Information Systems Management

ISSN: 1058-0530 (Print) 1934-8703 (Online) Journal homepage: https://www.tandfonline.com/loi/uism20

Exploratory Analysis of Internet of Things (IoT) in Healthcare: A Topic Modelling & Co-citation Approaches

Ramakrishna Dantu, Indika Dissanayake & Sridhar Nerur

To cite this article: Ramakrishna Dantu, Indika Dissanayake & Sridhar Nerur (2020): Exploratory Analysis of Internet of Things (IoT) in Healthcare: A Topic Modelling & Co-citation Approaches, Information Systems Management, DOI: 10.1080/10580530.2020.1746982

To link to this article: https://doi.org/10.1080/10580530.2020.1746982

Published online: 23 Apr 2020.

Submit your article to this journal

Article views: 3

View related articles

View Crossmark data

Full Terms & Conditions of access and use can be found at
https://www.tandfonline.com/action/journalInformation?journalCode=uism20

INFORMATION SYSTEMS MANAGEMENT
https://doi.org/10.1080/10580530.2020.1746982

Taylor & Francis
Taylor & Francis Group

Check for updates

Exploratory Analysis of Internet of Things (IoT) in Healthcare: A Topic Modelling & Co-citation Approaches

Ramakrishna Dantu[a], Indika Dissanayake[b], and Sridhar Nerur[c]

[a]Information Systems and Business Analytics Department, California State University, Sacramento, California, USA; [b]Department of Information Systems and Supply Chain Management, The University of North Carolina at Greensboro, Greensboro, North Carolina, USA; [c]Department of Information Systems & Operations Management, The University of Texas at Arlington, Arlington, Texas, USA

ABSTRACT
Internet of Things (IoT) have made a significant impact in healthcare domain. The purpose of this study is to unravel key themes latent in the academic literature on IoT applications in healthcare. Using topic modeling and author co-citation techniques, we identified five dominant clusters of research. Our results show that research in healthcare IoT has mainly focused on the technical aspects with little attention to social concerns. Our paper provides directions for future research.

KEYWORDS
Internet of things; healthcare; topic modeling; author co-citation; smart health

Introduction

Current technological trends are rapidly transforming organizations into digital businesses that will engage with the world in ways that we cannot yet fathom. Artificial Intelligence (AI), Natural Language Processing (NLP), Blockchain, Cloud-readiness, Internet of Things (IoT), and augmented & virtual reality are some of the technologies at the heart of this revolution. These have serious implications for how organizations evolve their enterprise architecture, plan their IT infrastructure, manage their data from its source to the point at which it is consumed (i.e., data governance), and manage their security/privacy. IoT have been used in a wide range of applications across domains such as food supply chain, transportation and logistics, firefighting, and healthcare (Da Xu et al., 2014). Healthcare IoT rely on an ecosystem that comprises a host of enabling technologies as well as other components such as smart devices, human resources, applications, connectivity, and a design methodology that seamlessly integrates the various elements (Yuehong et al., 2016). This study is an exploratory analysis of the current state of academic research on the application of IoT in the healthcare domain.

The Internet of Things or IoT refer to a network of interconnected objects and devices with embedded software and sensors that facilitate exchange of data and communication between the physical and virtual (i.e., Internet/Cyber) worlds (Zanella et al., 2014). The last few years have witnessed an explosion of data in terms of volume (amount of data), variety (data formats), velocity (speed at which data is generated), and veracity (uncertainty of data). It is estimated that Internet users around the world generate over 2.5 quintillion bytes of data every day (Zicari, 2016). This growth was fueled in no small measure by the proliferation of Internet-based applications and the ubiquity of smartphones, tablets, wearables, smartwatches, and other handheld devices.

IoT rely on the portability and interconnectivity of such devices to provide enormous amounts of real-time data that organizations can harness to derive actionable insights. For instance, Kaiser Permanente used big data analytics, to develop patient management solutions that suggest appropriate interventions at the point of care. When patients visit their primary care physicians for a checkup of, say, knee pain, tools developed using big data proactively alert the physician to recommend screening the patients for cancer (Versel, 2013). Propeller Health (formerly Asthmapolis), a company dedicated to asthma management, focuses more on prevention than on treatment. It uses sensors in asthma inhalers that track environmental conditions such as weather and air quality data. Their sensors record date and time of use, and pair with GPS-enabled devices to track location data. The result is that the providers can identify at-risk asthma patients before an attack occurs (NEJM Catalyst, 2018). Explorys leverages big data to provide tools for clinical support, at-risk patient population management, and cost of care measurement. Explorys' analytics tools help mine data and pinpoint variations among patients and treatments that influence health outcomes. These insights help

CONTACT Ramakrishna Dantu, Ph.D. Ramakrishna.dantu@csus.edu Information Systems and Business Analytics Department, College of Business Administration, California State University, Sacramento, 6000 J Street, Sacramento, CA 95819

© 2020 Taylor & Francis

providers determine more accurate treatment plans for individual patients or patient populations (Mansuri, 2018).

A survey conducted by Accenture Consulting on the Internet of Health Things found that remote patient monitoring (RPM), wellness and prevention, and operations are the three major areas positively impacted by healthcare IoT (Kalis & Wisdom, 2017). According to the survey, about 10% of IT investments by today's healthcare companies is for IoT-based solutions. Similarly, IoT- and patient-generated data can significantly enhance diagnosis, disease management, and treatment processes. Healthcare providers can use big data to detect and devise treatment plans for at-risk patients (Krawiec et al., 2015). IoT are redefining how people connect, interact, and exchange information, transforming practically every industry. Examples of Internet-enabled devices include kitchen appliances such as refrigerators, smart TVs, vending machines, transportation vehicles such as cars, and even biometric devices used for monitoring the heart (e.g., pacemakers) and blood pressure. This list of "things" that are connected continues to grow with more devices being added every day. By 2020, over 20 billion connected things will be in use (Gartner, 2017) and is projected to grow to over 75 billion by 2025 (Statista, 2018). These connected biometric devices are expected to generate more than 20 trillion gigabytes of data by 2025 and will have huge implications for healthcare, particularly in the areas of remote and real-time monitoring of patients, telemedicine, chronic illness management, physician–patient interaction, patient engagement, elderly care, and influencing patient behavior, to name but a few of the growing number of applications. By 2020, 40% of IoT-related technology is estimated to be health-related, constituting a 117 USD billion market that will far exceed any other domain (Bauer et al., 2014). It is conceivable that our lives will change dramatically as IoT realize their fullest potential.

Notwithstanding the current growth of IOT, their application in the healthcare domain is still in its nascent stage. However, over the last few years, there has been a marked increase in the number of articles published, both academic and non-academic, that have studied some form of IoT in healthcare context. Researchers and industry experts have discussed a variety of issues and recurring themes that are latent in this corpus. Unraveling these themes and assessing the extant literature in terms of what has been done so far should be of immense value to academics and practitioners alike. Such an effort would not only help us address current opportunities and challenges in the use of IoT in healthcare but also anticipate what lies ahead. This exploratory study aims to satisfy this need by using text analytics, particularly topic modeling and author co-citation techniques, to explicate dominant themes underlying the existing corpus involving IoT in the healthcare domain. The text analytic technique that we applied revealed five main streams of research – privacy and security, cloud and smart health, wireless network technologies, data, and applications.

Our paper makes several notable contributions to the extant literature on IoT. First, our study is arguably the first to articulate the technical and social perspectives of IoT in the healthcare domain. Second, it uses a combination of bibliometrics (i.e., citations) and text analysis to delineate the key themes that have dominated the conversation on the use of IoT to deliver quality healthcare in a timely manner. Finally, our findings provide a good starting point for researchers to identify current progress and opportunities for furthering the boundaries of knowledge related to IoT in healthcare.

The remainder of the paper is structured as follows. In the next section, we provide a brief overview of healthcare IoT. Next, the research methodology used in this study is described. This is followed by a discussion of the results and an elaboration of the topics identified. The concluding section summarizes our study and provides directions for future research.

Healthcare IoT

Solutions for healthcare problems through IoT have been either applied or proposed in several areas of patient care, including but not limited to monitoring blood glucose levels (Istepanian et al., 2011), blood pressure (Kario et al., 2017), heart rate (Z. Yang et al., 2016), blood oxygen level, body temperature (In, 2014), medication management (Whitmore et al., 2015), rehabilitation systems (Fan et al., 2014), wheelchair management, imminent healthcare solutions, and healthcare solutions using smartphones (Islam et al., 2015). For example, Istepanian et al. (2011) examined continuous, noninvasive monitoring of glucose levels using mobile Internet of Things (m-IoT). Z. Yang et al. (2016) designed and implemented a wearable using cloud-based IoT architecture for monitoring electrocardiogram (ECG). In a research study related to blood oxygen saturation measurement, authors Fu and Liu (2015) proposed an IoT-based near-infrared portable tissue oximeter to measure blood oxygen saturation and heart rate parameters. Islam et al. (2015) provide excellent examples of the growing number of healthcare IoT applications. These include IoT-based language training systems to help children with autism (also see Liang et al. (2011)) as well as other rehabilitation systems (e.g., for smart cities). Furthermore, they list a number of IoT solutions, including hemoglobin detection, peak expiratory flow, abnormal cellular growth, cancer treatment, eye disorder, skin infection, and remote surgery (Islam et al., 2015).

Healthcare is subject to stringent federal laws, and, as a consequence, individuals and organizations are required to comply with policies that safeguard patient information and assure the security and privacy of health data (HealthIT.Gov, n.d.). HIPAA (Health Insurance Portability and Accountability Act) regulations (U.S. Department of Health & Human Services, n.d.), the federal law that protects health information, provides detailed data privacy and security provisions for safeguarding individual medical information (U.S. Department of Health & Human Services, n.d.). While sharing and collecting information using biometric devices can offer benefits such as saving time and allowing proactive intervention, it also increases the risks. In a workshop on Privacy and Security of the Internet of Things hosted by the Federal Trade Commission (FTC) in 2013, members acknowledged the pervasive nature of IoT and the serious privacy and security challenges that these sensors and biometric devices pose (FTC Staff, 2015). However, not all devices are HIPAA regulated and there are oversight gaps between data collected by devices that are HIPAA regulated and those that are not (U.S. Department of Health and Human Services, 2016). To ensure appropriate security and privacy protections, the Commission agreed to enforce laws, educate consumers, and engage with industry, academics, and consumer advocates (FTC Staff, 2015). There have also been calls for built-in security features within IoT biometric devices, for minimizing data transfer and storage, and for new privacy legislation (Laplante et al., 2018).

Adoption of IoT in healthcare can be fostered with better IoT privacy and security features. From a security standpoint, studies have proposed several frameworks consisting of rules, guidelines, protocols, and standards that can enable the implementation of IoT applications in various domains (Ammar et al., 2018; Lin et al., 2017). Given the need for protecting the privacy and confidentiality of patient health information and securing electronic health records, privacy and security aspects of IoT are of considerable interest to both researchers and practitioners. The overall objective of using IoT solutions in healthcare is to facilitate real-time, high-quality patient care. These solutions are particularly helpful to those who do not have immediate access to medical facilities or a physician. IoT solutions typically involve wearable wireless biometric devices or sensors (Darwish & Hassanien, 2011; Gubbi et al., 2013) that are connected over a network. These wireless technologies enable collection and storage of data related to patients, providers, and hospitals, among others, in a cloud environment. Rapid strides in big data analytics now make it possible to analyze large volumes of data in real-time using the cloud-computing infrastructure. Researchers have proposed frameworks for collecting and processing IoT-related big data in a cloud environment (Botta et al., 2016; Cai et al., 2017) and have discussed the attendant challenges and opportunities.

In a recent study, Ng et al. (2018) performed a semantic similarity analysis of IoT in general and identified 10 critical factors, namely, frameworks and challenges, current situation, interactions, security issues, application domains, data management, smart cities, and recommender systems. By focusing on IoT in healthcare, we take a different approach and delve into just one specific domain. Furthermore, we employ topic modeling and author co-citation techniques to identify key research themes latent in the growing body of literature involving IoT-related studies in healthcare. We further distinguish our work by identifying research gaps, opportunities, and challenges in IoT-based healthcare with a social and technical perspective, as evident in the extant literature.

Methodology

Data collection

We performed a keyword search of the Web of Science database to retrieve abstracts of articles related to studies on IoT in the healthcare domain. The search term[1] yielded 819 articles. Of these, only 661 articles included abstracts that were used in our study for analysis. As can be seen in Figure 1, the number of IoT-related articles published in the healthcare domain grew at a very slow rate until 2013 and increased dramatically thereafter.

Out of the 661 abstracts extracted, 578 had keywords. Figure 2 shows the frequency distribution of keywords that appear in at least five of the articles. Subsequently, we extracted cited references for these articles and obtained the frequency with which they appear in various sources (see Figure 3). To understand research trends more clearly, we graphed the frequency distribution of a few prominent keywords across time (see Figure 4).

It is apparent from an examination of the keywords and the types of journals in which the articles appeared

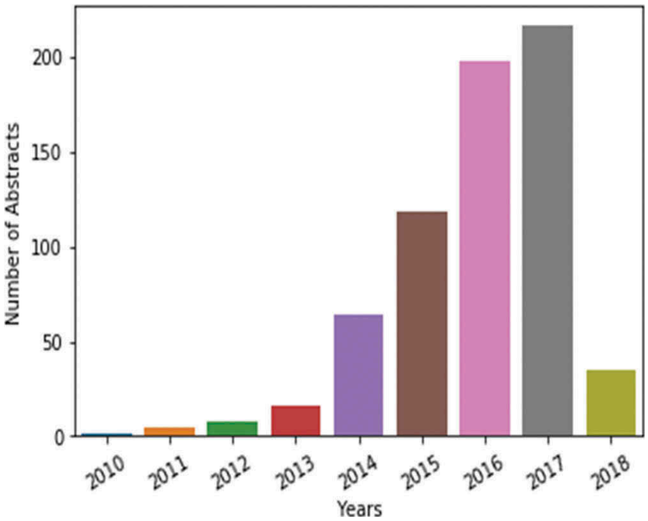

Figure 1. Number of IoT-healthcare articles per year.

that technical aspects have dominated the discourse on IoT in healthcare. Based on the analysis, the social aspects seem underrepresented in the extant literature.

Topic modeling

Topic Modeling is a Natural Language Processing (NLP) technique that has been widely used to unravel the hidden thematic structure of a corpus (Blei, 2012). The hidden topic structure comprises "topics, per-document topic distributions, and the per-document per-word topic assignments" (Blei, 2012). There are several algorithms available for performing topic modeling, with the popular ones being Latent Dirichlet Allocation (LDA), Latent Semantic Analysis (LSA), and Non-negative Matrix Factorization (NMF).

LDA model is an unsupervised algorithm that assumes that each document in the corpus exhibits multiple topics to varying extents, and each word in each document is generated from an underlying topic distribution across the vocabulary of the corpus (Blei et al., 2003). LDA is best suited to situations in which each document represents multiple topics (Lee et al., 2010). Specifically, the algorithm is a generative process that starts with a random assignment of a topic to each word in each document. It then iteratively assigns weights to each document-word-topic based on current values of the topic proportion for that document and the probability of the word for that topic (Blei, 2012; Grus, 2015). Thus, the algorithm endeavors to generate a joint sample from two underlying distributions – one that involves the proportion of topics for each document and the other that represents the probability distribution of topics across the words in the corpus (Grus, 2015). LSA is a vector-based dimensionality reduction technique that maps and reduces higher dimensional vectors of word frequencies in the corpus to a smaller number of dimensions (Hofmann, 2001). NMF is an unsupervised algorithm that performs dimensionality reduction. The technique derives latent semantic space in which each axis captures the base topic of a particular document cluster, and each document is represented by combining base topics (W. Xu et al., 2003).

LDA was chosen as the main method to identify latent themes in the abstracts. Prior to performing LDA, the abstracts were pre-processed to reduce the inherent noise in text data. The first step was to normalize the text by converting it to lower case. Next, we removed stopwords, punctuation, and digits. Stopwords refer to frequently occurring words (e.g., "the," "a," "is,"

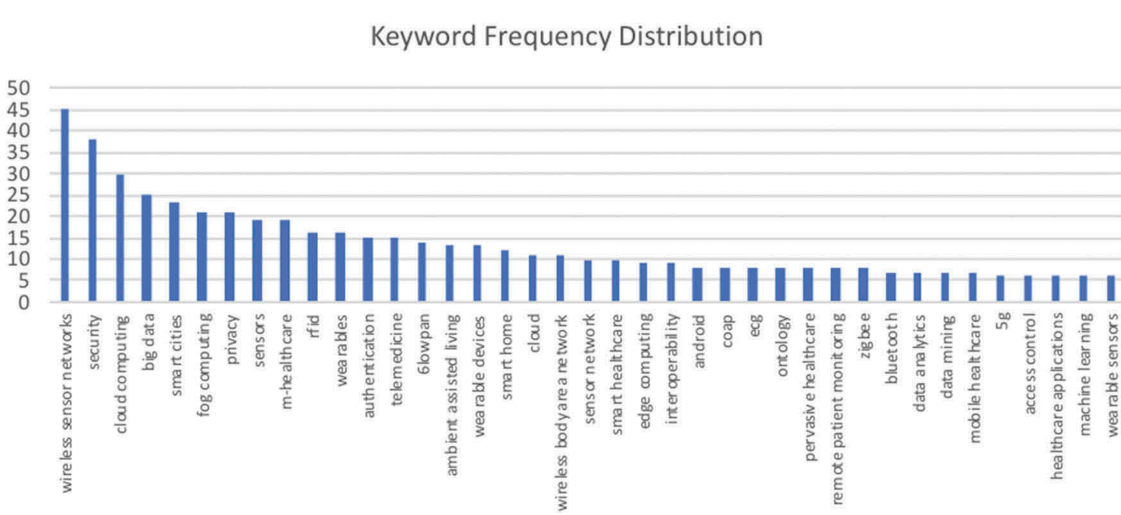

Figure 2. Frequency distribution of keywords.

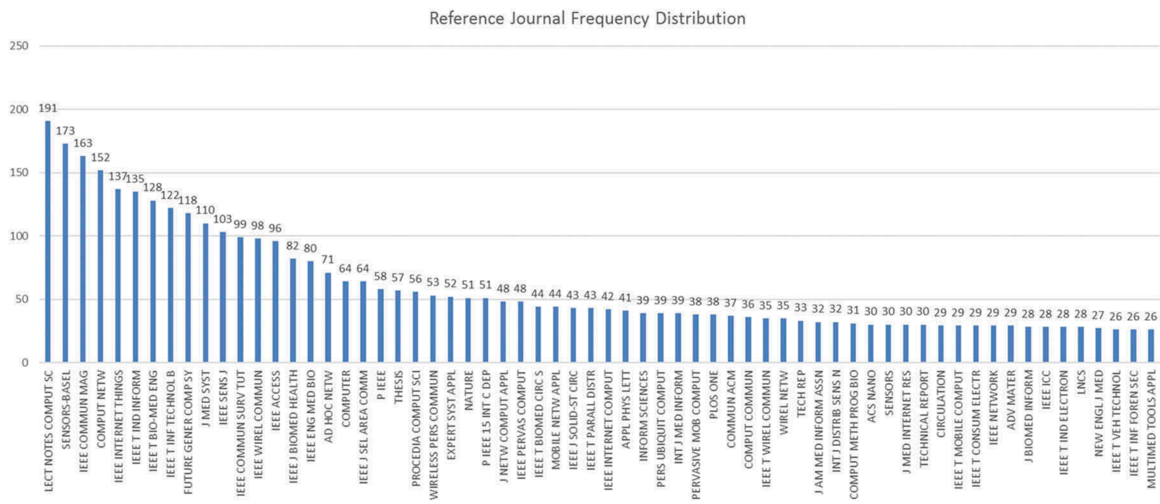

Figure 3. Frequency distribution by reference journal source.

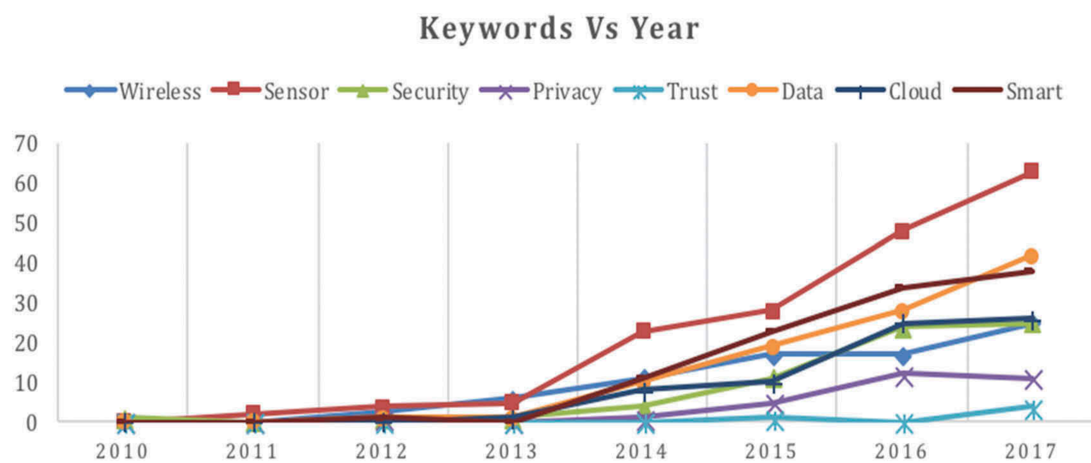

Figure 4. Keywords studied across the years.

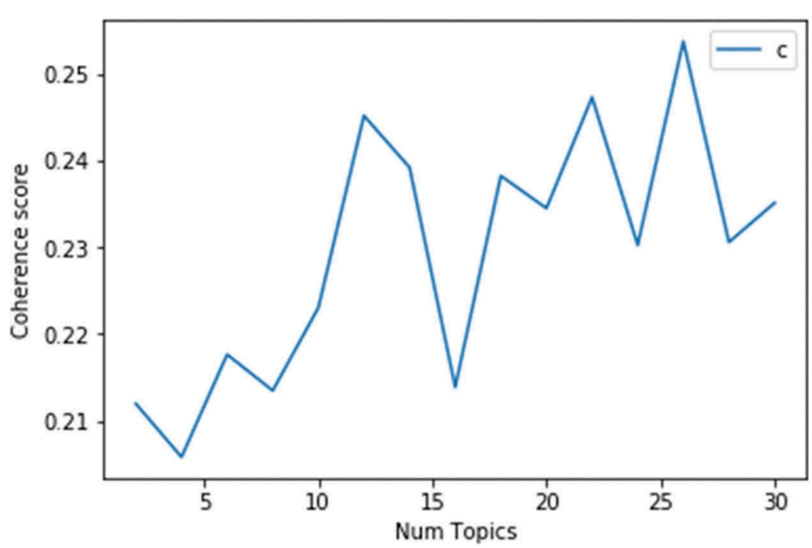

Figure 5. Number of topics using coherence score.

"of") that are likely to diminish interpretability of the results. Likewise, punctuations and digits are eliminated because they add no value to the analysis. The final preprocessing step involved lemmatization. Researchers often use stemming (i.e., reducing words to a root form) or lemmatization (i.e., reducing to a base dictionary form or a lemma). In this study, we used lemmatization as the form it reduces to is more interpretable and meaningful (Manning, Raghavan, & Schütze, 2008). The lemmatized text was then subjected to LDA.

LDA requires us to specify the number of topics to be extracted, which is a key parameter of the analysis and often not easy to determine. A very high number could lead to more meaningless topics while a low number could limit important results (Diegmann et al., 2018). In this study, we used the LDA algorithm available in Python's Scikit-Learn module to retrieve 50 topics. An examination of coherence graph (see Figure 5), which shows the optimum number of topics, indicates that our corpus consisted of 27 dominant topics. Therefore, we proceeded to extract 27 topics using LDA implemented in MALLET[2] (Machine Learning for Language Toolkit) from the University of Massachusetts at Amherst (McCallum, 2002). Subsequently, we identified five emerging categories across these 27 topics based on similarities and overlap among them. Finally, using the probability distribution of abstracts across the topics, we extracted five articles that contribute the most to each of the 27 topics, giving us a total of 135 articles. Two of the authors independently read these 135 articles and ratified the identified topics. The same authors independently evaluated commonalities among these topics and identified a few dominant clusters. Then, the results were compared and the reasoning for the categorization was discussed. The process was repeated until five dominant clusters emerged and consensus was reached.

In order to have a comparative analysis of different algorithms, the research team also performed topic modeling of the articles using LDA, NMF, and LSA algorithms and came up with 5, 8, 13, and 15 topics for each of the algorithms. The results generated by these algorithms were compared to find similarities and identify the most meaningful topics. Three independent raters reviewed these results and agreed that LDA provides the best results.

Co-citation analysis

Co-citation is defined as "an occurrence in which two papers are cited together by another paper" (Wang et al., 2016). The technique was introduced by Henry Small in 1973 (Small, 1973). The underlying assumption of this approach is that two articles are more likely to be semantically related if they are jointly cited more frequently (Wang et al., 2016). The general concept of co-citation was built based on bibliographic coupling, which was introduced by Kessler in 1963 (Kessler, 1963). Bibliographic coupling occurs between two papers if they share one or more common references. The main drawback of bibliographic coupling is that it provides a static view of relationships, as the references in a paper never change. Since citations to a paper, and therefore co-citations between papers, are likely to change over time, an analysis of co-citations can reveal changing semantic relationships. Thus, co-citation patterns have been identified as a more appropriate measure to explore developments of various fields (Ng et al., 2018).

Co-citation analysis has been widely used in various fields to identify subject similarity, intellectual structure, and changes in scientific trends. For example, Ng et al. (2018) adopted co-citation analysis to identify the intellectual core and structure of IoT. Nerur et al. (2008) applied co-citation analysis to investigate the conceptual foundations of the strategic management field. Walter and Ribière (2013) examined 10 years of research in knowledge management theory and practice using citation and co-citation analysis. Sircar et al. (2001) used author co-citation analysis to argue that object-oriented development is an architectural change that differs from the traditional structured approach when it comes to analyzing and designing systems.

There are three main types of co-citation analyses, namely, document co-citation analysis (DCA), author co-citation analysis (ACA), and journal co-citation analysis. In this study, we have focused on ACA. It must be noted that our analysis of authors is based on their co-citations within the corpus that was downloaded and not based on *all* co-citations they received across all their publications. This should not detract from our findings, as the co-citations within the corpus should be a fair representation of their similarities.

Results

Topic modeling

We identified five overarching and dominant clusters from 27 topics identified through topic modeling approach discussed earlier. These clusters highlight the topics of privacy and security, wireless network technologies, IoT applications (e.g., design/development of device/applications in healthcare, such as patient monitoring systems), data, and smart health and cloud. Furthermore, our findings suggest that these clusters are not isolated and unique. Instead, they overlap indicating several studies that fall at the intersection of these clusters. For example, some studies focused on Radio Frequency Identification (RFID) authentication mechanisms involving aspects of wireless network technologies and security. To further validate our clusters, we used a software tool called VOSViewer (see www.vosviewer.com) that has been widely used for visualizing and understanding scientific domains (Van Eck & Waltman, 2010). Figure 6 shows the term map generated by VOSViewer based on the co-occurrence of words in our corpus. As can be seen, the cluster compositions are quite consistent with the topics that we abstracted from the results of our topic modeling analysis.

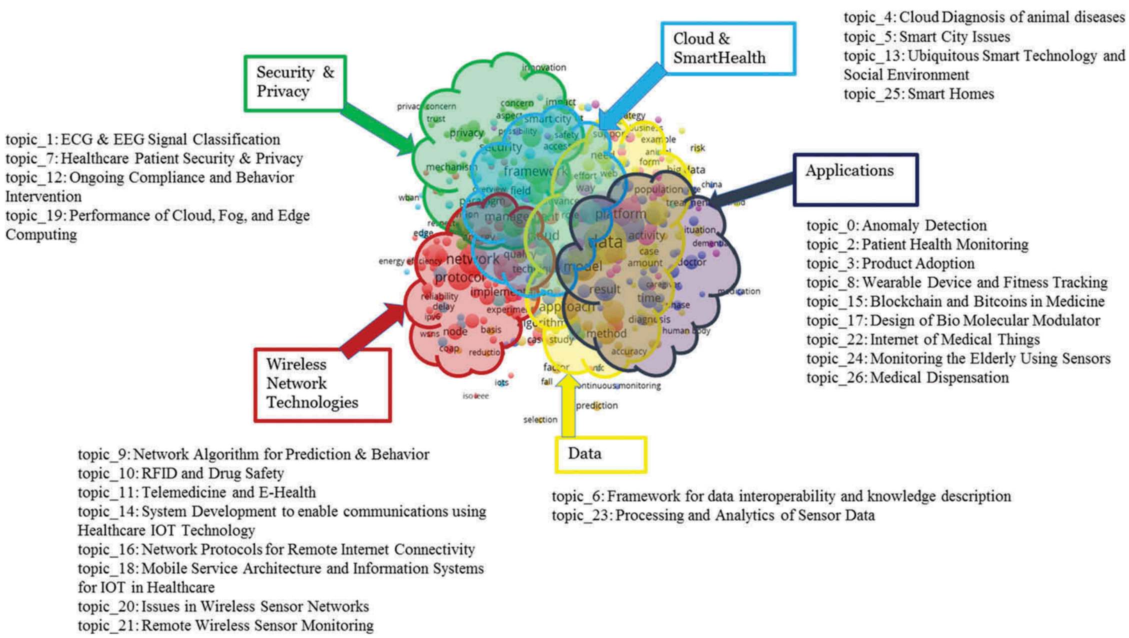

Figure 6. Topic clusters.

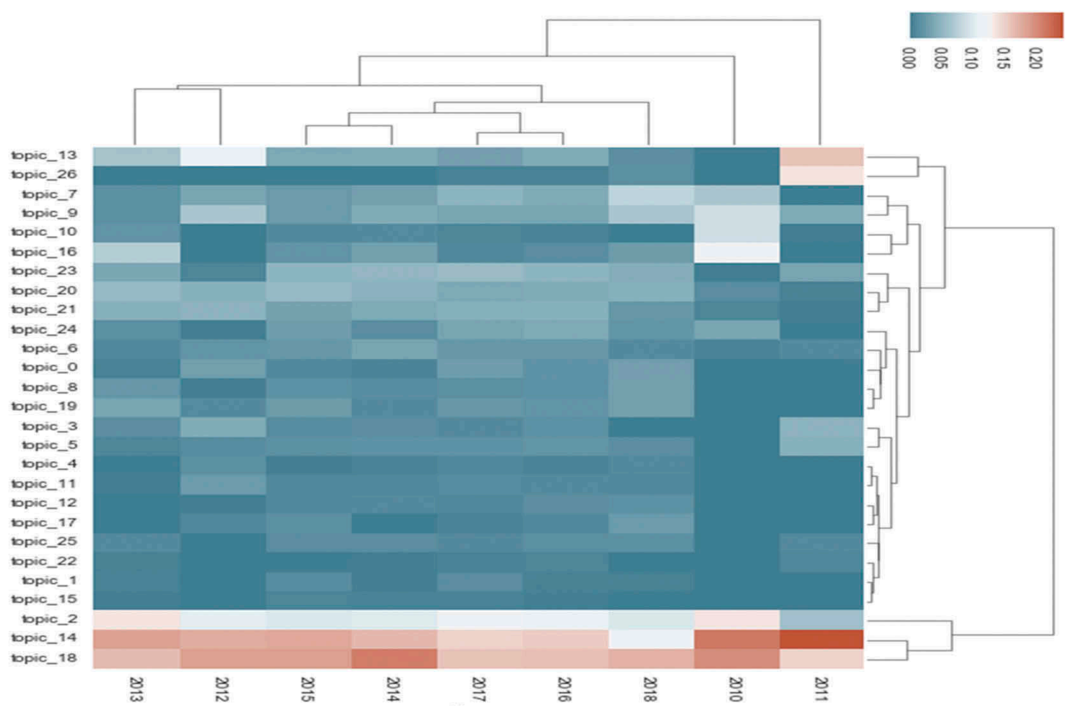

Figure 7. Dominant topics across years.

We further generated a cluster map, which shows dominant topics across years (see Figure 7). For example, mobile service architecture and information system development to enable communication using healthcare IoT technology (topic 14 and 18) are related topics and were dominant almost in all the years (in 2018, topic_14 seems to be slightly less dominant). A brief description of the topic clusters is given below. The titles for these topics are listed in Figure 6.

Topic cluster 1: security & privacy

It is clear that security and privacy have become critical factors for the development and application of IoT in any domain (Ng et al., 2018). The need to address these concerns is even more important in healthcare, as it deals with highly sensitive medical data. Based on our analysis, the core articles in this cluster focus on several topics related to privacy and security of medical data and biometric devices, including RFID authentication mechanisms, medical data security, and privacy. Security, privacy concerns, trust, safety, and mechanism are some of the keywords commonly associated with this cluster.

RFID is one of the key technologies used in IoT deployment in the healthcare domain. For example, RFIDs are used in wearable biometric devices such as patient monitoring systems to identify and access patients' medical records in real-time. Some research questions explored in this area include proposing and developing secure mutual RFID authentication schemes and protocols (e.g., elliptic curve cryptography-based authentication protocols) that are suitable for healthcare applications (An et al., 2016; He & Zeadally, 2015). This area also partially overlaps with the wireless network technologies cluster.

Protecting the privacy and confidentiality of patient data is at once critical and challenging. Privacy violations could hurt not only the patients but also healthcare firms (Sahi et al., 2018). These violations could lead to legal battles, erode patients' trust, and threaten the long-term viability of healthcare firms. Some examples of research topics explored in this area include proposing blind cloud storage to protect privacy through maintaining anonymity of patients' medical records (Sarkar et al., 2017), and advanced encryption methods such as attribute-based encryption (Qin et al., 2017). We have noticed that privacy and confidentiality also partially overlap with the data cluster.

Topic Cluster 2: Data

The application of IoT in healthcare generates massive amounts of medical data every day. This opens up a window of research opportunities in the areas of collecting, storing, handling, and analyzing medical data, improving data quality, and safeguarding data privacy and security. Some common keywords that appeared in this cluster include data, big data, method, approach, and algorithm.

Health IoT applications commonly use patient wearable biometric devices, mobile, and social media applications to collect data. Research related to data collection process include topics such as improving validity of data (P. Yang et al., 2018), accurately and precisely taking measurements in real-time (Yean et al., 2016), and collecting and aggregating data using different sources such as mobile, wearables, and social media applications (Deng et al., 2015). Not surprisingly, researchers have also focused their attention on effectively handling big data, which naturally overlaps with topics related to the cloud & smart health. Dominant topics in the big data realm included evolving an appropriate architecture to handle large-scale data (e.g., Hadoop-based medical emergency management system) (Din et al., 2015) as well as facilitating the sharing of large and diverse real-time data among all the biometric devices within a healthcare system (Rathore et al., 2017). Furthermore, although IoT are a major source of big data, it is not easy to process this data because they come in a variety of formats. Innovative solutions may be required to process such heterogenous data, particularly for medical devices in cloud-based environments (B. Y. X. Xu et al., 2014).

Analyzing healthcare data is particularly challenging. Several studies have focused on clustering and classification methods as well as on algorithms suitable for medical data. Examples include classification schemes to group human behaviors and daily activities into different categories (Kwon et al., 2017), and mechanisms to detect patients' activities and events (e.g., sitting, falling) (Tran et al., 2017).

Topic cluster 3: applications

This cluster includes the broad category of healthcare-related IoT applications, which includes the design and development of equipment and/or their components. Some common key words that appeared in this cluster are monitoring, diagnosis, treatment, medication, and caregiver. Patient monitoring devices and applications (mobile, wearable biometric devices, and web-based applications) are some of the main topics investigated in this cluster. Researchers have primarily focused on the design and development of biometric devices used for proactively detecting symptoms and monitoring the physical and cognitive functions of patients. Typical examples include sensing systems for facilitating long-term mobility of the elderly (Nishida et al., 2016), detecting early symptoms of dementia in elderly people living alone (Ishii et al., 2016), detecting aging-related neurological diseases (Sun et al., 2016), detecting voice disorders (Ali et al., 2017), monitoring foot pressure wirelessly (Malvade et al., 2017), detecting vital signals (Li, 2017), and biometric devices for pregnant women to check their and fetus vitals (Kumaresh et al., 2016). In addition to patient monitoring systems, IoT applications are also used in preventive management systems, and for detecting diseases such as zika, diabetes, and chikungunya (Sareen et al., 2017; Sood & Mahajan, 2017). From a commercial perspective, companies like Amazon, Google, and Apple are developing IoT-based biometric devices and the necessary infrastructure to facilitate diagnoses and treatment of illnesses. For instance, Amazon provides IoT solutions through its Amazon Web Services (AWS) that enable IoT device management, remote tracking, and monitoring of patient health applications. The data thus collected can be processed and analyzed for diagnosis and treatment (Marketplace, n.d.). Similarly, the Apple Watch can help in monitoring glucose levels as well as the symptoms related to depression and Parkinson's disease (Econsultancy, 2019). ResearchKit, an open-source framework from Apple, allows the development of powerful apps for medical research. Fitbit and Apple's ResearchKit collect vast amounts of biometric data that researchers use for suggesting nutrition, fitness, and treatment options to patients (Dimitrov, 2016).

IoT adoption is another area in this cluster that has received scant attention. Researchers on IoT adoption have investigated facilitators of and barriers to patients' adoption of healthcare IoT (Alaiad & Zhou, 2017), and have also explored ways to facilitate IoT adoption by urban poor communities (Roy et al., 2016).

Topic cluster 4: wireless network technologies

IoT applications and wearable devices use wireless sensors to remotely collect and transmit data. This cluster discusses topics including but not limited to wireless sensor network standards and protocols for healthcare applications (Ismail et al., 2014), network mobility management (NEMO) (to provide location-independent continued connectivity for patients) (Shahamabadi et al., 2016), and power efficiencies (e.g., energy autonomous wearable healthcare biometric devices) (Takamiya, 2015). Some common key words that appeared in this cluster include node, network, protocol, energy efficiency, and ipv6. Yan et al. (2015) proposed and validated a wearable wireless sensor network for detecting anomalies of health conditions such as tachycardia, arrhythmia, and myocardial infarction.

Topic cluster 5: cloud & smart health

This cluster includes research related to cloud & fog computing, and smart health applications such as IoT applications used in monitoring patients living in smart homes, in which home appliances are enabled with sensors and communication technologies to collect and transmit data to help facilitate the needs of the household members (Aldossari & Sidorova, 2018). Quite understandably, topics in this cluster overlap with research themes in the IoT application cluster that we discussed earlier. For example, Yang et al. (2014) proposed and implemented an IoT-based smart health application that is capable of integrating intelligent medical box, intelligent pharmaceutical packaging, and wearable biomedical sensor devices to provide enhanced user experience and more efficient service. Some common key words that appeared in this cluster are cloud, fog, computing, smart, and home. Tyagi et al. (2016) proposed a cloud-based conceptual framework for IoT applications in the healthcare domain. Bibani et al. (2016) proposed a prototype to demonstrate how an IoT healthcare application can be designed and developed in hybrid cloud/fog environment.

Standards and protocols for interacting with cloud technology are critical, particularly in the public cloud. These can potentially achieve greater flexibility. For instance, one study found that organizations that spend a greater share of their infrastructure investment on the public cloud (as a ratio when compared to hybrid cloud or private infrastructure) have better delivery rates against published project schedule (Taylor, 2017). As different types of IoT devices emerge, standardization of protocols becomes a key factor. IoT and Cloud Computing are intricately connected because of the massive amounts of data generated by IoT. Standardization (e.g., communication, security, data, protocols) in IoT can mitigate interoperability issues and enable the diffusion of IoT technologies (Xu et al., 2014).

Co-citation analysis

The VOSviewer software that was described earlier allows us to perform an author co-citation analysis. Only lead authors with a minimum of 12 citations were included in the analysis. This yielded a total of 64 authors whose co-citation frequencies were used in the analysis. VOSviewer extracted seven clusters. However, we dropped the seventh cluster, as it contained only two authors. The clusters and network diagrams show lead authors who tend to work in similar thematic areas. As evident from the frequency distribution of reference journal sources in Figure 4, many of the articles appeared in technical outlets such as computer science, and wireless communication and networks. Figure 8 represents the network diagram from the author co-citation analysis. The clusters of authors were superimposed on the ones identified using topic modeling. This overlay of topic clusters on top of the author co-citation clusters is shown in Figure 9. As can be seen, many scholars conducted research in overlapping areas of topics.

Author cluster 1: wireless network technologies

Authors in this cluster have mainly focused on wireless network technologies and overlapping areas. Jara A.J. is one of the most influential authors in this cluster, and some of his highly cited studies are related to a wireless network application in the healthcare domain. For instance, he proposed an architecture to manage patient's profile based on RFID technology and to provide global connectivity to patient's biometric devices for diabetes therapy management based on

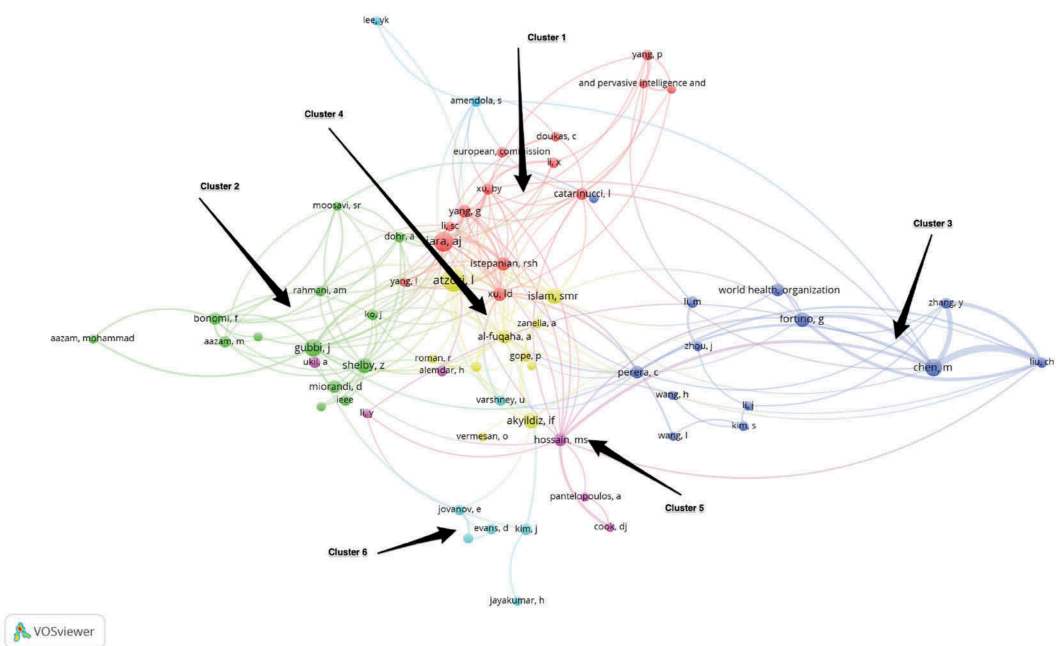

Figure 8. Author co-citation network.

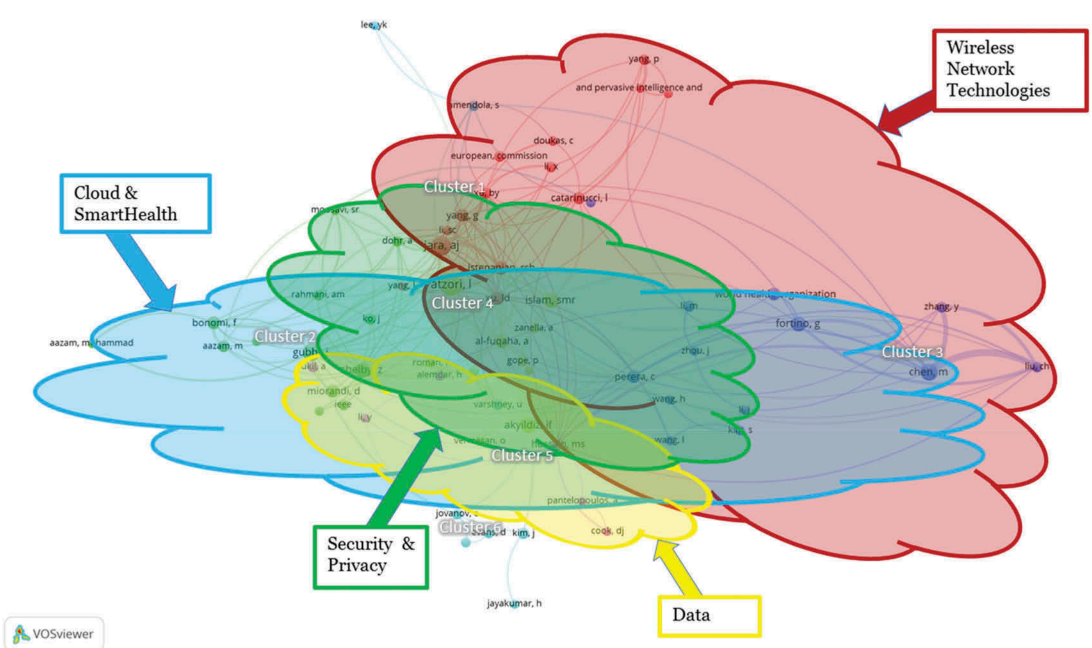

Figure 9. Topic clusters on author co-citation network.

IPv6 over Low-Power Wireless Personal Area Networks (6LoWPAN) technology (Jara et al., 2011). His works also have a significant overlap with Networks security. In a different study, he focused on security and privacy aspects of continuous transmission of vital signs from patients' biometric devices to a remote server (Jara et al., 2012). Catarinucci et al. (2015) proposed a smart hospital system that relies on different technologies, such as wireless sensor network, RFID, and smart mobile, interoperating with each other through a CoAP/6LoWPAN/REST network infrastructure.

Author cluster 2: cloud & smart health

A majority of the authors fall into this cluster and conduct research in the area of cloud and smart technologies. Gubbi is the most cited primary author in this cluster. One of the author's highly cited papers – that was not in our corpus – discusses open challenges and future trends in cloud centric IoT (Gubbi et al., 2013). Aazam's article related to fog computing is another highly cited paper in this cluster.

Author cluster 3: intersection of cloud & smart health and wireless network technologies

In this cluster, Chen M. has appeared as the primary author with most cited papers. The author's area of cited work lies at the intersection of wireless sensor network (Chen et al., 2011) and smart and cloud technologies (Chen et al., 2017). A few studies focused on integrating advanced cloud-based technologies (e.g., big data analytics and cognitive computing) to analyze physiological data gathered through advanced terminal technologies (e.g., smart clothing equipped with sensors) (Chen et al., 2017, 2016). Fortino, the second highest ranked author in this cluster, has also focused on cloud-assisted body area networks (Fortino et al., 2014).

Author cluster 4: IoT-related review studies (overlap with multiple areas)

Studies in this category are mainly devoted to a review of IoT. For example, Atzori, the most cited lead author in this group, has identified four main application domains of IoT research, including transportation and logistics, healthcare, smart environment, and personal and social. Healthcare domain was further categorized into four groups, namely, tracking, identification & authentication, data collection, and sensing. Islam et al. (2015) reviewed IoT-based healthcare technologies, solutions, applications, and platforms. They also analyzed IoT security and privacy features.

Author cluster 5: data

Studies in this category have mainly focused on data-related issues, including privacy and security of data and cloud-based data storage. The most cited primary author, Hossain, has presented a cloud-based industrial IoT enabled framework for health monitoring. Specifically, their approach has focused on collecting healthcare data through mobile and sensors and securely transmitting to cloud for access by healthcare professionals. Several methods (e.g., Signal enhancement, watermarking, and other analytics) were used to reduce clinical error and avoid identity theft (Hossain & Muhammad, 2016). Ukil et al. (2016) have focused on anomaly detection in IoT healthcare analytics.

Author cluster 6: challenges and potential solutions

Many studies in this cluster discuss challenges of healthcare and/or IoT, their potential solutions, and some future research directions. For example, Varshney (2014) classified mobile health challenges into categories from four different perspectives, namely, patients, healthcare professionals, information technology, and applications. Jovanov and Milenkovic (2011) explored opportunities and challenges of body area networks for ubiquitous health monitoring applications.

As per our exploratory analysis (see Figures 2, 3, and 4), most of the articles focused on the technical challenges of IoT. Furthermore, the distribution shown in Figure 4 also reveals that early research on IoT healthcare has largely failed to adopt a sociotechnical systems (STS) (Cavaleri & Obloj, 1993) that takes into account how people, processes, organizational structure, and technology will be affected by the proliferation of IoT in our daily lives.

Our analysis shows that the social challenges of IoT have received very little attention. For instance, technical aspects of security and privacy (e.g., advanced encryption mechanisms and authentication schemes) have been widely investigated but social concerns with regard to security & privacy of all stakeholders (e.g., patients' trust), appear to be understudied. Moreover, ecological impacts (e.g., rare earth metals and toxic chemicals in devices) (Islam et al., 2015), awareness, and training are some other social challenges that have received scant attention. Likewise, the other clusters (e.g., data) favor the technical dimension to social issues. Furthermore, within the technical domain of healthcare IoT, scholars seem to have lavished more attention on wireless network technologies. As can be seen in Figure 2, the most frequent keywords (e.g., wireless sensor networks, RFID, 6lowpan) are related to wireless network technologies.

In order to gain deeper insight into these clusters, we analyzed them with a view to eliciting opportunities, challenges, and research gaps of IoT in healthcare from social and technical perspectives reflected in the current literature. The resulting framework is shown in Table 1.

Contribution and implications

This study employs text-analytic and bibliometric techniques to provide a comprehensive review of the literature on IoT in the healthcare. Specifically, it delineates the field based on extant research and shows what has been investigated thus far and what opportunities lie ahead. Thus, it provides a platform for evolving a roadmap for future research on the transformative potential of IoT in the healthcare domain. Furthermore, it adds to the growing body of review papers that have started using recent advances in text analysis. By combining topic modeling and insights from bibliometric analysis, this study yields perspectives that either technique alone will not be able to provide.

In addition to the aforementioned contributions, the findings generate several insights for practitioners. Our analysis suggests that most of the studies on IoT in healthcare adopt a rather mechanistic, instrumental approach grounded in hard systems thinking (Cavaleri & Obloj, 1993). The advocates of sociotechnical systems (STS) thinking have long argued that an integrated and holistic approach that blends the technical (i.e., hard systems, mechanistic metaphor) with the social dimension (i.e., soft systems thinking, human/stakeholder concerns) is paramount to building work systems that guarantee organization effectiveness while enhancing the quality of human life. An STS perspective that is sensitive to the psychological needs of stakeholders (e.g., patients) and to the empowerment (e.g., training) and active engagement of humans is conspicuously absent from the current discourse. Such an approach would also embrace broader ramifications of IoT, such as ethical and social dilemmas that inevitably ensue when new technologies are introduced. It is apparent that opportunities to research the interplay among IoT, people, processes, and organizational structures abound.

Our study unearths key thematic areas that have dominated the research on IoT in the healthcare domain. It is clear from extant research that organizations in general, and healthcare companies in particular, can derive business value from the use of IoT only if they evolve a scalable and flexible infrastructure, pay attention to data governance, and develop an ecosystem that facilitates processing of massive amounts of diverse data while assuring security and privacy. Any strategy they pursue

Table 1. IoT in healthcare social-technical perspective.

Topic Cluster	Technical	Social
Security and Privacy	Healthcare Patient Security & Privacy • - RFID authentication schemes & protocols • - Advanced encryption mechanism	Healthcare Patient Security & Privacy • - Security and privacy of patient data • Ongoing Compliance and Behavior Intervention
Cloud and Smart Health	Smart City Issues Smart Homes Performance of Cloud, Fog, and Edge Computing Cloud Diagnosis of animal diseases	Ubiquitous Smart Technology and Social Environment
Applications	Anomaly Detection Medical Dispensation Internet of Medical Things Design of Bio Molecular Modulator Blockchain and Bitcoins in Medicine Wearable Device and Fitness Tracking	Patient Health Monitoring Monitoring the Elderly Using Sensors Production Adoption • - IoT adoption by urban poor communities
Data	Processing and Analytics of Sensor Data • - Big data management - Data quality • - Integrating heterogeneous data • - Classification algorithms for healthcare data	Framework for data interoperability and knowledge description
Wireless Network Technologies	Network Algorithm for Prediction & Behavior Remote Wireless Sensor Monitoring Issues in Wireless Sensor Networks Mobile Service Architecture and Information Systems for IOT in Healthcare Network Protocols for Remote Internet Connectivity System Development to enable communications using Healthcare IOT Technology Telemedicine and E-Health ECG & EEG Signal Classification RFID and Drug Safety	• RFID and Drug Safety • - Smart Governance

(e.g., a cloud platform) should strike a balance between the imperative to process both structured and unstructured data in a timely manner and the need to comply not only with current regulations but also with those that are likely to emerge in the future. The broad areas of research that have been undertaken thus far suggest that a holistic approach that encompasses the technological (e.g., technical platform, cloud, data integration and governance, real-time processing), social (e.g., security, privacy, safety, ethical issues), and organizational (e.g., human resources, key performance metrics, alignment with strategy) aspects should drive an organization's IoT strategy.

Conclusions and future research

The Internet is what facilitates the interchange of data among a variety of devices (referred to as "things"), and hence this network is referred to as the "Internet of Things" (i.e., IoT). We are living in an increasingly connected world where physical appliances, autonomous vehicles, drones, wearables, and smart "things" (e.g., homes, phones, watches, televisions, energy meters) equipped with software and sensors can seamlessly integrate the physical and virtual worlds. Cyber-Physical Systems (CPS), which are often associated with IoT, emphasize seamless interactions among physical, digital, and human components. Both CPS and IoT refer to integration of networks of physical devices and computational capabilities, and are poised to transform healthcare delivery through interoperable smart health systems (Greer et al., 2019). It is therefore important to explore research trends and advances in industrial implementation of CPS/IoT technologies (Kim, 2017). Current IoT solutions have their fair share of security and privacy concerns. The evolution of fifth-generation (5 G) networks, which are expected to accelerate the growth in IoT applications, can pose newer challenges (Li et al., 2018), particularly in the realm of healthcare IoT. Research on IoT in healthcare has proliferated in recent years and there is a need for us to understand what has been explored thus far in order to anticipate what challenges and opportunities lie ahead.

Since IoT are rapidly transforming the healthcare industry, our paper focused on the research that has been done in this area. Specifically, this paper explored academic research related to IoT in the healthcare domain. Our preliminary analysis showed that researchers mainly focused on technical aspects and many important social aspects are under investigation. Using topic modeling and co-citation analysis, we identified five main research areas, namely, security & privacy, data, wireless network technologies, cloud & smart health, and applications. Furthermore, we identify social, technical, and organizational challenges apparent in the corpus we studied. Thus, our paper elucidates key research themes and provides a platform for evolving a roadmap for future research on the transformative potential of IoT in the healthcare domain.

As is often the case with any empirical study, our research has some limitations. First, the corpus we used for text analysis contains only academic papers. While this provides insight into research streams being pursued by scholars in the field, it does not allow us to assess how research in academia compares with state-of-the-art in the industry. Future research might examine articles published in the popular press as well as white papers from industry to identify additional research challenges and opportunities in the application of IoT in healthcare. Second, the author co-citation analysis (ACA) carried out in this study uses only lead authors. This is a limitation that is acknowledged in many of the empirical studies that have used ACA (for example, see Nerur et al. (2008)). Finally, we have focused only on the key themes that have dominated the conversation on the use of IoT in healthcare. A deeper analysis of the text, including our topic modeling approach, could reveal peripheral topics that we have not emphasized. Despite these shortcomings, we believe our study is an important step toward understanding what research has been undertaken thus far to transform the delivery and quality of healthcare through IoT. This, in turn, can guide scholars in their efforts to extend the boundaries of knowledge related to the delivery of better healthcare services using biometric devices and sensors that interact with the Internet.

Notes

1. Results: 819 (from Web of Science Core Collection)
2. http://mallet.cs.umass.edu.

Notes on contributors

Ramakrishna Dantu is an Assistant Professor at the California State University, Sacramento. He teaches computer programming classes such as Python and Java for undergraduate students. His research has been published in several national and international conferences such as Americas Conference on Information Systems (AMCIS), Hawaii International Conference on System Sciences (HICSS), and Decision Sciences Institute (DSI). Prior to changing his career to academia, he worked in the IT industry for over 16 years. Some of his teaching and research interests include software development, healthcare IT, analytics, and social media.

Indika Dissanayake is an Assistant Professor of Information Systems and Supply Chain Management at the Bryan School of Business and Economics, University of North Carolina Greensboro. She received her Ph.D. in Information Systems from the College of Business Administration, the University of Texas at Arlington. Her research interests include crowd-sourcing, social media, online health communities, sharing economy, and virtual communities. Her research has been published in the Journal of Management Information Systems, Information & Management, and Journal of the Association for Information Systems.

Sridhar Nerur is the Goolsby-Virginia and Paul Dorman Endowed Chair in Leadership and Professor of Information Systems at the University of Texas at Arlington (UTA). His research has been published in premier outlets such as MIS Quarterly, Strategic Management Journal, Communications of the ACM, European Journal of Information Systems, Information & Management, and IEEE Software. He has served on the editorial boards of the European Journal of Information Systems (EJIS) and the Journal of Association for Information Systems (JAIS). His research and teaching interests include social networks, machine learning/AI/deep learning, text analytics, neuroeconomics, and agile software development.

References

A. W.S Marketplace. (n.d.). *Monitoring of remote patient health applications*. Amazon Web Services. November 20 2019 https://aws.amazon.com/marketplace/solutions/IoT/connected-healthcare-monitoring

Alaiad, A., & Zhou, L. (2017). Patients‘ adoption of WSN-based smart home healthcare systems: An integrated model of facilitators and barriers. *Ieee Transactions on Professional Communication*, *60*(1), 4–23. https://doi.org/10.1109/TPC.2016.2632822

Aldossari, M. Q., & Sidorova, A. (2018). Consumer acceptance of Internet of Things (IoT): Smart home context. *Journal of Computer Information Systems*, 1–11. https://doi.org/10.1080/08874417.2018.1543000

Ali, Z., Muhammad, G., & Alhamid, M. F. (2017). An automatic health monitoring system for patients suffering from voice complications in smart cities. *IEEE Access*, *5*, 3900–3908. https://doi.org/10.1109/ACCESS.2017.2680467

Ammar, M., Russello, G., & Crispo, B. (2018). Internet of things: A survey on the security of IoT frameworks. *Journal of Information Security and Applications*, *38*, 8–27. https://doi.org/10.1016/j.jisa.2017.11.002

An, R., Feng, H., Liu, Q., & Li, L. 2016. Three elliptic curve cryptography-based RFID authentication protocols for Internet of things. In: Barolli L., Xhafa F., Yim K. (eds.)., Advances on Broad-Band Wireless Computing, Communication and Applications. BWCCA 2016. Lecture Notes on Data Engineering and Communications Technologies, vol 2. Springer, Cham

Bauer, H., Patel, M., & Veira, J. (2014). *The Internet of Things: Sizing up the opportunity*. McKinsey & Company http://www.mckinsey.com/insights/high_tech_telecoms_internet/the_internet_of_t_hings_sizing_up_the_opportunity.

Bibani, O., Mouradian, C., Yangui, S., Glitho, R. H., Gaaloul, W., Hadj-Alouane, N. B., Morrow, M., & Polakos, P. 2016. A demo of IoT healthcare application provisioning in hybrid cloud/fog environment. 2016 IEEE International Conference on Cloud Computing Technology and Science (CloudCom).

Blei, D. M. (2012). Probabilistic topic models. *Communications of the ACM*, *55*(4), 77–84. https://doi.org/10.1145/2133806.2133826

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of Machine Learning Research*, *3*(Jan), 993–1022. http://www.jmlr.org/papers/volume3/blei03a/blei03a.pdf

Botta, A., De Donato, W., Persico, V., & Pescapé, A. (2016). Integration of cloud computing and internet of things: A survey. *Future Generation Computer Systems*, *56*, 684–700. https://doi.org/10.1016/j.future.2015.09.021

Cai, H., Xu, B., Jiang, L., & Vasilakos, A. V. (2017). IoT-based big data storage systems in cloud computing: Perspectives and challenges. *IEEE Internet of Things Journal*, *4*(1), 75–87. https://doi.org/10.1109/JIOT.2016.2619369

Catalyst, N. E. J. M. (2018). *Healthcare big data and the promise of value-based care. NEJM Catalyst, 4*(1). Massachusetts Medical Society. November 20 2019 https://catalyst.nejm.org/big-data-healthcare/

Catarinucci, L., De Donno, D., Mainetti, L., Palano, L., Patrono, L., Stefanizzi, M. L., & Tarricone, L. (2015). An IoT-aware architecture for smart healthcare systems. *IEEE Internet of Things Journal*, *2*(6), 515–526. https://doi.org/10.1109/JIOT.2015.2417684

Cavaleri, S., & Obloj, K. (1993). *Management systems: A global perspective*. Wadsworth.

Chen, M., Gonzalez, S., Vasilakos, A., Cao, H., & Leung, V. C. M. (2011). Body area networks: A survey. *Mobile Networks and Applications*, *16*(2), 171–193. https://doi.org/10.1007/s11036-010-0260-8

Chen, M., Ma, Y., Li, Y., Wu, D., Zhang, Y., & Youn, C. (2017). Wearable 2.0: Enabling human-cloud integration in next generation healthcare systems. *IEEE Communications Magazine*, *55*(1), 54–61. https://doi.org/10.1109/MCOM.2017.1600410CM

Chen, M., Ma, Y., Song, J., Lai, C.-F., & Hu, B. (2016). Smart clothing: Connecting human with clouds and big data for sustainable health monitoring. *Mobile Networks and Applications*, *21*(5), 825–845. https://doi.org/10.1007/s11036-016-0745-1

Da Xu, L., He, W, & Li, S. (2014). Internet of things in industries: A survey. *IEEE Transactions on Industrial Informatics*, *10*(4), 2233–2243.

Darwish, A., & Hassanien, A. E. (2011). Wearable and implantable wireless sensor network solutions for healthcare monitoring. *Sensors*, *11*(6), 5561–5595. https://doi.org/10.3390/s110605561

Deng, Z., Yang, P., Zhao, Y., Zhao, X., & Dong, F. 2015. Life-logging data aggregation solution for interdisciplinary healthcare research and collaboration. In 2015 *IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing*, 2315–2320. IEEE.

Diegmann, P., Dreesen, T., Binzer, B., & Rosenkranz, C. (2018). *Journey Towards agility: Three decades of research on agile information systems development*. Thirty Ninth International Conference on Information Systems, San Francisco, 2018.

Dimitrov, D. V. (2016, July). Medical Internet of things and big data in healthcare. *Healthcare Informatics Research*, *22* (3), 156–163. https://doi.org/10.4258/hir.2016.22.3.156

Din, S., Ghayvat, H., Paul, A., Ahmad, A., Rathore, M. M., & Shafi, I. (2015). *An architecture to analyze big data in the internet of things*. In *2015 9th International Conference on Sensing Technology (ICST)*, 677–682. IEEE.

Econsultancy. (2019). 10 examples of the Internet of Things in healthcare. *Internet of things healthcare*, 11 20 2019.

Fan, Y. J., Yin, Y. H., Da Xu, L., Zeng, Y., & Wu, F. (2014). IoT-based smart rehabilitation system. *IEEE Transactions on Industrial Informatics*, *10*(2), 1568–1577. https://doi.org/10.1109/TII.2014.2302583

Fortino, G., Di Fatta, G., Pathan, M., & Vasilakos, A. V. (2014). Cloud-assisted body area networks: State-of-the-art and future challenges. *Wireless Networks*, *20*(7), 1925–1938. https://doi.org/10.1007/s11276-014-0714-1

Fu, Y., & Liu, J. (2015). System design for wearable blood oxygen saturation and pulse measurement device. *Procedia Manufacturing*, *3*, 1187–1194. https://doi.org/10.1016/j.promfg.2015.07.197

Gartner. (2017, February 7). *Gartner says 8.4 billion connected "things" will be in use in 2017, up 31 percent from 2016*. May 30.

Greer, C., Burns, M., Wollman, D., & Griffor, E. 2019. *Cyber-physical systems and Internet of things*. NIST Special Publication, 1900, 202. https://doi.org/10.6028/NIST.SP.1900-202

Grus, J. (2015). *Data science from scratch: First principles with python*. O'Reilly Media, Inc..

Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of Things (IoT): A vision, architectural elements, and future directions. *Future Generation Computer Systems*, *29*(7), 1645–1660. https://doi.org/10.1016/j.future.2013.01.010

He, D., & Zeadally, S. (2015). An analysis of RFID authentication schemes for internet of things in healthcare environment using elliptic curve cryptography. *IEEE Internet of Things Journal*, *2*(1), 72–83. https://doi.org/10.1109/JIOT.2014.2360121

HealthIT.Gov. (n.d.). *HIPAA basics - privacy and security*. The Office of the National Coordinator for Health Information Technology (ONC). November 20 2019 https://www.healthit.gov/topic/privacy-security-and-hipaa/hipaa-basics

Hofmann, T. (2001). Unsupervised learning by probabilistic latent semantic analysis. *Machine Learning*, *42*(1/2), 177–196. https://doi.org/10.1023/A:1007617005950

Hossain, S., & Muhammad, G. (2016). Cloud-assisted Industrial Internet of Things (IIoT) – Enabled framework for health monitoring. *Computer Networks*, *101*, 192–202. https://doi.org/10.1016/j.comnet.2016.01.009

In, Z. L. (2014). Patient body temperature monitoring system and device based on Internet of things. *Chinese Patent*, *103*, 577–688.

Ishii, H., Kimino, K., Aljehani, M., Ohe, N., & Inoue, M. (2016). An early detection system for dementia using the M2 M/IoT platform. *Procedia Computer Science*, *96*, 1332–1340. https://doi.org/10.1016/j.procs.2016.08.178

Islam, S. M., Kwak, D., Kabir, M. H., Hossain, M., & Kwak, K.-S. (2015). The internet of things for health care: A comprehensive survey. *IEEE Access*, *3*, 678–708. https://doi.org/10.1109/ACCESS.2015.2437951

Ismail, N. H. A. B., Hassan, R., & Othman, N. E. 2014. LABC: Local route repair using artificial bee colony algorithm in 6LoWPAN network. In *2014 International Conference on Computational Science and Technology (ICCST)*, 1–5. IEEE.

Istepanian, R. S., Hu, S., Philip, N. Y., & Sungoor, A. (2011). The potential of Internet of m-health Things "m-IoT" for non-invasive glucose level sensing. *Conference proceedings:. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference, 2011*, 5264–5266. Boston, MA, USA. https://doi.org/10.1109/iembs.2011.6091302

Jara, A. J., Fernández, D., López, P., Zamora, M. A., Marin, L., & Skarmeta, A. F. 2012. Yoapy: A data aggregation and pre-processing module for enabling continuous healthcare monitoring in the internet of things. In: Bravo J., Hervás R., Rodríguez M. (eds) Ambient Assisted Living and Home Care. IWAAL 2012. Lecture Notes in Computer Science, 7657. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-35395-6_34

Jara, A. J., Zamora, M. A., & Skarmeta, A. F. (2011). An internet of things–based personal device for diabetes therapy management in ambient assisted living (AAL). *Personal and Ubiquitous Computing*, *15*(4), 431–440. https://doi.org/10.1007/s00779-010-0353-1

Jovanov, E., & Milenkovic, A. (2011). Body area networks for ubiquitous healthcare applications: Opportunities and challenges. *Journal of Medical Systems*, *35*(5), 1245–1254. https://doi.org/10.1007/s10916-011-9661-x

Kalis, B., & Wisdom, R. (2017). *Accenture 2017 Internet of health things survey*. Accenture. https://www.accenture.com/t20170215T191150__w__/us-en/_acnmedia/PDF-42/Accenture-Health-2017-Internet-of-Health-Things-Survey.pdf

Kario, K., Tomitani, N., Kanegae, H., Yasui, N., Nishizawa, M., Fujiwara, T., Shigezumi, T., Nagai, R., & Harada, H. (2017). Development of a new ICT-based multisensor blood pressure monitoring system for use in hemodynamic biomarker-initiated anticipation medicine for cardiovascular disease: The national IMPACT program project. *Progress in Cardiovascular Diseases*, *60*(3), 435–449. https://doi.org/10.1016/j.pcad.2017.10.002

Kessler, M. M. (1963). Bibliographic coupling between scientific papers. *American Documentation*, *14*(1), 10–25. https://doi.org/10.1002/asi.5090140103

Kim, J. H. (2017). A review of cyber-physical system research relevant to the emerging IT trends: Industry 4.0, IoT, big data, and cloud computing. *Journal of Industrial Integration and Management*, *2*(3), 1750011. https://doi.org/10.1142/S2424862217500117

Krawiec, R., Nadler, J., Tye, E., & Jarboe, J. (2015). *No appointment necessary: How the IoT and patient-generated data can unlock health care value*. Deloitte. https://www2.deloitte.com/us/en/insights/focus/internet-of-things/iot-in-health-care-industry.html

Kumaresh, S., Sabareesh, M., & Srihari, R. (2016). Non-invasive fetus heart rate and growth measurement with abnormality detection using IoT. *International Conference* *on Electrical, Electronics, and Optimization Techniques (ICEEOT)*, Chennai, India.

Kwon, M.-C., Ju, M., & Choi, S. (2017). *Classification of various daily behaviors using deep learning and smart watch*. In *2017 Ninth International Conference on Ubiquitous and Future Networks (ICUFN)*, 735–740. IEEE.

Laplante, P. A., Kassab, M., Laplante, N. L., & Voas, J. M. (2018). Building caring healthcare systems in the Internet of things. *IEEE Systems Journal*, *12*(3), 3030–3037. https://doi.org/10.1109/JSYST.2017.2662602

Lee, S., Song, J., & Kim, Y. (2010). An empirical comparison of four text mining methods. *Journal of Computer Information Systems*, *51*(1), 1–10. https://doi.org/10.1080/08874417.2010.11645444

Li, C. T. W, Chen, T. Y, Lee, C. L, & Chen, C. C. (2017, Jul). An efficient user authentication and user anonymity scheme with provably security for iot-based medical care system. *Sensors, 17 (7),article 1482*. https://doi.org/10.3390/s17071482

Li, S., Da Xu, L., & Zhao, S. (2018). 5G Internet of Things: A survey. *Journal of Industrial Information Integration*, *10*, 1–9. https://doi.org/10.1016/j.jii.2018.01.005

Liang, X., Wang, Q., Yang, X., Cao, J., Chen, J., Mo, X., Huang, J., Wang, L., & Gu, D. (2011). Effect of mobile phone intervention for diabetes on glycaemic control: A meta-analysis. *Diabetic Medicine: A Journal of the British Diabetic Association*, *28*(4), 455–463. https://doi.org/10.1111/j.1464-5491.2010.03180.x

Lin, J., Yu, W., Zhang, N., Yang, X., Zhang, H., & Zhao, W. (2017). A survey on internet of things: Architecture, enabling technologies, security and privacy, and applications. *IEEE Internet of Things Journal*, *4*(5), 1125–1142. https://doi.org/10.1109/JIOT.2017.2683200

Malvade, P. S., Joshi, A. K., & Madhe, S. P. (2017). IoT based monitoring of foot pressure using FSR sensor. *International Conference on Communication and Signal Processing (ICCSP)*, Chennai, India.

Manning, C. D., Raghavan, P., & Schütze, H. (2008). Stemming and lemmatization. In *Introduction to information retrieval,* 32. Cambridge University Press.

Mansuri, S. (2018). *How can big data leverage healthcare industry*. HealthWorks Collective. November 20 2019. https://www.healthworkscollective.com/how-can-big-data-leverage-healthcare-industry/

McCallum, A. K. (2002). *Mallet: A machine learning for language toolkit*. http://mallet.cs.umass.edu

Nerur, S. P., Rasheed, A. A., & Natarajan, V. (2008). The intellectual structure of the strategic management field: An author co-citation analysis. *Strategic Management Journal*, *29*(3), 319–336. https://doi.org/10.1002/smj.659

Ng, C. K., Wu, C. H., Yung, K. L., Ip, W. H., & Cheung, T. (2018). A semantic similarity analysis of Internet of things. In *Enterprise Information Systems*, *12*(7), 820–855. https://doi.org/10.1080/17517575.2018.1464666).

Nishida, Y., Takahashi, Y., Kitamura, K., & Mizoguchi, H. (2016). Handrail-shaped IoT sensor for long-term monitoring of the mobility in elderly people. In: Di Bucchianico G., Kercher P. (eds) *Advances in Design for Inclusion. Advances in Intelligent Systems and Computing, 500.* Springer, Cham

Qin, Z., Sun, J., Chen, D., & Xiong, H. (2017). Flexible and lightweight access control for online healthcare social networks in the context of the internet of things. *Mobile Information Systems*, *2017*, 1–15. https://doi.org/10.1155/2017/7514867

Rathore, M. M., Paul, A., Ahmad, A., Anisetti, M., & Jeon, G. (2017). Hadoop-Based Intelligent Care System (HICS): Analytical approach for big data in IoT. *ACM Transactions on Internet Technology (TOIT)*, *18*(1), 8. https://doi.org/10.1145/3108936

Roy, A., Zalzala, A. M., & Kumar, A. (2016). Disruption of things: A model to facilitate adoption of IoT-based innovations by the urban poor. *Procedia Engineering*, *159*, 199–209. https://doi.org/10.1016/j.proeng.2016.08.159

Sahi, M. A., Abbas, H., Saleem, K., Yang, X., Derhab, A., Orgun, M. A., Iqbal, W., Rashid, I., & Yaseen, A. (2018). Privacy preservation in e-healthcare environments: State of the art and future directions. *IEEE Access IEEE Access*, *6*, 464–478. https://doi.org/10.1109/ACCESS.2017.2767561

Sareen, S., Gupta, S. K., & Sood, S. K. (2017). An intelligent and secure system for predicting and preventing Zika virus outbreak using Fog computing. *Enterprise Information Systems*, *11*(9), 1436–1456. https://doi.org/10.1080/17517575.2016.1277558

Sarkar, S., Chatterjee, S., Misra, S., & Kudupudi, R. (2017). Privacy-aware blind cloud framework for advanced healthcare. *IEEE Communications Letters*, *21*(11), 2492–2495. https://doi.org/10.1109/LCOMM.2017.2739141

Shahamabadi, M. S., Ali, B. M., Noordin, N. K., Rasid, M. F. B., & Jara, A. J. (2016). *The challenges of NEMO in 6LoWPAN smart building area*. In *2016 International Conference on Identification, Information and Knowledge in the Internet of Things (IIKI),* 305–310. IEEE.

Sircar, S., Nerur, S. P., & Mahapatra, R. (2001). Revolution or evolution? A comparison of object-oriented and structured systems development methods. *MIS Quarterly*, *25*(4), 457–471. https://doi.org/10.2307/3250991

Small, H. (1973). Co-citation in the scientific literature: A new measure of the relationship between two documents. *Journal of the American Society for Information Science*, *24*(4), 265–269. https://doi.org/10.1002/asi.4630240406

Sood, S. K., & Mahajan, I. (2017). Wearable IoT sensor based healthcare system for identifying and controlling chikungunya virus. *Computers in Industry*, *91*, 33–44. https://doi.org/10.1016/j.compind.2017.05.006

Staff, F. T. C. (2015). *Internet of things - Privacy & security in a connected world*. Federal Trade Commission. https://www.ftc.gov/system/files/documents/reports/federal-trade-commission-staff-report-november-2013-workshop-entitled-internet-things-privacy/150127iotrpt.pdf

Statista. (2018). *IoT: Number of connected devices worldwide 2012-2025*. May 30, 2018

Sun, J., Guo, Y., Wang, X., & Zeng, Q. (2016). mHealth for aging China: Opportunities and challenges. *Aging and Disease*, *7*(1), 53. https://doi.org/10.14336/AD.2015.1011

Takamiya, M. (2015). *Energy efficient design and energy harvesting for energy autonomous systems*. In *VLSI Design, automation and test (VLSI-DAT)*, 1–3. IEEE.

Taylor, J. (2017). Going public: Using the cloud to improve project delivery. *Information Systems Management*, *34*(2), 105–116. https://doi.org/10.1080/10580530.2017.1288521

Tran, H. A., Ngo, Q. T., & Van, T. (2017). A new fall detection system on android smartphone: Application to a SDN-based IoT system. In *20179th International Conference on Knowledge and Systems Engineering (KSE),* 1–6. IEEE

Tyagi, S., Agarwal, A., & Maheshwari, P. (2016, January). *A conceptual framework for IoT-based healthcare system using cloud computing*. In *2016 6th International Conference-Cloud System and Big Data Engineering (Confluence)*, 503–507. IEEE.

U.S. Department of Health & Human Services. (n.d.). *Health information privacy*. U.S. Department of Health & Human Services. November 20 2019 https://www.hhs.gov/hipaa/index.html

U.S. Department of Health and Human Services. (2016). *Examining oversight of the privacy & security of health data collected by entities not regulated by HIPAA*. US Dept of HHS.

Ukil, A., Bandyoapdhyay, S., Puri, C., & Pal, A. (2016). IoT healthcare analytics: The importance of anomaly detection. *2016 IEEE 30th International Conference on Advanced Information Networking and Applications (AINA), Le Régent Congress Centre, Crans-Montana, Switzerland.* 994–997. IEEE.

Van Eck, N. J., & Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics*, *84*(2), 523–538. https://doi.org/10.1007/s11192-009-0146-3

Varshney, U. (2014). Mobile health: Four emerging themes of research. *Decision Support Systems*, *66*, 20–35. https://doi.org/10.1016/j.dss.2014.06.001

Versel, N. (2013). Big data helps Kaiser close healthcare gaps. *InformationWeek*. (https://www.informationweek.com/healthcare/electronic-health-records/big-data-helps-kaiser-close-healthcare-gaps/d/d-id/1108977).

Walter, C., & Ribière, V. (2013). A citation and co-citation analysis of 10 years of KM theory and practices. *Knowledge Management Research & Practice*, *11*(3), 221–229. https://doi.org/10.1057/kmrp.2013.25

Wang, N., Liang, H., Jia, Y., Ge, S., Xue, Y., & Wang, Z. (2016). Cloud computing research in the IS discipline: A citation/co-citation analysis. *Decision Support Systems*, *86*, 35–47. https://doi.org/10.1016/j.dss.2016.03.006

Whitmore, A., Agarwal, A., & Da Xu, L. (2015). The internet of things—A survey of topics and trends. *Information Systems Frontiers*, *17*(2), 261–274. https://doi.org/10.1007/s10796-014-9489-2

Xu, B. Y. X., Da Xu, L. D., Cai, H. M., Xie, C., Hu, J. Y., & Bu, F. (2014, May). Ubiquitous data accessing method in IoT-based information system for emergency medical services. *Ieee Transactions on Industrial Informatics*, *10* (2), 1578–1586. https://doi.org/10.1109/tii.2014.2306382

Xu, W., Liu, X., & Gong, Y. (2003). *Document clustering based on non-negative matrix factorization*. . In *Proceedings of the 26th annual international ACM SIGIR conference on Research and development in informaion retrieval*, 267–27.

Yan, H., Xu, L. D., Bi, Z., Pang, Z., Zhang, J., & Chen, Y. (2015). An emerging technology – Wearable wireless sensor networks with applications in human health condition monitoring. *Journal of Management Analytics*, *2*(2), 121–137. https://doi.org/10.1080/23270012.2015.1029550

Yang, G. X., Xie, L., Mantysalo, M., Zhou, X. L., Pang, Z. B., Xu, L. D., Kao-Walter, S., Chen, Q., & Zheng, L.-R. (2014). A health-IoT platform based on the integration of intelligent packaging, unobtrusive bio-sensor, and intelligent medicine box. *IEEE Transactions on Industrial Informatics*, *10*(4), 2180–2191. https://doi.org/10.1109/tii.2014.2307795

Yang, P., Stankevicius, D., Marozas, V., Deng, Z., Liu, E., Lukosevicius, A., Dong, F., Xu, L., & Min, G. (2018). Lifelogging data validation model for internet of things enabled personalized healthcare. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *48*(1), 50–64. https://doi.org/10.1109/TSMC.2016.2586075

Yang, Z., Zhou, Q., Lei, L., Zheng, K., & Xiang, W. (2016). An IoT-cloud based wearable ECG monitoring system for smart healthcare. *Journal of Medical Systems*, *40*(12), 286. https://doi.org/10.1007/s10916-016-0644-9

Yean, S., Lee, B. S., Yeo, C. K., & Vun, C. H. (2016). *Algorithm for 3D orientation estimation based on Kalman filter and gradient descent*. In *2016 IEEE 7th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)*, 1–6. IEEE.

Yuehong, Y., Zeng, Y., Chen, X., & Fan, Y. (2016). The internet of things in healthcare: An overview. *Journal of Industrial Information Integration*, *1*, 3–13. https://doi.org/10.1016/j.jii.2016.03.004

Zanella, A., Bui, N., Castellani, A., Vangelista, L., & Zorzi, M. (2014). Internet of things for smart cities. *IEEE Internet of Things Journal*, *1*(1), 22–32. https://doi.org/10.1109/JIOT.2014.2306328

Zicari, R. (2016). *The explosion of big data in healthcare*. May 30, 2018 http://www.odbms.org/2016/03/the-explosion-of-big-data-in-healthcare/