go beyond piloting and experimentation. In 2016, Gartner actually conducted an online survey among 199 Gartner Research Circle members and the results indicated that only 15% of businesses deployed their big data projects from pilot to production.

These statistics show that although big investments are taking place in big data projects, the generation of value does not match the expectations. The obvious question is, of course, *why*? Why are investments in big data failing, or in other words, why having the data is not sufficient to yield the expected results? In 2014, Watson advanced that "the keys to success with big data analytics include a clear business

need, strong committed sponsorship, alignment between the business and IT strategies, a fact-based decision-making culture, a strong data infrastructure, the right analytical tools, and people skilled in the use of analytics" (p. 1247). Although informative and without doubt useful, today nonetheless, these tips seem to be insufficient; otherwise stated, if we know what we need in order to succeed with big data analytics, then why don't we succeed in creating full value? The truth is that we are yet to profoundly understand how big data can be translated into economic and societal value (Günther, Rezazade Mehrizi, Huysman, & Feldberg, 2017) and the sooner we recognize this shortcoming, the sooner we can find solutions to correct it.

In this chapter, we advance that *ethnography* can support *big data analytics* in the generation of greater societal value. Although perceived to be in opposition, ethnography and big data analytics have much in common and in many ways, they have a shared purpose. In the following sections, we explore the intersection of the two approaches. Ultimately, we advance that researchers can blend big data analytics and ethnography within a research setting; hence, that big data analytics and ethnography together can inform the *greater good* to a larger extent than each approach on its own.

1.1 What is big data?

'Big data': a concept, a trend, a mindset, an era. No unique definition, but a great potential to impact on essentially any area of our lives. The term *big data* is generally understood in terms of the four Vs advanced by Gartner (Laney, 2001): volume, velocity, variety, and veracity. In time, the number of Vs has increased, reaching up to ten Vs (Markus, 2015). Other authors have further expanded the scope of the definition, broadening the original framework: Charles and Gherman (2013), for example, advocated for the inclusion of three Cs: context, connectedness, and complexity. One of the most elegant and comprehensive definitions of big data can be found in the none other than the Oxford English Dictionary, which defines it as: "extremely large datasets that may be analysed computationally to reveal patterns, trends, and associations, especially relating to human behaviour and interactions."

Big data comes from various structured and unstructured sources, such as archives, media, business apps, public web, social media, machine log data, sensor data, and so on. Today, almost anything we can think of produces data and almost every data point can be captured and stored. Some would say: also, analysed. This may be true, but in view of the statistics presented in the introduction above, we are reticent to so state. Undoubtedly, data is being continuously analysed for better and deeper insights, even as we speak. But current analyses are incomplete, since if were to be able to fully extract the knowledge and insights that the datasets hold, we

would most probably be able to fully capitalize on their potential, and not so many big data projects would fail in the first place.

The big data era has brought many challenges with it, which deemed the traditional data processing application software unfit to deal with them. These challenges include networking, capturing data, data storage and data analysis, search, sharing, transfer, visualization, querying, updating and, more recently, information privacy (Charles, Tavana, & Gherman, 2015). But the list is not exhaustive and challenges are not static; in fact, they are dynamic, constantly mutating and diversifying. One of the aspects that we seem to generally exclude from this list of challenges is human behaviour. Maybe it is not too bold to say that one of the biggest challenges in the big data age is the extraction of insightful information not from the existing data, but from the data originating from emergent human dynamics that either haven't happened yet or that would hardly be traceable through big data.

One famous example in this regard is Nokia, a company that in the 1990s and part of 2000s was one of the largest mobile phone companies in the world, holding by 2007 a market share of 80% in the smartphone market (Bouwman *et al*., 2014). Nevertheless, Nokia's over-dependence on quantitative data has led the company to fail in maintaining its dominance on the mobile handset market. In a post published in 2016, technology ethnographer Tricia Wang (2016a) describes how she conducted ethnographic research for Nokia in 2009 in China, which revealed that low-income consumers were willing to pay for more expensive smartphones; this was a great insight at the time that led her to conclude that Nokia should replace their then strategy from making smartphones for elite users to making smartphone for low-income users, as well. But Nokia considered that Wang's sample size of 100 was too small to be reliable and that moreover, her conclusion was not supported by the large datasets that Nokia possessed; they, thus, did not implement the insight. Nokia was bought by Microsoft in 2013 and Wang concluded that:

> *There are many reasons for Nokia's downfall, but one of the biggest reasons that I witnessed in person was that the company over-relied on numbers. They put a higher value on quantitative data, they didn't know how to handle data that wasn't easily measurable, and that didn't show up in existing reports. What could've been their competitive intelligence ended up being their eventual downfall.*

Netflix is at the other end of the game, illustrating how ethnographic insights can be used to strengthen a company's position on the market. Without doubt, Netflix is a data-driven company, just like Nokia. In fact, Netflix pays quite a lot of attention to analytics to gain insight into their customers. In 2006, Netflix launched the Netflix Prize competition, which would reward with $ 1 million the creation of an algorithm that would "substantially improve the accuracy of predictions about how much someone is going to enjoy a movie based on their movie preferences". But at the same time, Netflix was open to learning from more qualitative and contextual

data about what users really wanted. In 2013, cultural anthropologist Grant McCracken conducted ethnographic research for Netflix and what he found was that users *really enjoyed* to watch chapter after chapter of the same series, engaging in a new form of consumption, now famously called *binge watching.* A survey conducted in the same year among 1,500 TV streamers (online U.S. adults who stream TV shows at least once per week) confirmed that people did not feel guilty about binge watching, with 73% of respondents actually feeling good about it (Netflix Media Center, 2013). This new insight was used by Netflix to re-design its strategy and release whole seasons at once, instead of releasing one episode per week. This, in turn, changed the way users consumed media and specifically Netflix's products and how they perceived the Netflix brand, while improving Netflix's business.

1.2 What is Ethnography?

Having already introduced the notion of ethnographic research in subsection 1.1 above, let us now consider the concept of *ethnography* and discuss it further. Ethnography, from the Greek words *ethno*s, meaning 'folk, people, nation', and *grapho*, meaning 'I write' or 'writing', is the systematic study of people and cultures, aimed at understanding and making sense of social meanings, customs, rituals, and everyday practices (Brewer, 2000; Madden, 2010). Ethnography has its origin in the work of early anthropologists, such as Bronislaw Malinowski (1922) and Margaret Mead (1943), who largely focused on mapping out the cultures of small and isolated tribes, before they became 'contaminated' by contact with the industrial world (Denscombe, 2007). In time, this simple definition has been refined by many authors.

For example, Brewer (2000, p. 6) defined ethnography as:

> *The study of people in naturally occurring settings or 'fields' by methods of data collection which capture their social meanings and ordinary activities, involving the researchers participating directly in the setting, if not also the activities, in order to collect data in a systematic manner but without meaning being imposed on them externally*.

Delamont (2004, p. 218), on the other hand, stated that:

> *Participant observation, ethnography and fieldwork are all used interchangeably… they can all mean spending long periods watching people, coupled with talking to them about what they are doing, thinking and saying, designed to see how they understand their world*.

Ethnography is about becoming part of the settings under study. 'Ethnographies are based on observational work in particular settings' (Silverman, 2000, p. 37),

allowing researchers to 'see things as those involved see things' (Denscombe, 1998, p. 69); 'to grasp the native's point of view, his relation to life, to realize his vision of his world' (Malinowski, 1922, p. 25). Consequently, the writing of ethnographies is viewed as an endeavour to describe 'reality' (Hammersley & Atkinson, 1983; Silverman, 2001), as this is being experienced by the people who live it.

Ethnography depends greatly on *fieldwork*. Generally, data is collected through participant or nonparticipant observation. The primary data collection technique used by ethnographers is, nonetheless, *participant observation*, wherein the researchers assume an insider role, living as much as possible with the people they investigate. Participant observers interact with the people they study, they listen to what they say and watch what they do; otherwise stated, they focus on people's doings in their natural setting, in a journey of discovery of everyday life. *Nonparticipant observation*, on the other hand, requires the researchers to adopt a more 'detached' position. The two techniques differ, thus, from one another based on the weight assigned to the activities of 'participating' and 'observing' (Le Compte & Preissle, 1993; Madden, 2010).

Finally, ethnography aims to be a holistic approach to the study of cultural systems (Whitehead, 2004), providing 'the big picture' and depicting the intertwining between relationships and processes; hence, it usually requires a long-term commitment and dedication. In today's fast-paced environment, however, mini-ethnographies are also possible. A mini-ethnography focuses on a specific phenomenon of interest and as such, it occurs in a much shorter period of time than that required by a full-scale ethnography (White, 2009).

2 Big Data Analytics and Ethnography: Points of Intersection

Ford (2014) advanced that "data scientists and ethnographers have much in common, that their skills are complementary, and that discovering the data together rather than compartmentalizing research activities was key to their success" (p. 1). In a more recent study, Laaksonen *et al*. (2017) postulated that "ethnographic observations can be used to contextualize the computational analysis of large datasets, while computational analysis can be applied to validate and generalize the findings made through ethnography" (p. 110). The latter further proposed a new approach to studying social interaction in an online setting, called *big-data-augmented-ethnography*, wherein they integrated ethnography with computational data collection.

To the best of our knowledge, the literature exploring the commonalities between big data analytics and ethnography is quite limited. In what follows, we attempt, thus, to contribute to the general discussion on the topic, aiming to highlight additional points of intersection. The below Figure 1 briefly depicts these points.

Figure 1. The intersection between big data analytics and ethnography.

2.1 Depicting 'reality'

Big data analytics comprise the skills and technologies for continuous iterative exploration and investigation of past events to gain insight into what has happened and what is likely to happen in the future (Mustafi, 2016). In this sense, data scientists develop and work with models. Models, nonetheless, are simplified versions of reality. Models built aim, thus, to represent the reality and in this sense, are continuously revised, checked, and improved upon and, furthermore, tested to account for the extent to which they actually do so.

On the other hand, ethnographies are conducted in a naturalistic setting in which real people live, with the writing of ethnographies being viewed as an endeavour to describe 'reality' (Hammersley & Atkinson, 1983; Silverman, 2001). Furthermore, just as big data analytics-informed models are continuously being revised, "ethnography entails continual observations, asking questions, making inferences, and continuing these processes until those questions have been answered with the greatest emic validity possible" (Whitehead, 2004). In other words, both big data and ethnography are more concerned with the processes through which 'reality' is depicted rather than with judging the 'content' of such reality.

2.2 Changing the definition of knowledge

Both big data analytics and ethnography change the definition of *knowledge* and this is because both look for a more accurate representation of reality. On the one hand, big data has created a fundamental shift in how we think about research and how we define knowledge, reframing questions about the nature and the categorization of reality and having a profound change at the levels of epistemology and ethics (boyd & Crawford, 2012). Big data analytics offers what Lazer *et al*. (2009) called "the capacity to collect and analyse data with an unprecedented breadth and depth and scale" (p. 722). Or as boyd and Crawford (2012) wrote, "just as Du Gay and Pryke (2002) note that 'accounting tools... do not simply aid the measurement of economic activity, they shape the reality they measure' (pp. 12-13), so big data stakes out new terrains of objects, methods of knowing, and definitions of social life" (p. 665).

On the other hand, ethnographies aim to provide a detailed description of the phenomena under study, and as such, they may reveal that people's reported behaviour does not necessarily match their observed behaviour. As a quote widely attributed to the famous anthropologist Margaret Mead states: "What people say, what people do, and what they say they do are entirely different things". Ethnographies can and are generally performed exactly because they can provide insights that could lead to new hypotheses or revisions of existing theory or understanding of social life.

2.3 Searching for patterns

Both data scientists and ethnographers collect and work with a great deal of data and their job is, fundamentally, to identify patterns in that data. On the one hand, some say that the actual value of big data rests in helping organizations find patterns in data (Hayes, 2014), which can further be converted into smart business insights (Brynjolfsson & McAfee, 2012). Big data analytics or machine learning techniques help find hidden patterns and trends in big datasets, with a concern more towards the revelation of solid statistical relationships. Generally, this means finding out whether two or more variables are related or associated.

Ethnography, on the other hand, literally means to 'write about a culture' and in the course of so doing, it provides think descriptions of the phenomena under study, trying to make sense of what is going on and reveal understandings and meanings. By carefully observing and/or participating in the lives of those under study, ethnographers thus look for shared and predictable patterns in the lived human experiences: patterns of behaviour, beliefs and customs, practices, and language (Angrosino, 2007).

2.4 Aiming to predict

A common application of big data analytics includes the study of data with the aim to predict and improve. The purpose of predictive analytics is to measure precisely the impact that a specific phenomenon has on people and to predict the chances of being able to duplicate that impact in future activities. In other words, identifying patterns in the data is generally used to build predictive models that will aid in the optimization of a certain outcome.

On the other hand, it is generally thought that ethnography is, at its core, descriptive. But this is somehow misunderstood. Today, there is a shift in an ethnographer's aims, whose ethnographic analyses can take the shape of predictions. Evidence of this are Wang's (2016a, b) ethnographic research for Nokia and McCracken's ethnographic research for Netflix, described in subsection 1.1 of this chapter. In the end, in practical terms, the reason why we study a phenomenon, irrespective of the method of data collection or data analysis used, is not just because we want to understand it better, but because we also want to predict it better. The identification of patterns enables predictions, and as we have already implied before, both big data analytics and ethnography can help in this regard.

2.5 Sensitive to context

Big data analytics and ethnography are both context-sensitive; in other words, taken out of context, the insights obtained from both approaches will lose their meaning. On the one hand, big data analytics is not just about finding patterns in big data. It is not sufficient to discover that one phenomenon correlates with another; or otherwise stated, there is a big difference between identifying correlations and actually discovering that one causes the other (cause and effect relationship). Context, meaning and interpretation become a necessity, and not a luxury. This observation was also made by Maxwell (2013, p. 182), when he elegantly stated that:

> *Analytics often happens in a black box, offering up a response without context or clear transparency around the algorithmic rules that computed a judgment, answer, or decision. Analytics software and hardware are being sold as a single- source, easy solution to make sense of today's digital complexity. The promise of these solutions is that seemingly anyone can be an analytics guru. There is real danger in this do-it-yourself approach to analytics, however. As with all scientific instruments and approaches, whether it be statistics, a microscope, or even a thermometer, without proper knowledge of the tool, expertise in the approach, and knowledge of the rules that govern the process, the results will be questionable.*

On the other hand, inferences made by ethnographers are tilted towards the explanation of phenomena and relationships observed within the study group. Ethnography supports the research endeavours of understanding the multiple realities of life *in context* (Rossman & Rallis, 2003, emphasis added); hence, by definition, ethnography provides detailed snapshots of contextualized social realities. Generalization outside the group is limited and taken out of context, meanings will also be lost.

2.6 'Learning' from smaller data

Bigger data are not always better data. Generally, big data is understood as originating from multiple sources (the 'variety' dimension) or having to be integrated from multiple sources to obtain better insights. Nevertheless, this creates additional challenges. "Every one of those sources is error-prone… […] we are just magnifying that problem [when we combine multiple datasets]" (Bollier 2010, p. 13, cited by boyd & Crawford, 2012). In this sense, smaller data may be more appropriate for intensive, in-depth examination to identify patterns and phenomena, an area in which ethnography holds the crown.

Furthermore, data scientists have always been searching for new or improved ways to analyse large datasets to identify patterns, but one of the challenges encountered has been that they need to know what they are looking for in order to find it, something that is particularly difficult when the purpose is to study emergent human dynamics that haven't happened yet or that will not show up that easily in the datasets. Both big data analytics and ethnography can, thus, learn from smaller datasets (or even single case analyses). On the other hand, we must acknowledge that there are also situations in which researchers generally rely on big data (such as clinical research), but sometimes they have to rely on surprisingly small datasets; this is the case of, for example, clinical drug research that analyses the data obtained after drugs are released on the market (Bollier, 2010).

2.7 Presence of behavioural features

Le Compte and Preissle (1993) once said that: "Those who study humans are themselves humans and bring to their investigations all the complexity of meaning and symbolism that complicates too precise an application of natural science procedures to examining human life" (p. 86). This has generally been presented as a difficulty that ethnographers, in particular, must fight to overcome. But it does not have to be so in the big data age. The truth is we need as many perspectives and as many insights as possible. Fear that we might go wrong in our interpretations will only stop progression. A solution to this is posed by the collaboration between data

scientists and ethnographers. In this sense, ethnographers should be allowed to investigate the complexity of the data and come out with propositions and hypotheses, even when they are conflicting; and then data scientists could use big data analytics to test those propositions and hypotheses in light of statistical analyses and see if they hold across the larger datasets.

Studying human behaviour is not easy, but the truth is that both big data analytics and ethnography have a behavioural feature attached to them, in the sense that they are both interested in analysing the content and meaning of human behaviour; the 'proximity' between the two approaches is even more evident if we consider the change that the big data age has brought with it. While in the not so far past, analytics would generally be performed by means of relying upon written artefacts which recorded past human behaviour, today, big data technology enables the recording of *current* human behaviour, *as this happens* (consider live feed data, for example). And as technology will keep evolving, the necessity of 'collaboration' between big data analytics and ethnography will become more obvious.

2.8 Unpacking unstructured data

Big data includes both structured (*e.g.*, databases, CRM systems, sales data, sensor data, and so on) and unstructured data (*e.g.*, emails, videos, audio files, phone records, social media messages, web logs, and so on). According to a report by Cisco (2014), an estimated 90% of the existing data is either semi-structured or unstructured. Furthermore, a growing proportion of unstructured data is video. And video constituted approx. 70% of all Internet traffic in 2013. One of the main challenges of big data analytics is just how to analyse all these unstructured data. Ethnography (and its newer addition, online ethnography) may have the answer.

Ethnography is a great tool to 'unpack' unstructured data. Ethnography involves an inductive and iterative research process, wherein data collection and analysis can happen simultaneously, without the need to have gathered all the data or even look at the entire data. Ethnography does not follow a linear trajectory, and this is actually an advantage that big data analytics can capitalize on. Ethnography is par excellence a very good approach to look into unstructured data and generate hypotheses that can be further tested against the entire datasets.

3 Final Thoughts

Today, most companies seem to be still collecting massive amounts of data with a 'just in case we need it' approach (Charles, Tavana, & Gherman, 2015). But in the wise words of William Bruce Cameron, *not everything that can be counted*

counts, and not everything that counts can be counted. What should probably happen is that: before going ahead and collecting huge amounts of data, companies could use initial ethnographic observations to identify emergent patterns and phenomena of interest, advancing various, even conflicting, hypotheses. This could then inform and guide the overall strategy of massive data collection. Big data analytics could then analyse the data collected, testing the hypotheses proposed against these larger datasets. In this sense, ethnography can help shed light on the complexities of big data, with ethnographic insights serving as input for big data analytics and big data analytics can be used to generalize the findings.

Employing an ethnographic approach is generally understood in a traditional sense, which is that of having to undertake long observations from within the organization, with the researcher actually having to become an insider, a part of the organization or context that he decides to study. The good news is that today, new methods of ethnography are emerging, such as virtual ethnography (also known as online ethnography, netnography, or webnography (Purli, 2007)), which may turn out to be of great help in saving time and tackling the usual problem of having to gain access to the organization. The virtual world is now in its exponential growth phase and doing virtual ethnography may just be one of the best, also convenient answers to be able to explore and benefit from understanding these new online contexts. The web-based ethnographic techniques imply conducting virtual participant observation via interactions in online platforms such as social networks (such as Facebook or Twitter), blogs, discussion forums, and chat rooms. Conducting ethnographies in today's world may, thus, be easier than it seems.

In this chapter, we have aimed to discuss the points of intersection between big data analytics and ethnography, highlighting both their similarities and complementary nature. Although the list is far from being exhaustive, we hope to have contributed to the discussions that focus on how the two approaches can work together to provide a more comprehensive picture of big data. As Maxwell (2013, p. 186) stated, "ethnographers bring considerable skills to the table to contextualize and make greater meaning of analytics, while analytics and algorithms are presenting a new field site and complementary datasets for ethnographers".

One of the most important advantages of combining big data analytics and ethnography is that this 'intersection' can provide a better sense of the realities of the contexts researched, instead of treating them as abstract, reified entities. And this better sense can translate into better understandings and better predictions, which can further assist in the creation of better practical solutions, with greater societal added value. There are indeed many points of intersection between big data analytics and ethnography, having in many ways a shared purpose. They are also complementary, as data scientists working with quantitative methods could supplement their own 'hard' methodological techniques with findings and insights obtained from ethnographies. As Goodall (2000, p. 10) stated:

> *Ethnography is not the result of a noetic experience in your backyard, nor is it a magic gift that some people have and others don't. It is the result of a lot of reading, a disciplined imagination, hard work in the field and in front of a computer, and solid research skills…*

Today, we continue to live in a world that is being influenced by a *quantification bias,* the unconscious belief of valuing the measurable over the immeasurable (Wang, 2016b). We believe it is important we understood that big data analytics has never been one size fits all. We mentioned in this chapter that many big data projects fail, despite the enormous investments that they absorb. This is because many people still fail to comprehend that a deep understanding of the context in which a pattern emerge is not an option, but a must. Just because two variables are correlated does not necessarily mean that there is a cause and effect relationship taking place between them. boyd and Crawford (2012, p. 668) meant exactly that when they stated that:

> *Too often, Big Data enables the practice of apophenia: seeing patterns where none actually exist, simply because enormous quantities of data can offer connections that radiate in all directions. In one notable example, Leinweber (2007) demonstrated that data mining techniques could show a strong but spurious correlation between the changes in the S&P 500 stock index and butter production in Bangladesh.*

Ethnography can provide that so very necessary deep understanding. In this sense, big data analytics and ethnography can work together, complementing each other and helping in the successful handcrafting and implementation of bigger projects for a bigger, greater good.

References

1. Angrosino, M. (2007). Doing ethnographic and observational research. Thousand Oaks, CA: Sage.
2. Bollier, D. (2010). The promise and peril of big data. Retrieved from https://assets.aspeninstitute.org/content/uploads/files/content/docs/pubs/The_Promise_and_Peril_of_Big_Data.pdf
3. Bouwman, H., et al. (2014). How Nokia failed to nail the smartphone market. Conference Paper. 25th European Regional Conference of the International Telecommunications Society (ITS), 22-25 June 2014, Brussels, Belgium.
4. boyd, D., & Crawford, K. (2012). Critical questions for big data: provocations for a cultural, technological, and scholarly phenomenon. Information, Communication & Society, 15(5), 662-679.
5. Brewer, J. D. (2000). Ethnography. Philadelphia, PA: Open University Press.
6. Brynjolfsson, E. & McAfee, A. (2012). Big data: the management revolution. Harvard Business Review, 90(10), 60-68.

7. Capgemini & Informatica. (2016). The big data payoff: Turning big data into Business Value. A joint report by Informatica and Capgemini on the keys to operationalizing Big Data projects. Retrieved from https://www.capgemini.com/de-de/wp-content/uploads/sites/5/2017/07/the_big_data_payoff_turning_big_data_into_business_value.pdf
8. Cisco. (2014). Big data: Not just big, but different. Retrieved from https://www.cisco.com/c/dam/en_us/about/ciscoitatwork/enterprise-networks/docs/i-bd-04212014-not-just-big-different.pdf
9. Charles, V. and Gherman, T. (2013). Achieving competitive advantage through big data. Strategic implications. Middle-East Journal of Scientific Research, 16(8), 1069-1074.
10. Charles, V., Tavana, M., & Gherman, T. (2015). The right to be forgotten – is privacy sold out in the big data age? International Journal of Society Systems Science, 7(4), 283-298.
11. Delamont, S. (2004). Ethnography and participant observation. In C. Seale, G. Gobo, J. Gubrium, and D. Silverman (Eds.), Qualitative Research Practice (pp. 217-229). London: Sage.
12. Descombe, M. (1998). The Good Research Guide for Small-scale Social Research Projects. Buckingham: Open University Press.
13. Descombe, M. (2007). The Good Research Guide for Small-scale Social Research Projects (3rd ed.). Berkshire, UK: Open University Press, McGraw-Hill.
14. Du Gay, P., & Pryke, M. (2002). Cultural Economy: Cultural Analysis and Commercial Life. London, UK: Sage.
15. Fichman, R. G., Dos Santos, B. L., & Zheng, Z. (2014). Digital innovation as a fundamental and powerful concept in the information systems curriculum. MIS Quarterly, 38(2), 329-353.
16. Ford, H. (2014). Big data and small: Collaborations between ethnographers and data scientists. Big Data & Society, July-December, 1-3.
17. Gartner. (2015). Gartner Says Business Intelligence and Analytics Leaders Must Focus on Mindsets and Culture to Kick Start Advanced Analytics. Gartner Business Intelligence & Analytics Summit 2015, 14-15 October 2015, Munich, Germany. Retrieved from https://www.gartner.com/newsroom/id/3130017
18. Gartner. (2016). Gartner Survey Reveals Investment in Big Data Is Up but Fewer Organizations Plan to Invest. Gartner Business Intelligence & Analytics Summit 2016, 10-11 October 2016, Munich, Germany. Retrieved from https://www.gartner.com/newsroom/id/3466117
19. Goodall, H. L. (2000). Writing the new ethnography. Lanham, MA: AltaMira.
20. Günther, W. A., Rezazade Mehrizi, M. H., Huysman, M., & Feldberg, F. (2017). Debating big data: A literature review on realizing value from big data. Journal of Strategic Information Systems, 26, 191-209.
21. Hammersley, M., & Atkinson, P. (1983). Ethnography: principles in practice. New York, NY: Tavistock.
22. Hayes, B. (2014). Big Data Relationships. Blog. Big Data & Analytics Hub. Retrieved from http://www.ibmbigdatahub.com/blog/big-data-relationships
23. Infochimps. (2013). CIOs & Big Data: What Your IT Team Wants You to Know. Whitepaper. Retrieved from http://www.infochimps.com/resources/report-cios-big-data-what-your-it-team-wants-you-to-know-6/
24. Kumar, S. (2017). How to deal with big data/data lake failures in 2017.
25. Laaksonen, S. M., Nelimarkka, M., Tuokko, M., Marttila, M., Kekkonen, A., & Villi, M. (2017). Working the fields of big data: Using big-data-augmented online ethnography to study candidate–candidate interaction at election time. Journal of Information Technology & Politics, 14(2), 110-131.
26. Laney, D. (2001). 3D Data Management: Controlling Data Volume, Velocity and Variety. Applications Delivery Strategies, META Group (now Gartner). Retrieved from http://blogs.gartner.com/doug-laney/files/2012/01/ad949-3D-Data-Management-Controlling- Data-Volume-Velocity-and-Variety.pdf

27. Lazer, D. et al. (2009). Computational Social Science. Science vol. 323, pp. 721-723.
28. LeCompte, M. D. & Preissle, J. (1993). Ethnography and qualitative design in educational research (2nd ed.). San Diego, California: Academic Press, Inc.
29. Leinweber, D. (2007). Stupid data miner tricks: overfitting the S&P 500. The Journal of Investing, 16(1), 15-22.
30. Madden, R. (2010). Being ethnographic: A guide to the theory and practice of ethnography. London, England: Sage Publications.
31. Malinowski, B. (1922). Argonauts of the Western Pacific. London: Routledge and Kegan Paul.
32. Markus, L. (2015). New games, new rules, new scoreboards: the potential consequences of big data. Journal of Information Technology, 30(1), 58-59.
33. Maxwell, C. R. (2013). Accelerated Pattern Recognition, Ethnography, and the Era of Big Data. In B. Jordan (Ed.), Advancing Ethnography in Corporate Environments. Challenges and Emerging Opportunities (pp. 175-192). Walnut Crest, CA: Left Coast Press.
34. Mead, M. (1943). Coming of Age in Samoa: A Study of Adolescence and Sex in Primitive Societies. Harmondsworth: Penguin.
35. Mustafi, J. (2016). Natural Language Processing and Machine Learning for Big Data. In B. S. P. Mishra, S. Dehuri, E. Kim, and G-N., Wang (Eds.), Techniques and Environments for Big Data Analysis. Parallel, Cloud, and Grid Computing (pp. 53-74). Studies in Big Data 17. Switzerland: Springer.
36. Netflix Media Center. (2013). Netflix Declares Binge Watching is the New Normal. Retrieved from https://media.netflix.com/en/press-releases/netflix-declares-binge-watching-is-the-new-normal-migration-1
37. Purli, A. (2007). The web of insights: The art and practice of webnography. International Journal of Market Research, 49, 387-408.
38. Rossman, G. B., & Rallis, S. F. (2003). Learning in the field: An introduction to qualitative research. London: Sage.
39. Silverman, D. (2000). Doing Qualitative Research. A Practical Handbook. Thousand Oaks, CA: Sage.
40. Silverman, D. (2001). Interpreting qualitative data (2nd ed.). London: Sage.
41. Wang, T. (2016a). Why Big Data Needs Thick Data. Retrieved from https://medium.com/ethnography-matters/why-big-data-needs-thick-data-b4b3e75e3d7
42. Wang, T. (2016b). The human insights missing from big data. TEDxCambridge. Retrieved from https://www.ted.com/talks/tricia_wang_the_human_insights_missing_from_big_data?utm_campaign=BeepBeepBites%20-%20Nieuwsbrief&utm_source=hs_email&utm_medium=email&_hsenc=p2ANqtz--7oPMYWkbR5qOYKPstYMAsHEGbE6QbX-JomT640MphOUn6HVSsFpVNuB-FjTJyhYnW1gtI6
43. Watson, H. J. (2014). Tutorial: big data analytics: concepts, technologies, and applications. Communications of the Association for Information Systems, 34(1), 1247-1268.
44. White, K. L. (2009). Meztizaje and remembering in Afro-Mexican communities of the Costa Chica: Implications for archival education in Mexico. Archival Science, 9, 43-55.
45. Whitehead, T. L. (2004). What is Ethnography? Methodological, Ontological, and Epistemological Attributes. Ethnographically Informed Community and Cultural Assessment Research Systems (EICCARS) Working Paper Series. Cultural Ecology of Health and Change (CEHC). Retrieved from http://www.cusag.umd.edu/documents/workingpapers/epiontattrib.pdf