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A study on significant aspects of big data analytics and internet of things with special reference to governance, development and sustainability measures and avenues in present context

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Abstract: Big Data (BD), with its potential to provide valuable insights for improved decision-making, has recently piqued the interest of academics and practitioners alike.Big Data Analytics (BDA) is quickly becoming a popular method that many businesses are adopting in order to extract useful information from big data.Organizations view the analytics process, which includes the deployment and usage of BDA tools, as a tool to increase operational efficiency, even though it has strategic potential for generating new revenue streams and gaining competitive advantages over competitors.Some of the drivers bridging the worlds of data, people, and things are recent advances in computing capabilities, increases in data transparency and open data sources, rise in IOT (Internet of Things), and smartphone device adoption.Because of the increased availability of heterogeneous and complicated data, new analytics methodologies are required.The existence of large volume, high velocity, and high variation in such complex datasets or big data, defined in a variety of domains, is typically characterized by the presence of large volume, high velocity, and high variety.Depending on the application context, this data could be generated by a machine or by a human.Autonomous systems, such as robotic facilities in production systems, sensors such as RFID tags in supply chain contact points like warehouses and retail, environmental/weather related sensors, streaming sources like wearables, and so on, can all contribute to machine generated data.Human-generated data can come from a variety of sources, including social media participation, mobile phone usage, online forums, search/purchase actions, and so on.

Keywords: Big Data Analytics, Autonomous systems, data transparency, robotic facilities

Introduction:

Analytics apps have already begun to have a tangible impact on businesses (Chen et al. 2012). These topics have been the subject of several recent editorials. Baesens et al. (2016), for example, recognized big data's disruptive influence and identified some of its novel applications, including online-to-offline commerce, proactive customer support, and IoT connected autos. Pick et al. (2017) examined the use of location analytics for decision support in geographic phenomena (e.g., location-based services) with societal applications such as recognizing patterns of information diffusion, criminality, and disease. Chen et al. (2012) went on to talk about wide application areas such science and technology, smart health and well-being, and security and public safety. We discuss a few big data applications in this paper, such as lifestyle, disaster relief, energy and sustainability, vital infrastructure, and so on, that show promise for having a social influence through analytics.We provide a basic paradigm for comprehending big data applications for societal impact research (Fig. 1).The three concentric circles indicate a) data and infrastructure, b) big data analysis and interpretation techniques, and c) domains of application.The essential building element for producing big data applications is data, as well as the infrastructure required to acquire, store, and process it.The innermost circle represents this.Infrastructure refers to the gear and software required for big data processing, and it can be located on-site in a data center or in the cloud.Various cloud-based technologies that are used as virtual big data clusters, such as Amazon Web Services (AWS), Google Cloud Platform, and Microsoft Azure, have become more stable over time and are a viable option if establishing a localized data center is prohibitive for reasons such as cost, cluster maintenance, information security, and so on.Traditional relational databases (e.g., Oracle, SQL Server, Teradata) or NoSQL (schema-less) databases (e.g., HBase, Cassandra), as well as key-value based (e.g., Redis, Riak, MemcacheDB), document-based (e.g., MongoDB, CouchDB, Couchbase), and graph-based systems (e.g., MongoDB, CouchDB, Couchbase (e.g., Neo4J, OrientDB).Big data processing is usually done in environments like Hadoop and Apache Spark.While Hadoop uses divide-and-conquer operations like Map and Reduce to speed up data processing, Spark uses RDD (Resilient Data Dataset) as a fundamentally different data structure abstraction for distributed collections of data objects that can be operated in parallel on different nodes of the cluster to achieve better computational efficiency than Map Reduce operations.

The analytical approaches are highlighted in the middle layer.To make sense of the data, several machine learning, visualization, and network analytics approaches can be used.Deep Learning, also known as Deep

Neural Nets, is another new method that is gaining a lot of attention in the industry and scientific world.Many standard machine learning algorithms can be outperformed by Deep Learning approaches such as convolutional neural nets and recursive neural nets.The implementation and even the choice of analytical techniques that might be employed for analysis are clearly influenced by the big data environments defined in the innermost layer.Finally, the outer circle denotes a societally significant location where various data analytic methodologies could be used to generate value.In the sections that follow, we'll go through some of the areas of societal relevance that can benefit from big data applications.

Applications for Societal Impact:

Healthcare:

Healthcare spending accounts for about 17% of US GDP, according to reports from the World Health Organization (WHO) and the US Department of Health and Human Services (HHS).Despite this spending, the US healthcare system is not among the best in the world.Fragmentation of care, a lack of care coordination and continuity, bad lifestyle choices, a lack of interoperable data and systems, and other issues could all be leading to inefficiencies and poor outcomes (Gupta and Sharda 2013; Gupta et al. 2013).More patient and healthcare data is now available at hospitals because to the rising usage of Electronic Health Record (EHR) technologies, which can be used for functions beyond than standard medical billing applications.When data from diverse points in time and geography is combined, data analytics can reveal useful insights.When EHR data is linked with lifestyle data, care coordination data (e.g., continuity of care records), claims data, and Patient Health Records (PHR), a patient's 360-degree view of health can be developed (Pickering et al. 2015).Social and network analytics, sensor (IoT driven) informatics for disease prevention, and image informatics for improved diagnosis and detection are examples of areas where IS researchers can make a significant contribution to future healthcare systems.In this special issue, we give a brief overview of these subjects and associated works.

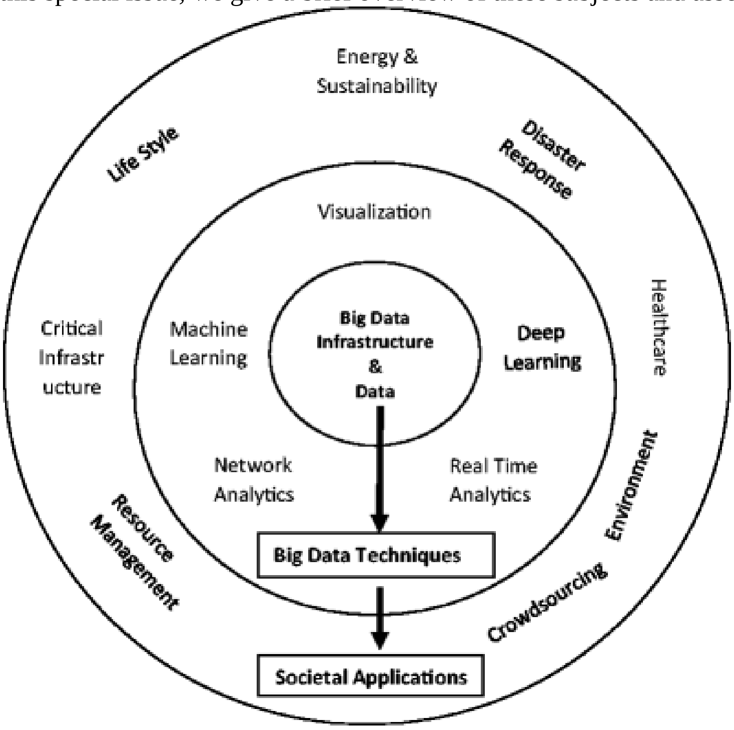

Figure to show framework for societal applications of big data

Network analytics can aid in the understanding of disease patterns such as the spread of new pandemics. In applications such as influenza outbreaks and smoking side effects, social network technologies have shown to be effective. Applying network analytics techniques to free-flowing social media data can help separate the features and nature of underlying networks, which can aid with not only clinical decision-making but also resource allocation and policy-making. Furthermore, the healthcare industry generates a constant flow of data. A stream is, for example, the data that is recorded for each patient at a hospital on a regular basis. The analysis of such data necessitates the use of stream analytics. The exact patterns in the occurrences may suggest impending outcomes, such as the health of an organ such as the heart or lungs. Kalgotra et al. (2017) give an example of how such data should be arranged to make analytics easier. They also use data from an electronic medical record (EMR) system to show how tobacco users' health progresses in specific diseases compared to non-tobacco users, demonstrating the application of their data organization strategy. Some of the findings are surprising; many diseases progress in the same way in tobacco users and non-users. Sensors in healthcare have opened up a slew of new research prospects for analytics applications in sectors that previously relied solely on observational data that was often limited (e.g., mobility data) or self-reported data that could be skewed (e.g. self-reported injuries). Wilkerson et al. (2016), for example, show how inertial movement units (IMUs or sensors) can be used in sports. They use accelerometers to objectively and accurately capture individual football players' movement data throughout the season and link that data with the students' medical records to offer recommendations for measures to help prevent injuries. Such approaches could also be used to hazardous occupational situations, where improvements in workflow procedures or the addition of an integrated sensor-based mobile technology that drives providing suggestions or recognizing performance patterns could be achieved (Wilkerson et al. 2018). Finally, imaging recognition allows IS researchers to experiment with the next generation of analytics techniques, such as deep learning and reinforcement learning. Recent advances in the processing powers of graphical processing units (GPUs) and in-memory capabilities have fueled a surge in novel methodologies like deep learning for better specificity and sensitivity, as well as automatic feature extraction. Depending on the task at hand, many forms of deep neural nets can be employed. Recurrent neural nets, for example, can be used to analyze streams of data like social media data, while convolutional neural networks can be used to process 2D and 3D images (Rav et al. 2017). Gruetzemacher and Gupta (2016) show how a large database of annotated CT scans was used to train deep nets for cancer nodule detection using a huge collection of annotated CT scans. Functional magnetic resonance imaging (fMRI) for neuroscience applications, larger cancer data sets, and applications in the marketing realm that rely on image sharing could all benefit from more research.

Lifestyle:

The focus of healthcare, particularly in North America, is shifting from reactive to proactive.Much of the prior healthcare analytics research, for example, focused on claims data in order to help healthcare practitioners gain a better knowledge of the services provided.According to a research on health IT conducted by the Robert Wood Johnson Foundation (2014), 80 percent of health outcomes are linked to factors outside than traditional health care, such as behavioral and economic factors.Given that clinical services can only control 20% of health outcomes, the focus in health management is changing to improving an individual's overall lifestyle rather than only when he or she is a patient (Bresnick 2016).When lifestyle data is combined with EHR data, clinicians can recommend suitable lifestyle management techniques to clients in order to improve their personal health and, as a result, reduce hospitalization.Fitzgerald (2015) singles out Intermountain Healthcare as a trailblazer in its attempts to harness the power of data analytics to improve population health by combining lifestyle and EHR data.The increasing proliferation of mobile and emerging big data technologies hold enormous promise for empowering individuals to take control of their personal well-being through effective lifestyle management.Furthermore, as previously said, wearable sensors for medical and lifestyle purposes have expanded the volume, velocity, and variety of data, allowing for analytics to enhance population health (Kankanhalli et al. 2016).Andreu-Perez et al. (Andreu-Perez et al. 2015) suggest a number of interesting unique study directions that can aid in understanding and improving healthy lifestyles.Lifestyle-oriented research could alternatively concentrate on a persuasion computing paradigm, in which technology is utilized to influence human behavior.Personal assistants like Amazon Alexa, Google Home, and others are used to provide information and recommendations when a user requests it.These same tools might theoretically be utilized to make proactive lifestyle suggestions.Analytics or a recommendation engine could be used to drive the feedback loop.Future research could focus on the integration of mobile computing, persuasive computing, and analytics-driven decision making as mobile computing becomes a prominent and pervasive technology.Traditionally, analytics has been the missing piece.Khanal et al. (2014), who used persuasive technology to reduce medical errors, and Fukuoka et al. (2011), who demonstrated in an experiment how virtual communities enhance accessibility through mobile phones and how they might help control type-2 diabetes through lifestyle modifications.Integrative research like this could help with drug or program adherence problems.This will also aid in identifying elements that encourage users to stay in the program and impediments that threaten its long-term viability.Given how much of social media communication is text-based; research may focus on demonstrating how topic modeling can be used to mine text for prominent themes in a given context.Aggarwal and Wang (2011) provide a solid survey-based summary of different methodologies that can be used to mine text data for social networking applications.

Several foundations have urged for collaborative collaborations between healthcare providers, educators, corporate leaders, and other stakeholders to integrate data from various sources in order to promote mental and physical health.With an aging population, there are unique ways for data on day-to-day caregiving processes to be gathered and relayed to healthcare experts so that suitable measures for caregivers can be recommended (Adler 2015).The Centers for Disease Control and Prevention (CDC) and the CDC Foundation have recently made city and neighborhood data for over 500 cities in the United States online, resulting in some surprising conclusions (Wojcik 2017) that would have been impossible to comprehend in the past without such data.The social impact of such coordinated initiatives provides the required and suitable resources to assist communities who are in desperate need.Researchers face a number of difficulties, including a lack of access to demographic and health data.RJWF has created a Health Data for Action (HD4A) effort in partnership with other partners with similar interests, with the goal of improving population health through good lifestyle and a health culture (Hempstead 2017).While claims data is a good place to start for gaining valuable insights, the addition of data from EHRs, socioeconomic conditions, lifestyle, wearable fitness tracking, and the Internet of Things (IoTs) opens up a plethora of research opportunities for general health management, such as determining what data is critical for population health management, developing mechanisms for predicting health risk based on integrating diverse data sources, and prescribing meaningful interventions to manage health risks.Such efforts can have a huge impact on the public's ability to make healthy lifestyle choices on a daily basis, whether or not they are guided by a healthcare expert.

Critical Infrastructure:

The Department of Homeland Security has identified sixteen vital infrastructures that require protection and resilience.Chemicals, commercial facilities, communications, critical manufacturing, dams, defense, emergency services, energy, financial services, food&agriculture, government facilities, healthcare, information technology, nuclear reactor & system, transportation system, and water & waste water system (Presidential Policy Directive-21 (PPD-21, 2017).Intrusion detection based on dynamic decision rules, anomaly detection, Supervisory Control and Data Acquisition (SCADA) system protection, and other applications based on big data and analytics could be used to secure these resources.The use of analytics to safeguard and improve smart grids is a solid example of such an application.Smart grids have become increasingly significant in modern energy or electrical systems, resulting in remarkable transformation and tremendous research, development, and investment prospects (Department of Energy report on the Future of Smart Grid 2015).According to the World Economic Forum, more than $7.6 trillion in investment will be required over the next 25 years to repair, modernize, and expand global power infrastructure (Astarloa et al. 2015).Despite its bright future, smart grid technology faces numerous challenges, including accurate load flow prediction from renewable assets, efficient distribution control, effective information about and management of power delivery and critical peak loads, and the optimal balance of availability, efficiency, reliability, and costs (Department of Energy report on The Future of Smart Grid 2015).To address these issues, further research is needed on how to best employ smart grids, given that customer demand differs geospatially at different times of the day, month, and year.Future research could focus on determining the optimum conceptual architecture for analyzing data from smart grids that generate vast amounts of data from smart meters, SCADA systems, and other databases.To identify customer groups, we must investigate the aggregated structure of the data, summarizing and visualizing energy usage and patterns by census tract and tapestry segment.Based on this study, decision support systems can be constructed to determine which geographical locations will deliver the biggest reduction in essential peak consumption using dynamic pricing schemes.Individual and corporate users would benefit from such data analytics systems in monitoring their energy usage and encouraging sustainability efforts.Researchers can also utilize this information to examine other location-based services, such as utility infrastructure recovery following natural catastrophes and storms.

Environment, Energy, and Sustainability:

Researchers and practitioners alike are paying attention to sustainability.While environmental sustainability is tied to phenomena such as climate change, economic sustainability refers to managing the complete corporate value chain in an economically sustainable manner.Ryoo and Koo (2013) conducted an empirical investigation to discover that environmental performance is a significant predictor of organizational economic success.Only recently have studies been published that use analytics to solve this problem.Hertel and Wiesent (2013), for example, propose an analytics approach with a decision model for IS investments that promotes a company's energy and economic sustainability.This is one of the approaches that IS researchers interested in long-term economic sustainability might take.Within the healthcare industry, the United States' blood system can be considered as an example of a system that displays fundamental features of sustainability.Hurricanes Harvey, Irma, and Maria, as well as other recent disasters, have shown that the blood supply chain is not immune to disasters.Various analytics methodologies could be used to investigate donor prediction, supply chain disruption issues, blood flow system networks, and so forth.In a similar vein, RAND Corporation's recent study report assesses sustainability (Mulcahy et al. 2016).A sustainable blood system is one that can: (a) maintain or increase acceptable safety standards for blood and related products, (b) uniformly serve a wide range of clinical applications, and (c) meet blood or related blood product demand in a timely way without putting patient health at risk (Mulcahy et al. 2016).Analytics plays a critical role in ensuring smooth operations while reacting to typical market changes while also being able to accept disruptive changes caused by natural catastrophes, pandemic breakouts, terrorism-related incidents, and other occurrences.The system's resilience has been demonstrated in the aftermath of major catastrophes such as 9/11 in 2001, the Sandy Hook shooting in 2012, and the Orlando nightclub shooting in 2016.Several of these places experienced an increase in blood supply demand over the course of a few hours.Such calamities put a pressure on the local supply chain.Approaches based on network analytics could aid in the evaluation of successful strategies for dealing with such situations.Studies by Simonetti et al. (2014) and Osorio et al. (2015) demonstrate the benefit of analytics in estimating and regulating supply demand levels in a complex supply chain system such as the United States blood system.

Current difficulties and long-term solutions are being examined through the use of analytics in other industry categories as well.Food related infections and outbreaks, for example, have been demonstrated to have closely matched characteristics using visual analytics by Ebel et al. in the food safety industry (2016).There are several applications for analytics in detecting foodborne pathogens and health outbreaks.While Google Flu Trends, one of the first algorithms for detecting flu outbreaks based on user search queries, was initially very accurate in 2008, it later turned out to miss flu trends by as much as 140 percent in 2013, owing to, among other things, prevention-focused search searches (McAfee and Brynjolfsson 2012). This analytics application demonstrates both the potential for analytics applications to use user-generated data (e.g., search queries) to predict a phenomenon (e.g., flu outbreaks) as well as the caveat that such applications can have on user behavior (e.g., prevention-focused search queries), which can negatively impact prediction metrics.

Crowdsourcing and Disaster Relief:

Geo-mobile technologies, particularly the utilization of social media platforms on these technologies, have made it far easier than ever before for disaster-stricken people and communities to call out for support in disaster emergencies (Poblet et al. 2017).Humanitarian aid and disaster management organizations and platforms, on the other hand, can respond to important situations by using analytic solutions based on crowdsourced data to deliver much-needed help and resources to individuals in need (Gao et al. 2011).During Hurricane Sandy in 2012 and the earthquake in Nepal in 2015, examples of crowdsourced data were noticed.In terms of data collection, analytics solutions rely on both passive and active data sources by utilizing the community as data reporters.Raw data created by individuals through position sensors (e.g., GPS receivers) in mobile devices by simply carrying and utilizing these devices are considered passive data sources.Active data sources, on the other hand, rely on the crowd's Bpower to generate data and process information iteratively to provide unstructured (e.g., tweets, photos, and videos) and semi structured data (in some circumstances) (e.g., geotags, hashtags).In recent years, research and experience have shown promise for a few disaster response platforms.For example, Ushahidi (Hiltz et al. 2011), a system that has been deployed internationally in Kenya, Mexico, Afghanistan, and Haiti, focuses on creating a real-time crisis map using disparate data sources, including crowdsourced data, which is then used by disaster relief organizations to mobilize aid.Geo Commons (Gao et al. 2011) is a data visualization tool that offers temporal analysis and is focused on disaster relief cooperation.Researchers at the University of Tokyo employed a classification technique to examine real-time tweets to develop a spatiotemporal model for earthquake detection with a high probability of up to 96 percent (Sakaki et al. 2010).

Disaster relief research can benefit from crowd sourced data.Text mining techniques, for example, can be developed to solve data quality and trustworthiness difficulties in present research.Similarly, utilizing location analytics, mechanisms for identifying patterns of information diffusion in crowdsourced applications (e.g., Waze) can be applied to disaster relief scenarios (Pick et el., 2017).In terms of methodologies, the previously mentioned new computational AI techniques, such as Deep Learning, offer novel ways to improve prediction performance on big data sources like crowdsourced data.According to Fang et al study, .'s IoT technologies are also being used in early warning systems (2015).By applying location analytics in a new context, another significant IoT application, telematics (Karapiperis et al. 2015), which is disrupting the car insurance market, can be used to improve disaster relief systems.

Organizational Resource Management:

Organizations are continuously working to improve their processes by implementing tactics that are both efficient and effective.Analytics play a critical role in enhancing several aspects of a company's value chain activities (Bedeley et al. 2018).Abbasi et al. (2016) concentrate on research opportunities at the crossroads of big data features, the information value chain, and prominent IS research traditions.Any company, for-profit or not-for-profit, may benefit from good analytics-based insights to develop differentiation strategies and make educated decisions that bring value to their stakeholders.Models, methodologies, typologies, domains, and criteria that contribute to successful business analytics implementations in enterprises have been proposed in previous research (Chen et al. 2012; Evangelopoulos et al. 2012; Wixom et al. 2013; Yeoh and Koronios 2010).The World Bank's Poverty and Social Impact Analysis (PSIA) is a versatile analytical approach for assessing the distributional and social implications of policy reforms on the well-being of various groups of people, notably the poor and most vulnerable (World Bank 2015).PSIA can use both quantitative and qualitative methodologies before and after a policy change.The end result, perhaps, will be increased policy efficacy and greater national debate.In addition, policies and initiatives may be held to a higher standard of accountability and openness.According to Stimmel (2014), many countries are unable to generate enough energy efficiently and must rely on highly polluting fuels to meet basic demands.Collecting and analyzing data on the sort of energy they consume, as well as the health consequences, can help these countries become more aware of broader issues and adopt energy-sustainable intervention programs to enhance general health.These are excellent opportunities for researchers to cooperate with government and non-governmental organizations (NGOs) on proper analytics methodologies to aid in the identification of acceptable reforms and/or initiatives that can aid developing countries.In their viewpoint article, Loebbecke and Picot (2015) look at how digitization and big data analytics (BDA) mechanisms transform business and society.They also discuss how digitization and BDA may affect employment, particularly in the context of cognitive work.They identify five mechanisms via which digitalization and BDA complement and replace labor in different ways depending on the industry sector and work process.They advocate for more study to assist address the impact of this technology tsunami, given the benefits and drawbacks of each and a lack of understanding.

Conclusion:

Connectivity between diverse data sources is frequently required in innovative big data and analytics solutions.This raises serious ethical and privacy concerns.Regulations and policy compliance must be respected while also demanding data integration, data misuse, and misinterpretation in order to address major societal issues.In this paper, we look at a variety of big data and analytics methodologies that might be used to investigate social concerns.We've highlighted a few significant elements that were influenced by the pieces in this special issue.Healthcare, lifestyle, vital infrastructure, environment, energy and sustainability, disaster response, crowdsourcing, and resource management are examples of specialized societal uses.For a discernible societal impact, significant future analytics-driven research is required in each of these domains.

References:

[1]. Abbasi, A., Sarker, S., & Chiang, R. H. L. (2016). Big Data Research in Information Systems: Toward an Inclusive Research Agenda Journal of the Association for Information Systems, 17(2), i – xxxii.

[2]. Adler, (2015) Bringing the technology revolution to caregiving. RWJF Report. http://www.rwjf.org/en/culture-of-health/2015/09/bringing_the_technol.html, Retrieved March 2017.

[3]. Aggarwal, C. C, & Wang, H., (2011). Text mining in social networks social network data analytics (pp. 353–378): Springer.

[4]. Andreu-Perez, J., C. C.Y. Poon, R. D. Merrifield, S. T. C.Wong and G. Z. Yang, "Big data for health," in IEEE Journal of Biomedical and Health Informatics, vol. 19, no. 4, pp. 1193–1208, July 2015.

[5]. Astarloa, B., Critchlow, J., & Miller, M. (2015). The future of electricity attracting investment to build tomorrow’s electricity sector. World economic. Forum, 2015.

[6]. Baesens, B., Bapna, R., Marsden, J. R., & Vanthienen, D. (2016). Transformational issues of big data and analytics in networked business. MIS Quarterly, 40(4), 807–818.

[7]. Bedeley, R., Ghoshal, T., Iyer, L. S., & Bhadury, J. (2018). Business analytics and organizational value chains: a relational mapping. Journal of Computer Information Systems, 58(2), 151–161. https://doi.org/10.1080/08874417.2016.1220238.

[8]. Besaleva, L. I., & Weaver, A. C. (2016). Applications of social networks and crowdsourcing for disaster management improvement. Computer, 49(5), 47–53. https://doi.org/10.1109/MC.2016.133.

[9]. Bresnick, J. (2016). BSmart Big Data is Key to Population Health, Value-Based Care^, Healthcare Analytics, healthitanalytics.com/news/smart-big-data-is-key-to-population-health-value-based-care, retrieved: August 20, 2017.

[10]. Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. MIS Quarterly, 36(4), 1165–1188.Department of Energy (2015) The Future of Grid: Evolving to meet America’s need (report prepared by New West Technologies).

[11]. Ebel, E. D., Williams, M. S., Cole, D., Travis, C. C., Klontz, K. C., Golden, N. J., & Hoekstra, R. M. (2016). Comparing characteristicsof sporadic and outbreak-associated foodborne illnesses, UnitedStates, 2004-2011. Emerging Infectious Diseases, 22(7), 1193–1200. https://doi.org/10.3201/eid2207.150833

[12]. Evangelopoulos, N., Zhang, X., & Prybutok, V. R. (2012). Latent semantic analysis: Five methodological recommendations. European Journal of Information Systems, 21, 70–86.

[13]. Fang, S., Xu, L., Zhu, Y., Liu, Y., Liu, Z., Pei, H., &Zhang, H. (2015). Anintegrated information system for snowmelt flood early-warning based on internet of things. Information Systems Frontiers, 17(2),321–335. https://doi.org/10.1007/s10796-013-9466-1.

[14]. Fitzgerald, M. (2015).When health care gets a healthy dose of data. MITSloan Management Review.

[15]. Fukuoka, Y., Kamitani, E., Bonnet, K., & Lindgren, T. (2011). Real-time social support through a mobile virtual community to improvehealthy behavior in overweight and sedentary adults: A focus groupanalysis. Journal of Medical Internet Research, 13(3), e49. https://doi.org/10.2196/jmir.

[16]. Gao, H., Barbier, G., & Goolsby, R. (2011). Harnessing the crowd sourcing power of social media for disaster relief. IEEE Intelligent Systems, 26(3), 10–14. https://doi.org/10.1109/MIS.2011.52.

[17]. Gruetzemacher, R., Gupta, A., (2016) Using Deep Learning for Pulmonary Nodule Detection & Diagnosis, Twenty-secondAmericas Conference on Information Systems (AMCIS 2016), San Diego.

[18]. Gupta, A., & Sharda, R. (2013). Improving the science of healthcare delivery and informatics using modeling approaches. Decision Support Systems, 55(2), 423–427.

[19]. Gupta, A., Li, H., & Sharda, R. (2013) Should I send this message? Understanding the impact of interruptions, social hierarchy and perceivedtask complexity on user performance and perceived workload. Decision Support Systems, 55(1), 135–145.

[20]. Gupta, A., Kumaraguru, P., Castillo, C., & Meier, P. (2014). Tweet Cred: Real-time credibility assessment of content on twitter. In L. M.Aiello & D. McFarland (Eds.), Social informatics. SocInfo 2014.Lecture notes in computer science, vol 8851 (pp. 228–243). Cham: Springer. https://doi.org/10.1007/978-3-319-13734-6_16.

[21]. Harrison, C., Jorder, M., Stern, H., Stavinsky, F., Reddy, V., Hanson, H., & Balter, S. (2014). Using online reviews by restaurant patrons to identify unreported cases of foodborne illness — New York City, 2012–2013. Morbidity and Mortality Weekly Report (MMWR), 63(20), 441–445.

[22]. Hempstead, (2017). B New effort will give researchers access to valuable health datasets. RWJF Report. http://www.rwjf.org/en/culture-ofhealth/2017/04/effort-will-give-researchers-access-to-healthdatasets.html, Retrieved August 20, 2017.

[23]. Hertel, M., & Wiesent, J. (2013). Investments in information systems: Acontribution towards sustainability. Information Systems Frontiers, 15(5), 815–829. https://doi.org/10.1007/s10796-013-9417-x.

[24]. Hiltz, S. R., Diaz, P., &Mark, G. (2011). Introduction. ACM Transactions on Computer-Human Interaction, 18(4), 1–6. Doi: https://doi.org/10.1145/2063231.2063232 https://energy.gov/oe/activities/technologydevelopment/grid-modernization-and-smart-grid last Visited, Sept 5th, 2017 https://www.smartgrid.gov/files/Read_Ahead_Document_-_Central_Region_Workshop.pdf, last visited: Sept 5th 2017.

[25]. Kankanhalli, A., Hahn, J., Tan, S., & Gao, G. (2016). Big data and analytics in healthcare: Introduction to the special section.Information Systems Frontiers, 18(2), 233–235. https://doi.org/10.1007/s10796-016-9641-2.

[26]. Karapiperis, D., Birnbaum, B., Brandenburg, A., Castagna, S., Greenberg, A., Harbage, R., & Obersteadt, A. (2015). Usage-Based Insurance and Vehicle Telematics: Insurance Market and

[27]. Regulatory Implications. National Association of Insurance Commissioners & The Center for Insurance Policy and Research, (March), 1–80. Retrieved from http://www.naic.org/documents/cipr_study_150324_usage_based_insurance_and_vehicle_telematics_study_series.pdf

[28]. Loebbecke, C., & Picot, A. (2015) Reflections on societal and businessmodel transformation arising from digitization and big data analytics: A research agenda. Journal of Strategic Information Systems, 24(3), 149–157. https://doi.org/10.1016/j.jsis.2015.08.002.

[29]. Ludwig, T., Reuter, C., & Pipek, V. (2015). Social haystack: Dynamicquality assessment of citizen-generated content during emergencies. ACM Transactions on Computer-Human Interaction, 22, 17), 1–17), 27. https://doi.org/10.1145/2749461.

[30]. McAfee, A., & Brynjolfsson, E. (2012). Big data: The management revolution.Harvard Business Review, 90(10), 60–6, 68, 128. Retrievedfrom http://www.ncbi.nlm.nih.gov/pubmed/23074865

[31]. Mulcahy, Andrew, A., Kapinos, K., Briscombe, B., & Uscher-Pines, L.(2016). Toward a Sustainable Blood Supply in the United States: An Analysis of the Current System and Alternatives for the Future. Retrieved from http://www.rand.org/pubs/research_reports/RR1575.html

[32]. Osorio, A. F., Brailsford, S. C., & Smith, H. K. (2015). A structured review of quantitative models in the blood supply chain: A taxonomic framework for decision-making. International Journal of Production Research, 53(24), 7191–7212. https://doi.org/10.1080/00207543.2015.1005766.

[33]. Pickering, B.W., Dong, Y., Ahmed, A., Giri, J., Kilickaya, O., Gupta, A., Gajic, O., & Herasevich, V. (2015). The implementation of clinician designed, human-centered electronic medical record viewer in theintensive care unit: A pilot step-wedge cluster randomized trial. International Journal of Medical Informatics, 84(5), 299–307.

[34]. Plachkinova, M., Vo, A., Bhaskar, R., & Hilton, B. (2018) A conceptual framework for quality healthcare accessibility: A scalable approach for big data technologies. Information Systems Frontiers, 20(2).https://doi.org/10.1007/s10796-016-9726-y.

[35]. Poblet, M., Garcia-Cuesta, E., & Casanovas, P. (2017). Crowd sourcing roles, methods and tools for data-intensive disaster management. Information Systems Frontiers, 1–17. https://doi.org/10.1007/s10796-017-9734-6.

[36]. Ryoo, S. Y., & Koo, C. (2013) Green practices-IS alignment and environmental performance: The mediating effects of coordination. Information Systems Frontiers, 15(5), 799–814. https://doi.org/10.1007/s10796-013-9422-0.

[37]. Sakaki, T., Okazaki, M., & Matsuo, Y. (2010). Earthquake shakes twitter users: Real-time event detection by social sensors. Proceedings ofthe 19th international conference on World Wide Web, 851–860.https://doi.org/10.1145/1772690.1772777.

[38]. Schuff, D., Corral, K., St. Louis, R. D., & Schymik, G. (2018). Enabling self-service BI: A methodology and a case study for a model management warehouse. Information Systems Frontiers, 20(2). https://doi.org/10.1007/s10796-016-9722-2.

[39]. Siering, M., Koch, J.-A., & Deokar, A. V. (2016). Detecting fraudulent behavior on crowd funding platforms: the role of linguistic andcontent-based cues in static and dynamic contexts. Journal of Management Information Systems, 33(2), 421–455. https://doi.org/10.1080/07421222.2016.1205930

[40]. Trivedi, N., Asamoah, D.A., & Doran, D. (2018) keep the conversationsgoing: engagement-based customer segmentation on online socialservice platforms. Information Systems Frontiers, 20(2). https://doi.org/10.1007/s10796-016-9719-x.

[41]. Wilkerson, G. B., Gupta, A., Allen, J. R., Keith, C.M., & Colston, M. A.(September 2016). Utilization of practice session average inertialload to quantify college football injury risk. Journal of Strength & Conditioning Research, 30(9), 2369–2374.

[42]. Wilkerson, G. B., Gupta, A., & Colston, M. A. (2018). Mitigating sportsinjury risks using internet of things and analytics approaches. Risk Analysis. https://doi.org/10.1111/risa.12984.

[43]. Wixom, B. H., Yen, B., & Relich, M. (2013). Maximizing value from business analytics. MIS Quarterly Executive, 12(2), 111–123.Wojcik, O. (2017). The 500 cities project: New data for better health RBWJ Report. http://www.rwjf.org/en/culture-of-health/2017/02/the_500_cities_proje.htm, Retrieved August 20, 2017.

[44]. World Bank (2015). Poverty and Social Impact Analysis (PSIA). http://www.worldbank.org/en/topic/poverty/brief/poverty-and-socialimpact-analysis-psia

[45]. Yeoh, W., & Koronios, A. (2010). Critical success factors for business intelligence systems. Journal of Computer Information Systems, 50(3), 23–32.

[46]. Zhou, M., Lu, B., Weiguo, F., & Wang, G. A. (2018). Project description and crowd funding success: an exploratory study. Information Systems Frontiers, 20(2). https://doi.org/10.1007/s10796-016-9723-1.