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"Technology enabled Health" – Insights from twitter analytics with a socio-technical perspective

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ABSTRACT

Technology had been used in health domain for various purposes such as for storing electronic health records; monitoring; education; communication; and for behavioural tracking. The evident benefits have triggered a huge amount of discussions surrounding health technology in the web 3.0 space and users around the globe are sharing their experiences and perspective on social media platforms. Social media had been used for creating awareness, sharing information and providing emotional support to public in different diseases. This study focuses on exploring the health technology related discussions in Twitter. For this study around 105,489 tweets were collected from Twitter by 15,587 unique users. These tweets were analysed through social media analytics approaches (i.e. CUP framework). The study presents the top technologies in health domain through hashtag analysis and top diseases (acute, chronic, communicable and non-communicable) through word analysis and their association through co-occurrence of words within the tweets. The association depicts technology had been used in treating, identifying and heeling of the various diseases. The discussion on social media is skewed towards computing algorithms. The acute and chronic diseases were discussed on social media, and our study indicates that statistically, there is no difference in the discussion of acute and chronic diseases. The communicable and non-communicable diseases are also discussed on social media, and our study indicates no statistically difference in the discussion of communicable and non-communicable diseases which signifies users are referring to Twitter for discussing various type of diseases irrespective of acute, chronic, communicable and non-communicable diseases. Future researchers can use the study as the evidence of extracting insights related to socio-technical perspective from Twitter data. The literature contains lot of evidences where technology had been useful in health domain, but the bigger picture of how the various technologies are being related to health domain is missing, therefore this study tries to contribute to this area by mining tweets.

1. Introduction

Social media had been used for creating awareness related to various diseases (Al-Taee & Abood, 2012; Esposito et al., 2018; Ghanavati, Abawajy, Izadi, & Alelaiwi, 2017; Msayib, Gaydecki, Callaghan, Dale, & Ismail, 2017; Nedungadi, Jayakumar, & Raman, 2018; Triantafyllidis et al., 2017;) for the betterment of the society (Casino, Patsakis, Batista, Borràs, & Martínez-Ballesté, 2017; Platt, Outlay, Sarkar, & Karnes, 2016; De la Torre Díez, Garcia-Zapirain, López-Coronado, Rodrigues, & del Pozo Vegas, 2017). Social media had played a great role in raising warning to diseases such as Swine Flu in 2009 (Kostkova, Szomszor, & St Louis, 2014); Ebola in 2014 (Odlum & Yoon, 2015; Seltzer, Jean, Kramer-Golinkoff, Asch, & Merchant, 2015); and Zika virus in 2016 (Sharma, Yadav, Yadav, & Ferdinand, 2017). The arrival of Zika virus in America had generated lot of awareness on social media platforms such as Facebook (Sharma et al., 2017).

The health information when shared on social media, the reach of the messages increases for following groups: (a) for the people living in remote areas (Al-Taee & Abood, 2012; Eze, Gleasure, & Heavin, 2016; Manda & Herstad, 2015; Miah, Hasan, Hasan, & Gammack, 2017; Zhang, Thurow, & Stoll, 2015); (b) for individuals with low income and in lower socio-economic communities of the society (Campbell, Caine, Connelly, Doub, & Bragg, 2015; Kim & Zhang, 2015; Thomas & Narayan, 2016); (c) for individuals having little or no access to treatment (Campbell et al., 2015; Kim & Zhang, 2015; Thomas & Narayan, 2016). Social sharing also stimulates social connect among the patients suffering from similar diseases (Barrué, Cortés, Cortés, Tétard, & Gironès, 2017; Owen, Curran, Bantum, & Hanneman, 2016) and e-

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Table 1
Use cases of technology used in medical domain.

Use Case	Literature Evidences	Impact
Electronic health records storage	● Lavariega, Garza, Gómez, Lara-Diaz, & Silva-Cavazos, 2016; ● Li et al., 2017 ● Liu, Xia, Yang, & Yang, 2018; ● Lomotey & Deters, 2014; ● Manda & Herstad, 2015 ● Quwaider & Jararweh, 2015; ● Roehrs, da Costa, & da Rosa Righi, 2017	a Access to the health records. b Secure documentation of records for future usage. c Recommendation of medicines, dosage, treatment and prescriptions.
Health Monitoring System: Personalized and commercial	● Al-Taee & Abood, 2012 ● Esposito et al., 2018 ● Ghanavati et al., 2017 ● Msayib et al., 2017 ● Nedungadi et al., 2018	a Better and improve quality of life b Personalized and customized health services.
Medical education and awareness	● Briz-Ponce, Juanes-Méndez, García-Peñalvo, & Pereira, 2016; ● Briz-Ponce, Pereira, Carvalho, Juanes-Méndez, & García-Peñalvo, 2017; ● Fahlman, 2017;	a Awareness through public health programs b Knowledge sharing new updates in the domains
Communication (a) in remote areas; (b)emergency situations;	● Al-Taee & Abood, 2012; ● Eze et al., 2016; ● Khalemsky & Schwartz, 2017 ● Manda & Herstad, 2015; ● Miah et al., 2017; ● Schwartz, Bellou, Garcia-Castrillo, Muraro, & Papadopoulos, 2016; ● Zhang et al., 2015;	a Treatment for the individuals having low income b Treatment for lower socio-economic communities c Emergency medical response d Life-saving prescription medication
Behavioural trajectories and Disease detection	● Harari et al., 2017 ● Matthews, Abdullah, Gay, & Choudhury, 2014; ● Matthews et al., 2017; ● Njafa & Engo, 2018	a Socio-demographic characteristics of individual b Early warning signal of mood and mental illness

patients seek for information and emotional support on social media platforms (Jiang & Yang, 2017).

A lot of innovative technological solutions have emerged in recent times (like telemedicine, e-health, sensor based devices, electronic health records, etc) to address the health related needs of people. When technology is built into a product that fulfuills a particular need, the product becomes a technological solution. Such information technology has also been used in medical domain for monitoring, awareness, education, communication and storage of information (elaborated in Table 1 of literature review section). If the information shared on social media is accurate and credible it can be beneficial but otherwise can mislead the users (Sharma et al., 2017; Matthews et al., 2017). For example, in Zika virus case in America, number of misleading posts were more as compared to accurate posts (Sharma et al., 2017).

This study tries to explore the (a) nature of discussions surrounding the top technologies in the health domain; (b) nature of discussions surrounding top diseases; (c) nature of the association of top technologies with various diseases; and (d) nature of socio-technical network in health domain. Socio-technical networks help us in understanding the human society, nature and technology together. This study tries to address the literature gap of studying the socio-technical system in the health domain with respect to diseases by carrying out a multi-stakeholder analysis of both human and nonhuman interests using actor network theory. To best of our knowledge there is no study in literature which indicates mean discussions surrounding (a) acute and chronic diseases; (b) communicable and non-communicable diseases; on social media platforms. Therefore this study tries to investigate this in the sample.

Actor network theory treats human and non-human artefacts as inseparable. In this case study technology, people and diseases are artefacts, therefore actor network theory had been adopted as a theoretical lens for the socio-technical system. Walsham (1997) had pointed out actor network theory had been used for studying the people and information technology together in the cases such as pilots and computer-controlled planes; computer and people playing games; and robots in surgery. In this study we had tried to study the technology with respect to human diseases by using the discussions on Twitter on technologies in health domain.

For studying the socio-technical network in health domain inductive, deductive, qualitative and quantitative approaches can be adopted but for this study to have a bigger and generic picture of social-technical system social media analytics was adopted for analysing the technology enabled health discussions. The discussions were extracted from Twitter because following reasons: (a) large number of the users are available on Twitter; (b) the discussions on Twitter contains different meta data information such as geo-tag, time stamp, user profile, network information and many more; and (c) discussions can be extracted from Twitter in cost effective manner (He, Zha, & Li, 2013).

In this manuscript, we focused on how technologies related to health domain are being discussed in social media platform (Twitter) with respect to various diseases. The study had been divided into the eight section such as: first section introduces the pros and cons of sharing the health information on the social media platforms. Second section contains the literature review on usage of technology in health domain, followed by the social media usage in health domain, followed by research gaps and major contributions. The third section introduces the research questions and hypothesis of the study. The fourth section describes the research methodology followed for the study. The fifth section presents the results of analysis. The sixth section discussed the implication of the findings and insights. The seventh section contains the conclusions derived from the study followed by the limitations of the existing study in the last section.

2. Literature review

The literature review had been divided into the three sections: (a) technology usage in health domain; (b) social media usage in health domain, and (c) the research gaps and contribution of the study. The first section, health and technology highlights some of the use cases where technology had been used in medical domain. The second section

Table 2
Social media usage for health care.

Disease	Objective	Literature Evidence
Cancer	Content analysis of discussion on side effects related to medications	Mao et al., 2013
	Use of Facebook and Twitter groups for chronic diseases	De la Torre-Díez, Díaz-Pernas, & Antón-Rodríguez, 2012
	Differences in peer support	Setoyama, Yamazaki, & Namayama, 2011
Heart	How Twitter users seek and share information	Bosley et al., 2013
	Predicts country level mortality due to heart disease	Eichstaedt et al., 2015
Flu / Influenza	To identify trends in flu posts	Corley, Cook, Mikler, & Singh, 2010
	Detecting and predicting influenza spread	Pawelek, Oeldorf-Hirsch, & Rong, 2014
		Yuan et al., 2013
Diabetes	To evaluate the content of communication in Facebook communities	Greene et al., 2011
	Identifying support groups	Chen, 2012
		Fergie, Hunt, & Hilton, 2016
	To identify the concerns of the users related to diabetes	Eriksson-Backa et al., 2016
Hiv / Aids	Detecting and monitoring of HIV outcomes	Young, Rivers, & Lewis, 2014
	Prevention awareness	Ramallo et al., 2015
Stroke	To improve public knowledge relating to stroke	Alberts, 2012
Obesity	To analyse the public opinion regarding obesity	Karami, Dahl, Turner-McGrievy, Kharrazi, & Shaw, 2018

illustrates the literature evidences of health discussion on social media followed by the research gaps and contribution of the study.

2.1. Technology usage in health domain

Literature indicates technologies can play an important role in providing healthcare services at the regional, community and individual levels and has the potential of influencing in social, cultural, economic context (O'Connor, Heavin, & O'Donoghue, 2016). Using technology in the health domain ubiquitous, mobile, personalised and quality services can be provided (Luppicini & Aceti, 2011; Motamarri, Akter, Ray, & Tseng, 2014). For example telemedicine (Chandwani, De, & Dwivedi, 2018; Parajuli & Doneys, 2017), reduces travel and treatment expenses, and at the same time provide timely access to healthcare services.

Some of the use cases where technology had been used in the medical domain are listed in the Table 1. The table illustrates an overview of use cases, literature evidences and their impact from the usage of technology in health. The use case column contains the five scenarios where technology had been used in health domain these are storing of health records electronically and replacing the paper-based reporting (Manda & Herstad, 2015). The technology is being personalized and customized for the health services. Literature indicates technology had been used in medical domain for the educating, learning and providing emotional support (Monshat, Vella-Brodrick, Burns, & Herrman, 2011; Owen et al., 2016; Yoo, Shah, Chih, & Gustafson, 2018). Technology had been used for communication to remote areas in emergency situations. Technology-mediated communication patterns had been used for detecting behavioural trajectories and detecting diseases in individuals. Literature indicates information technology can be beneficial in managing immunization records and public health crisis responses (Li, Du, Xin, & Zhang, 2017).

Table 1 indicates there are various benefits of using the technology in the health domain. One of the biggest barrier of applying the technology in the health domain is the usability (Zapata, Fernández-Alemán, Idri, & Toval, 2015). The successful implementation of the technology in health domain is influence by cultural (Jayasuriya, 1999), economic, institutional, political, social and technological factors (O'Connor et al., 2016).

2.2. Social Media usage in Health domain

The information shared in social media can provide updates on new technologies, resolve the queries of different users in various part of the world (Kapoor et al., 2017) through history of discussions and introduce the users to the best practises for caring, avoiding and taking precautions (Hajli, 2014). Social media had been used for reaching to millions in emergency situations (Kim, Bae, & Hastak, 2018; Li, Zhang, Tian, & Wang, 2018; Pogrebnyakov & Maldonado, 2018). There are evidences in the literature which shows 95% of top ranked hospitals use social media for engaging with patients (Smith, 2017) and had increased their trust and satisfaction among the patients (Jiang, 2017).

Literature indicates accurate and credible information increases trust of a user in online forums and communities which in turn lead to user returning to the platform for more information and social support (Hajli, Sims, Featherman, & Love, 2015). Using Twitter discussion the concerns of the users related to diabetes had mapped in the literature (Eriksson-Backa, Holmberg, & Ek, 2016). Social influence had positive impact on the willingness of the user to exercise (Hamari & Koivisto, 2015). Emojis icons within health tweets can capture the participant attention (Willoughby & Liu, 2018). Mental health messages on social media has a potential for engaging large number of audiences (Monshat et al., 2011; Yap, Zubcevic-Basic, Johnson, & Lodewyckx, 2017).

Social media usage in health domain is facing challenges such as professional boundaries, defamation and privacy breaches (Lim, 2016; Lupton, 2014). Literature indicates several factors which influence the adoption of social media use for health care (Mitra & Padman, 2014): (a) age; (b) gender; (c) health status; (d) presence of chronic diseases; (e) computer literacy; (f) health and media literacy; (g) social media usage; and (h) online engagement frequency. Table 2 list the diseases study wise done on social media platform along with the overview of the objectives of the studies.

2.3. Research gaps and major contributions

Table 1 depicts technologies had been used in health domain but the indication of which are the top technologies in health domain is missing in the literature. This is the first literature gap identify for the study. To the best of our knowledge there is no study in literature which considers the communication of the virtual communities on technologies in health domain. This is the second literature gap identified for the study. Table 2, depicts various diseases acute, chronic, communicable and non-communicable had been discussed on social media platforms but there is no clear indication which type of diseases had been discussed more, this is the third literature gap identified for this study.

Therefore this study tries to identify: (a) the top technologies in health domain; (b) the virtual networks formed on Twitter among users with respect to health discussions; (c) the popular diseases discussed on Twitter; (d) whether users are discussing about acute or chronic diseases more; (e) whether users are more concern about communicable or non-communicable diseases; (f) how the diseases being associated with top technologies; and (g) socio-technical network in health domain by taking users, technologies and diseases as actors.

3. Theoretical basis and hypothesis development

To best of our knowledge, there is no study in the literature which highlights how the technology being discussed on social media platform (such as Twitter) in relation to the various diseases. Therefore to understand the nature of the discussions, there is a need for investigating the health technology related discussions on Twitter platforms with respect to the three research questions (RQ). The main focus of the study is to explore the technology enabled health discussions in context of technologies, diseases and people. Therefore actor network theory (Walsham, 1997) had been used as the theoretical lens for framing the context of the technology enabled health discussion on Twitter.

Actor network theory had been proposed by Michel CalIon, Bruno Latour and John Law in early 1980s. Actor network theory enables the researchers to investigate the traces within a coextensive networks of human and nonhuman elements together within the same conceptual apparatus. Literature indicates actor network theory is a methodology and a theory both which enable us to explore hybrids of people and information technology together (Walsham, 1997). The theory is based on the principles of agnosticism, generalised symmetry and free association. Actor network theory had been used in literature for covering wide range of the contexts in different sectors such as health, transportation and government. Actor network theory had been used for framing the context of information system in different use cases of accounting, plant categorization and geographic information system. Callon (1999) had pointed out, market operations of disentanglement, framing, internalization and externalization can be explained using actor network theory along with the emergence of calculating agents within the socio-technical contexts.

Actor network theory indicates, actor or actant are entities that do things. Therefore, there is no distinctions between humans and nonhumans entities. In this case study, technology enabled health discussions, includes actors such as technologies, diseases and people. Interaction among these actors (humans and non-humans) had been explored. The subsequent subsections tries to identify the actors in socio-technical network of health domain followed by the actor's interactions within the network.

3.1. Actors of technology enabled health discussions

When tweets are tag with the hashtags their visibility increases across the world (Duguay, 2016) and results in decreased information asymmetry (Prokofieva, 2014). Literature points out that usage of Twitter has evolved from conversational usage to informational activity usage (Parra et al., 2016), which signifies people are looking for the accurate, credible and trustworthy information. Therefore research question (RQ1), tries to investigate popular technologies in health domain through social media discussions using the hashtag analysis.

RQ1: What are the popular information technologies in health domain?

The health technologies on Twitter can be classified into the three categories such as computing algorithm; devices and hardware; and domain requirements. The computing algorithm (CoA) includes artificial intelligence, machine learning, deep learning, big data and blockchain. Devices and algorithm (DeA) includes internet of things (iot), robotics, wearable and virtual reality. The application domains (AoD) includes telemedicine and telehealth, fintech, health information technology (hcit), electronic health records (ehr) and cyber security. Therefore to validate statistically H1 proposes:

H1. The mean discussion of users regarding computing algorithm (CoA), devices and hardware (DeA); and application domains (AoD) in relation to health domain is same on social media platforms.

$\mu_{\text{CoA}} = \mu_{\text{DeA}} = \mu_{\text{AoD}}$

To test whether there is significant difference in the mean discussion of users regarding computing algorithm, devices and hardware; and domain application anova was applied. Analysis Of Variance (ANOVA) is a statistical technique used to test whether the means of more than two groups are equal. Here mean discussion surrounding computing algorithms, devices and domains on social media were considered.

RQ2: Which type of diseases, i.e. acute or chronic; communicable or non-communicable diseases being discussed more on social media?

The popular health topic list was taken from Centers for Disease Control and Prevention (2018). This list was classified on the duration of diseases into acute and chronic diseases and further classified into the communicable and non-communicable diseases (McKenzie, Pinger, & Seabert, 2014). Acute diseases are those diseases that comes unexpectedly for short duration and requires immediate medical attention, the recovery from acute disease is complete. Influenza and fever are examples of acute diseases. Chronic diseases are those diseases in which symptoms continue for longer period than three months and may come and go. Recovery in chronic disease is slow and in some case incomplete as well. Diabetes, heart problems and hypertensions comes under the chronic diseases. Literature evidences indicates social media provides knowledge, social support, and engagement for patients with chronic diseases (Greene, Choudhry, Kilabuk, & Shrank, 2011) and these things help patient in managing and coping with chronic conditions (Munson, Cavusoglu, Frisch, & Fels, 2013). Therefore H2a proposes to explore whether the discussion on social media is towards acute or chronic diseases or equal across both the groups.

H2a. Mean discussions on acute diseases and chronic diseases is same on social media platform (Twitter).

$\mu_{acute} = \mu_{chronic}$

Communicable or infection diseases are those diseases which gets transmitted from one person to other (McKenzie et al., 2014). The person who is carrying the disease is the infected person. Non communicable or non-infectious diseases are those diseases which cannot be transmitted from an infected person to a susceptible person. Literature indicates social media platforms such as Twitter, YouTube and Facebook has the potential of rapid communication for control and surveillance of communicable diseases (Mandeville, Harris, Thomas, Chow, & Seng). Literature points out counter marketing campaigns can prevent non-communicable diseases (Palmedo, Dorfman, Garza, Murphy, & Freudenberg). Therefore H2b proposes to explore whether the discussions on social media is towards communicable or non-communicable diseases or in equal proportion across both the groups.

H2b. Mean discussions on communicable diseases and non-communicable diseases is same on social media platform (Twitter).

$\mu_{communicacble} = \mu_{non-communicable}$

3.2. Actor – Network associations

Technology is shaping human interaction in health related services including diagnostics and healthcare delivery. Technology controls and influences the nature of the humans. Technology is an integral part of understanding the human society, therefore RQ3 tries to explore how technology had been associated with different kinds of the diseases through exploring technology enabled health discussions on Twitter.

RQ3: How technological solutions had been associated with various diseases?

Actor network theory explains the socio-technical society by giving equal weightage to all the actors irrespective of humans and non-humans together within a network. Literature indicates network as a group of unspecified relationships among entities (both humans and things together) (Callon, 1995). Actor network theory suggests within a

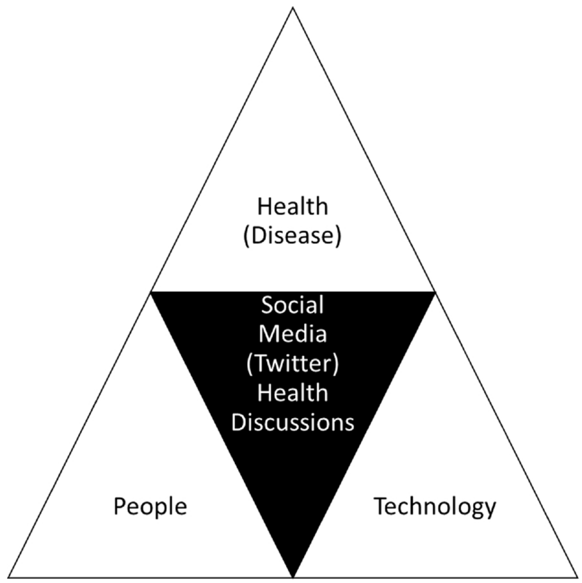

Fig. 1. Technology enabled health discussion on social media a conceptual model based on actor network theory.

network black box can be identified. Actor network theory identifies lead actors and also identifies other actors in a network for making connections.

H3. There is no association between the technological solutions and diseases.

The chi-square test of independence can be used for evaluating the significance of association between technology and diseases. On the basis of the research question and hypothesis, the study tries to propose the conceptual model based on the actor network theory. The conceptual model is presented in the Fig. 1. The model tries to investigate the technology enabled health discussion from three perspectives: people, health (special case to disease) and technology through social media health discussions.

The research questions (RQ1, RQ2 and RQ3) had been explored using social media analytics, through capture, understand and process (CUP) framework (Fan & Gordon, 2014) for making domain specific explorations (Aswani, Kar, Ilavarasan, & Dwivedi, 2018; Chae, 2015) and big data analytics (Grover and Kar, 2017a, 2017b; Joseph, Kar, Ilavarasan, Ganesh et al., 2017, Joseph, Kar, Ilavarasan et al., 2017) on 105,489 tweets with 10 variables. These approaches are based on machine learning algorithms to derive insights from unstructured data (Chakraborty & Kar, 2017; Kar, 2016) and requires the approaches from the domains of data science and machine learning to derive useful insights.

4. Research approach

Literature indicates social media analytics had been used for various purposes in health domain, some of it listed below: (a) to analyse the request on Twitter for blood donations (Abbasi et al., 2018); (b) to analyse the relationship between illness and sentiments on social media (Volkova, Charles, Harrison, & Corley, 2017); (c) measuring user similarity in healthcare information and recommending the information to similar users (Jiang & Yang, 2017); (d) for extracting adverse drug event reports (Liu & Chen, 2015).

Social media analytics (Fan & Gordon, 2014; Mohan & Kar, 2017; Rathore, Kar, & Ilavarasan, 2017) approaches had been adopted for analysing the technology enabled health discussion from different perspectives of people, health (disease) and technology. The literature suggests to use empirical surveys and structured and semi-structured interviews to validate the study. However, such methods suffer from responses having biases like social desirability, optimism and selective perception whereas on Twitter users can freely express their views these types of biases reduces within social networking ecosystem. Therefore Twitter data had been used for the study and subsequently social media analytics for analysing the data.

Fan and Gordon (2014) had pointed out using social media analytics data can be collected, monitored, analysed, summarized and visualized for extracting useful patterns and intelligence. Therefore they had divided the social media analytics into the three stage process: capture, understand and present. For executing the study same three stage process had been followed. Stage one, **capture**: (a) helps in identifying the conversation on social media using keywords and hashtags; (b) archives the data to meet the needs; (c) pre-process the data for the further stages. Stage two, **understand**: tries to derives the insights from data through various techniques such as: (a) data mining; (b) text mining / natural language processing – topic modelling; word count; lexical distances; co-occurrence frequencies; (c) sentiment analysis/ opinion mining; (c) trend analysis; (d) statistical testing; and (e) network analysis. Stage three, **present** the results in easy to understand format. Visualization techniques such as graphs-bar, box, histogram

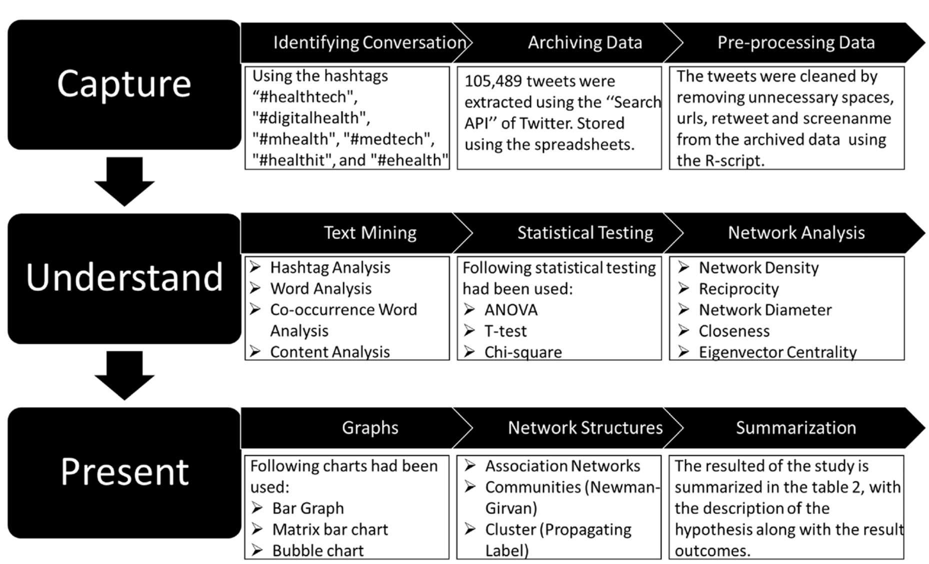

Fig. 2. Proposed approach for mining Social Media (Twitter) Health Discussions.

and many more; and dashboards can be used.

The CUP framework had been adopted for the study, the various steps at each stage had been briefly outlined in Fig. 2. The first stage, capture had been divided into the three steps for this study of: identifying conversation, archiving data and pre-processing of the data. The data for the study was extracted through six hashtags from Twitter, related to health and technologies domain both. These hashtags are "#healthtech", "#digitalhealth", "#mhealth", "#medtech", "#healthit", and "#ehealth". Firstly the tweets containing "#digitalhealth" was extracted, using these tweets top 50 hashtags associated with "#digitalhealth" were examined. The hashtags which are related to health and technologies domain and having high association with "#digitalhealth" was found. These were "#healthtech", "#mhealth", "#medtech", "#healthit", and "#ehealth". In second phase the data from twitter containing these six hashtags were extracted.

For "#digitalhealth" around 38,844 tweets were collected; for "#healthtech" around 27,910 tweets were collected; for "#mhealth" around 19,055 tweets were collected; for "#medtech" around 8461 tweets were collected; for "#healthit" around 10,265 tweets were collected; and for " #ehealth" around 14,970 tweets were collected. In total 105,489 tweets were extracted using the "Search API" of Twitter. The tweets were cleaned by removing unnecessary spaces, urls, retweet and screenanme from the archived data through R-script.

The second stage, understand had been divided into the three steps for this study of: text mining (He et al., 2013), statistical testing and network analysis. Using the hashtag analysis (Chae, 2015; Joseph, Kar, Ilavarasan, Ganesh et al., 2017, Joseph, Kar, Ilavarasan et al., 2017) the top information technologies associated with the health domain were identified and using word analysis (Chae, 2015) the top diseases which were discussed in Twitter were identified. The list of the popular health topics relating to diseases was taken from Centers for Disease Control and Prevention (2018). These topics were searched in the tweets collected for the study. The top health topics related to diseases were identified. Once the technology and diseases had been identified. The top diseases and top technologies being were searched within a tweets using co-occurrence frequencies of words (Fan & Gordon, 2014) for determining the association between technologies and diseases. ANOVA, *t*-test and chi-square statistical testing had been applied over the discussion for statistically validation. The network parameters such as density, reciprocity, diameter, closeness, betweeness and centrality had been computed to derive the insights of the network of the users.

The third stage, present had been divided into the three steps for this study of: graphs, network structures and summarization. The bar graphs had been used to depict the frequency of the technologies and diseases within the discussions. The bubble chart had been used to depict the contribution of each cell in total chi-square. The association between technologies and diseases had been visualised through a network. To identify which technologies had been used frequently with diseases the community detection algorithms Newman-Girvan and propagating label was applied.

5. Finding and interpretation

This section had been divided into three sub-sections. First subsection contains discussion surrounding popular technologies in health domain, followed by second sub-section, trending diseases contains the analysis for RQ2 and last sub-section, depicts the association between the technologies and various diseases.

5.1. Popular technologies

Using the hashtag analysis, top 20 hashtags associated with the health domain are illustrated in Fig. 3. The hashtags using content analysis were grouped into the four groups of: computing algorithm (illustrated with green color); devices and hardware (illustrated with orange color); and domain requirements (illustrated with yellow color). Among all artificial intelligence, discussed with the hashtags #ai and #artificialintelligence is the top technology discussed on social media platform followed by machine learning (discussed with #ml and #machinelearning) and deep learning (discussed with #dl and #deeplearning).

Big data technology (discussed with #bigdata) stands at the fourth rank in the discussion related to health technology discussions followed by the internet of things (discussed with #iot) and telemedicine (discussed with #telemedicine and #telehealth). Blockchain (discussed with #blockchain) and virtual reality (discussed with #vr) are also among the top technologies being discussed related to health domain. It seems like users are worried about their security while discussing about their health-related issues (Mitra & Padman, 2012), therefore cybersecurity (discussed with #cybersecurity) is among top hashtags.

We had proposed the hypothesis,

H1. The mean discussion of users regarding computing algorithm (CoA), devices and hardware (DeA); and application of domain (AoD) in relation to health domain is same on social media platforms.

$$\mu_{\text{CoA}} = \mu_{\text{DeA}} = \mu_{\text{AoD}}$$

At $\alpha = 0.05$ (assumption), the degree of freedom is (k-1, n-k), where k is the number of samples ($k = 3$; CoA, DeA, and DoR) and n is the total number of observation ($n = 14$). The degree of freedom for the sample is (2, 11). The decision rule states, if the calculated value greater than table value, reject H1. The table value at 5% level of significance for degrees of freedom (2, 11) is 3.98. The calculated value regarding technology discussion is 5.261 which is greater than the threshold value of 3.98. Therefore, H1 is rejected. Hence there is a significant difference in mean discussions regarding technologies in the health domain

Fig. 4(a) shows the users network related to health technology discussions on Twitter. There were around 1129 nodes and 1695 edges. The density of the graph in Fig. 4(a) equals to 0.00266, which signifies the network of the queries on the social media is very much dispersed. The reciprocity of the graph equals to 0.00472, which signifies the proportion of reciprocated ties is very low within the network. A network diameter is the shortest path between two nodes within the network. The diameter of the graph in Fig. 4(a) equals to 14. The centrality in networks is measured in terms of closeness; betweenness; and eigenvector centrality. The closeness of the graph is equals to 0.0001. The betweeness of the graphs equals to 0.9979. The eigenvector centrality of the graph is equal to 9.388576e-06.

It is evident from the graph the users are using social media for health technology related discussions and in these discussions users are forming their communities in the virtual domains leading to the fragmented groups, the inter-community discussions are very less as compared to the intra-community discussion. For the community detection in network Newman-Girvan, community detection algorithm (Newman, 2004) based on edge betweenness was used. This indicates that the groups discussing health technologies are fragmented and they do not overlap significantly for forming virtual communities based on participation in discussions.

Twitter profile such as @JohnNosta, @DeepLearn007, @GetAHSolutions (Access Healthcare and @isansys (Isansys Lifecare) had been queried by common people through Twitter for the information regarding the services such as monitoring, personal care, financial health management and technology related to health. Literature indicates social media had leveraged the connection among the users with similar interests (Kye, Shim, Kim, & Park, 2017).

5.2. Trending diseases

Using word analysis the diseases (Centers for Disease Control & Prevention, 2018) were searched in the tweets. The top diseases which were discussed in the tweets are listed and classified on the (a) basis of acute and chronic diseases in Fig. 5; and (b) basis of communicable and

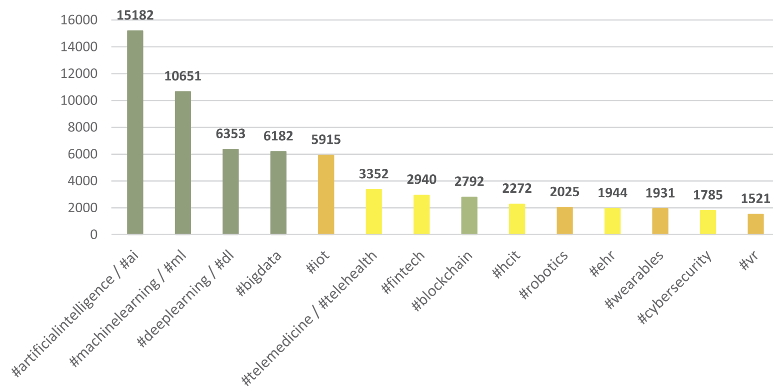

Fig. 3. Top hashtags in the health domain.

non- communicable diseases in Fig. 6. Cancer is the top diseases being discussed in social media followed by the diseases related to heart and influenza. Diseases such as diabetes (Eriksson-Backa et al., 2016), HIV and stroke are among the top diseases discussed in social media. Due to environmental changes, diseases related to respiration and water related diseases are also being discussed on social media platforms. Obesity is consider as a chronic disease (Rippe, Crossley, & Ringer, 1998) in modern lifestyle and as the eating habits of the people are changing the obesity and overweight are one of the concerns which had been discussed highly in social media platforms.

We had proposed the hypothesis,

H2a. Mean discussions on acute diseases and chronic diseases is same on social media platform (Twitter).

$\mu_{acute} = \mu_{chronic}$

For testing this hypothesis the two tail independent *t*-test was applied to diseases. The significance level was fixed at 0.05. There are 6 acute diseases in the sample having a mean discussion of 197 with standard deviation of 360.90. There are 15 chronic diseases in the sample having mean inclination of 332.40 with standard deviation of 593.64. The degree of freedom for the disease sample is n_1+n_2-2, where n_1 and n_2 are the sample sizes for acute and chronic diseases. Here the degree of freedom is 19. The table value of T at 0.05 significance and 19° of freedom is 2.093. The decision rule states, if calculated value of T is greater than table value of T, reject H_0. The calculated value of T is 0.637 which is lesser than the threshold value of 2.093. Therefore, **H2a is not rejected**. Hence there is no significant difference in sample means discussion of acute and chronic diseases.

We had proposed the hypothesis,

H2b. Mean discussions on communicable diseases and non-communicable diseases is same on social media platform (Twitter).

$\mu_{communicacble} = \mu_{non-communicable}$

For testing this hypothesis the two tail independent *t*-test was applied to the discussions of communicable and non-communicable diseases. The significance level was fixed at 0.05. There are 9 communicable diseases in the sample were discussed with a mean discussion of 161.67 and with standard deviation of 312.04. There are 12 non-communicable diseases discussed in the sample having mean inclination of 392.75 with standard deviation of 647.37. The degree of freedom for the CEOs sample is n_1+n_2-2, where n_1 and n_2 are the sample sizes for communicable and non-communicable diseases. Here the degree of freedom is 19. The table value of T at 0.05 significance and 19° of freedom is 2.093. The decision rule states, if calculated value of T is greater than table value of T, reject H_0. The calculated value of T is 1.08 which is lesser than the threshold value of 2.093. Therefore, **H2b is not rejected**. Hence there is no significant difference in sample means based on communicable and non-communicable diseases although absolute number of discussions on non-communicable diseases is more.

5.3. Technological solutions and diseases

A two dimension table of the association between technology solution and diseases being prepared by using the co-occurrence

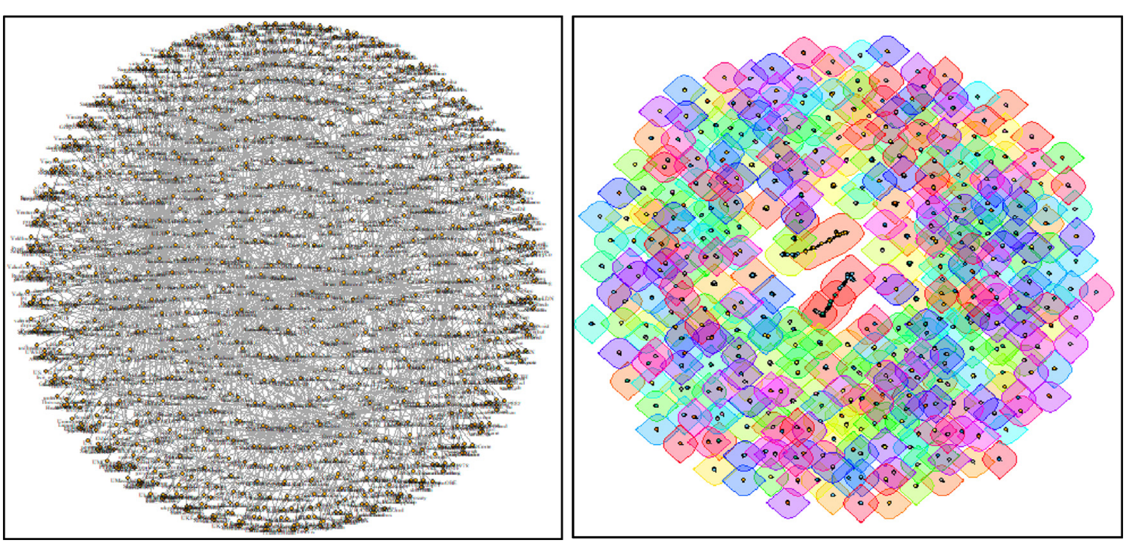

Fig. 4. (a) Network topology of the users participating in the health technology related discussion; (b) Virtual community discussions on health technology topics.

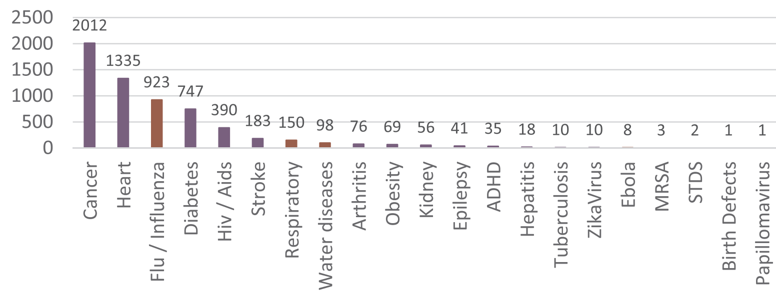

Fig. 5. Acute diseases in brown and chronic diseases in purple in tweets. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

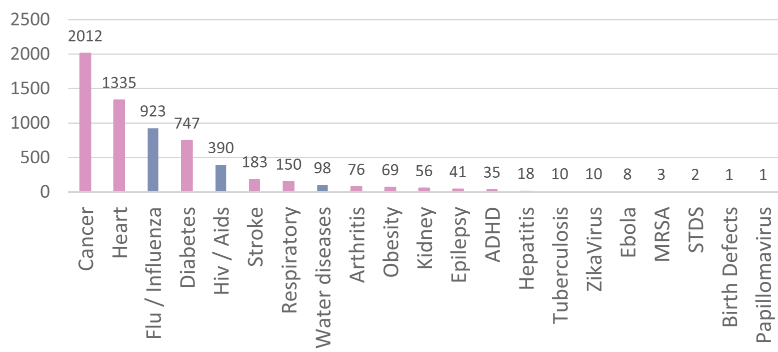

Fig. 6. Communicable diseases in blue and Non Communicable diseases in pink. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Technologies Diseases	#ai / #artificial intelligence	#bigdata	#ml / #machinelearning	#iot	#dl / #deeplearning	#blockchain	#robotics	#ehr	#wearables	#telemedicine / #telehealth	#vr
Cancer	1016	382	1803	8	1686	0	6	3	92	10	3
Heart	145	91	38	11	25	26	0	6	15	21	2
Flu / Influenza	213	17	102	114	0	25	0	6	3	66	0
Diabetes	26	11	13	12	8	0	0	4	11	36	0
Hiv / Aids	7	40	2	0	0	12	1	0	9	48	0
Stroke	21	1	24	0	0	0	0	0	3	1	31
Respiratory	5	0	0	3	0	0	0	0	1	11	0
Water Diseases	14	0	1	1	0	0	0	0	0	0	5
Obesity	6	0	0	4	0	0	4	0	0	2	0

Fig. 7. The graph illustrates the number of the times the technology occurred with the diseases in the tweets.

frequencies of words (i.e. technology and disease) within a tweet. The two dimension views, rows contains 11 technologies identified in Section 5.1 and columns contains 10 diseases identified in Section 5.2. The two dimension views can be visualized using matrix bar chart presented in Fig. 7.

The different colours of the Fig. 7, were used to differentiate between the hashtags of the technologies. Each value in the cell of the Fig. 7, presents the number of the tweets encountered discussing out the diseases (in row) and technology (in column) together in the sample extracted for the study. For example, (a) flu/influenza had been discussed with #iot in 114 tweets; (b) hiv/aids had been discussed with #telemedicine/#telehealth in 48 tweets. The bars in the cells were constructed column-wise (technologies), to derive which technology had been frequently discussed with a particular disease. For example the #vr had been mostly discussed with stroke as comparison to other diseases, likewise the #iot had been mostly discussed with flu / influenza.

The association between the technologies and diseases is depicted using association network in Fig. 8(a), where circle represents the technology and square represents the diseases and the node size indicates the frequency. The clusters of technology and diseases detected using propagating label community detection algorithm illustrated in Fig. 8(b). Fig. 8(b) depicts five clusters as: obesity, wearable, IoT, bigdata, cancer, dl, ml, ai, influenza, diabetes and water diseases; respiratory, HIV, telemedicine, blockchain, IoT, influenza and diabetes; stroke and VR; robotics; ehr.

We had proposed the hypothesis,

H3. There is no association between the technological solution and diseases.

The critical value obtained from Chi-square statistical table with $df = (r-1)(c-1)$ degrees of freedom at $p = 0.05$, where r is the number of rows (here $r = 11$) and c is the number of columns (here $c = 9$), $df = 80$, is 101.880. The decision rule states, if calculated Chi-square statistic is greater than the critical value, then we must conclude that technologies and diseases variables are not independent of each other and are significantly associated. The total Chi-square statistic is 6198.5. Therefore on basis of statistical testing it can be concluded there is an association between technological solutions and diseases.

The association between concerns and domains can be interpreted

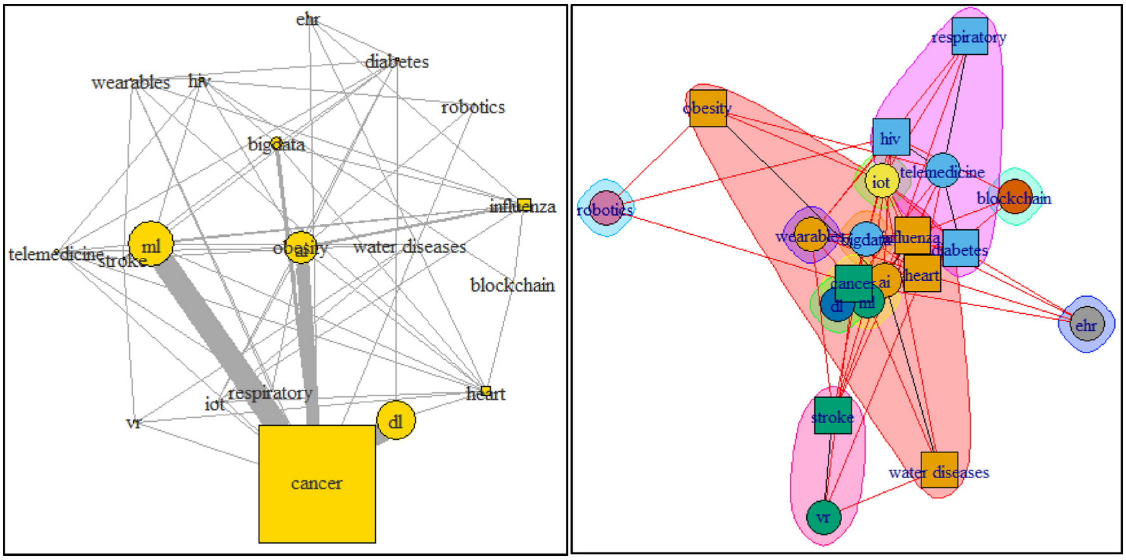

Fig. 8. (a) Association between technologies (nodes in circle) and diseases (nodes in square), edge width depicts the support of the people (Twitter users) between the nodes; (b) Clustering of technologies and diseases on the basis of propagating label algorithm.

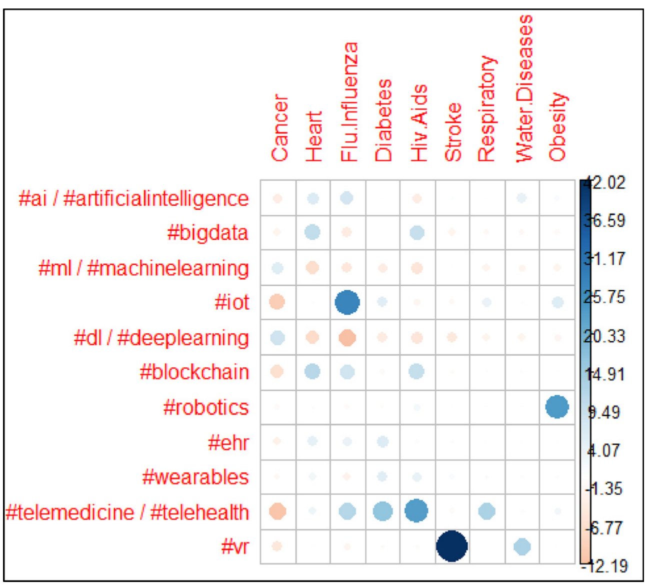

Fig. 9. Pearson residuals between technologies and diseases.

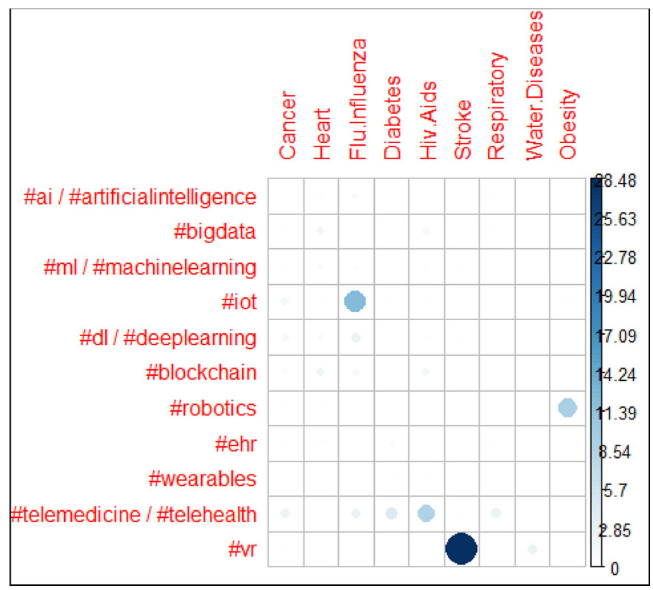

Fig. 10. The nature of the dependency between technologies and diseases.

using Pearson residuals. Fig. 9 shows Pearson residuals. Blue indicates positive values in cells and signifies positive association (attraction) between the technology and diseases. It is evident form Fig. 9 there is a positive association between: (i) virtual reality (#vr) and stroke; (ii) robotics and obesity; (iii) telemedicine and HIV/AIDS; and (iv) IoT and influenza. Red indicates negative association (repulsion) between technology and disease. Fig. 9 depicts no dominant negative association.

The relative contribution of each cell to total Chi-square score give some indication of the nature of the dependency between disease and technology association. Fig. 10 indicates, (i) stroke is strongly associated with virtual reality; (ii) Influenza is associated with IoT. From Fig. 10, it can be seen that the most contributing cells to the Chi-square are stroke/ virtual reality (#vr) (28.48%), influenza / Iot (#iot) (12.38%), obesity/ #robotics (9.13%), Hiv.Aids/#telemedicine (8.62%), diabetes/ #telemedicine (4.49%); water diseases/ virtual reality (#vr) (2.79%); and influenza/ #telemedicine (2.31%).

6. Discussion

Ubiquitous access to social media can be beneficial for promoting healthier lifestyles. Literature indicates social media is an excellent tool for the health care discussions and promotes two way communication among the users (Jiang, 2017). The sample collected for the study contains the high usage of the words learning, innovation, wearable and care. The tweets collected for the study contain the high appeal of transforming, changing, monitoring, tracking and assisting in health domain practices.

The tweets showcase social media platforms had been used for providing the emotional and mental support to patients through the virtual community intra and inter communication and this finding is in line with the literature (Monshat et al., 2011). Literature indicates users who had suffered from disease or someone in their family are more likely to share health information on social media as compared to those who had not experienced the pain of the disease (Kye et al., 2017).

The tweets were personalized and customized as according to the audiences such as kid, women and family. Based on our analysis of the Twitter data, we found technology is being used for the following purposes in health domain such as: storage, monitoring, education, communication and behavioural trajectories. Among all these social media can be used for education, communication (Della, Griffin, Eroğlu, Bernhardt, & Wells, 2013) and behavioural trajectories. The health promotion strategies followed on Twitter depicts authors are posting on Twitter for professional health care promotions.

This study tries to analysed the data extracted using six hashtags "#healthtech", "#digitalhealth", "#mhealth", "#medtech", "#healthit", and "#ehealth". The tweets in these hashtags have high appeal of re-tweeting leading to the discussions in social media platforms. The technologies such as artificial intelligence, big data, machine learning, deep learning, virtual reality and internet of things are among top technologies discusses in health domain. These technologies had been used in the treatment of various diseases. The popular diseases discussed on social media platforms are cancer, heart, flu / influenza, diabetes (Eriksson-Backa et al., 2016), HIV / AIDs, stroke, respiratory diseases / asthma, water related diseases, arthritis and obesity.

Association between the diseases and technologies depicts the relations between the technologies and as well as diseases. Fig. 8(b) depicts five clusters. In the first cluster: diseases (obesity, influenza, diabetes, water diseases, cancer) and technology (wearable, iot, bigdata, dl, ml, ai); had been grouped together. Thus this indicate the technologies such as wearable, iot, bigdata, dl, ml, ai can be grouped together for the health care products in future. The second cluster had grouped diseases (respiratory, hiv, influenza and diabetes) and technology (telemedicine, blockchain, iot) may be in future health care companies can use telemedicine, blockchain and iot for the application related to treatment of respiratory, hiv, influenza and diabetes. The third cluster had grouped disease (stroke) and technology (vr) together, but how vr can be used in stroke is out of scope of this paper. Therefore future researchers can take this forward.

The posts on Twitter can be segregated according to the target audiences. The tweets for common people and professionals in the health domain. The companies in the health domain are posting tweets for the common people for leveraging personal health care, better family planning and transforming lifestyle through the usage of technology. Literature indicates health care promotions by the healthcare firms on social media improves patient trust and satisfaction for the firms (Jiang, 2017). The companies are boosting that with their technology there is a chance of better patient outcomes. Literature indicates health care professionals can provide assistance to physicians (Peluchette, Karl, & Coustasse, 2016).

The study tries to explain the association of the technology with various diseases using the actor network theory. For the theoretical contribution this study can be taken as a case study for studying the hybrids of people's health and information technology in health sector and that is by using the technology enabled health discussions available on Twitter. The researchers working on the open data or free data or on social media for deriving the big and generic view of society can be benefit from the study in framing the current status of research and proposing future directions (Hossain, Dwivedi, & Rana, 2016)

The study had adopted and enhanced the CUP framework to segregate the research methodology into three steps. Thus study had enhanced the framework into detailing how social media analytics may be used by researchers for theory building and case study analysis. The methodology can be used by future researchers for evaluating the general perspective through discussions on social media. Also there was no study in literature which had indicated whether users discuss about (a) acute or chronic diseases more; and (b) communicable or non-communicable diseases more. This study reveals both (a) acute and chronic diseases (H2a); (b) communicable and non-communicable diseases (H2b) had been discussed in equal proportions. The study also tries to briefly present the social and technical perspective in health domain through which the social discussions and the technology ecosystem surrounding these discussions have been mapped to each other.

The social perspective in this study reveals: (a) Twitter users (human beings) are using technologies for their health; and at the same time (b) users are sharing their experiences, views regarding technologies within their network. Literature indicates social enhancement play a role in user's participation and retention within online community (Kaur, Dhir, Rajala, & Dwivedi, 2018). Tweets in the sample reveals the technologies used in the health domain is leveraging the standard of the humans in various conditions, in both aspects informational and emotional. Thus the insights reveals users are getting influenced by other users in the network through social media platform.

The complementary insights are provided by the technical perspective in this study which reveals how the technologies, CoA, AoD and DeA have been used in health domain. The CoA had occupied 63.47% of the tweets in a sample; whereas AoD and DeA had occupied 18.97% and 17.56% respectively. Thus it reveals more than half of the tweets in sample is towards CoA. Among all the computing algorithms, artificial intelligence is among the top followed by machine learning. The tweets are specifying the technologies such as (a) artificial intelligence can help the medical professional in analysing datasets; (b) robotics can help the doctors in completing time consuming activities and tasks; (c) using robotics medical consultation can be provided to the patient door steps in weaker socio-economic societies; (d) technologies for mining electronic health records.

6.1. Implication for practice

The implication of the study for the practise can divided into three sub sections such as consumers (Twitter users) consuming and revealing health information on social media platform concerns, health care companies and governments. This multi-stakeholder perspective and segregation would facilitate a customised audience for the findings of our study. The following subsections discusses it in briefly.

6.1.1. Users concerns

The acute and chronic diseases were discussed on social media, and our study indicates that statistically, there is no difference in the discussion of acute and chronic diseases. The communicable and non-communicable diseases are also discussed on social media, and our study indicates no statistically difference in the discussion of communicable and non-communicable diseases which signifies users are referring to Twitter for discussing various type of diseases of acute, chronic, communicable and non-communicable diseases and Twitter is witnessing the diseases discussing in equal proportions.

The analysis of the study reveals: (a) patients are concerned about their privacy and security while discussing health issues on social media platforms, this finding is in line with the literature (Lim, 2016; Lupton, 2014); (b) the user should be able to identify the authentic source of the health related information on social media platform (Eriksson-Backa et al., 2016); (c) social media platforms are being used by individuals as the guidelines for the personal care, preventions (Pei, Yu, Tian, & Donnelley, 2017) and precautions (Feng & Hossain, 2016).

6.1.2. Health care companies

The study reveals that technologies can be used for treating, healing or identifying diseases within humans. Some of the instances highlighted in the study where technology can be used for diseases are: (a) robotics can be used for obesity; (b) virtual reality had been grouped with stroke, but how both of it is related not sufficient arguments is present in the tweets; (c) telemedicine can facilitate medications for diabetes and hiv patients. Therefore health care companies can take these technologies forward for providing the solutions to these disease conditions. The study depicts users are discussing about the technological solutions on social media, therefore health care companies can choose social media platforms as one of their channels for

Table 3
Summary of Contributions.

S.no	Description	Results / Outcomes
1	The mean discussion of users regarding computing algorithm (CoA), devices and hardware (DeA); and application of domain (AoD) and in relation to health domain is same on social media platforms.	There is significant difference in means discussions of users regarding computing algorithm, devices and hardware; and domain in health technology domain on social media platforms. Discussion on computing algorithm is leading in health domain.
2	Users interaction and nature of diffusion of topics of discussion within virtual communities	The community is highly fragmented and very specialised in terms of focus. Domains of super-specialism create engagement among focused user groups. The communities are yet to have acceptance and proliferation among participants who are not working in extensively in the domain
3.1	Mean discussions on acute diseases and chronic diseases is same on social media platform (Twitter).	There is no significant difference in sample means discussion of acute and chronic diseases. Type of disease does not attract significant different levels of social discussions.
3.2	Mean discussions on communicable diseases and non-communicable diseases is same on social media platform (Twitter)	There is no significant difference in sample means discussion of communicable and non-communicable diseases. Type of disease does not attract significant different levels of social discussions.
4	Association between the technological solution and diseases.	Statistically significant association had been proved between technological solution and diseases using chi-square. There is a positive association between: (i) virtual reality (#vr) and stroke; (ii) robotics and obesity; (iii) telemedicine and HIV/AIDS; and (iv) IoT and influenza.

advertisements and promotions in today's digital age.

6.1.3. Government

From the insights of the study followings can be suggested to governments for the betterment of the society: (a) governments can use social media (such as Twitter and Facebook) for creating the awareness surrounding the health issues; (b) governments can consider the association presented in Fig. 7 between technologies and diseases for facilitating the medication process within their country; (c) Table 2 illustrates social media data had been used for detecting, predicting and monitoring trends of the diseases, governments can use the social media for the same for acute, chronic, communicable and non-communicable diseases.

7. Conclusion

The study showcase social media platform (Twitter) is being used for health related discussions and technologies. Some of the tweets are written by the bloggers and influencers for giving the moral and emotional support through social media platforms. Computing algorithm related to health domain is being discussed on Twitter; followed by the technology requirements in the health field for the devices and hardware. The various technologies such as artificial intelligence is being discussed along with the diseases such as cancer, heart and influenza. The results of the study is summarized in Table 3.

The study presents the social technical perspective within the health domain as theoretical contribution of the study to literature along with the methodology followed. The study also tries to discuss some of the concerns of the users consuming health information on social media. The study tries to suggest the implication for practices related to technology within health domain for health care companies and governments.

8. Limitation and future work

This study also suffers from some limitations, firstly, the analysis of the study is based on 105,489 tweets only. Secondly, this article had focused on most popular diseases and technological solution only for word analysis. Therefore in the future studies can explore and deep derive into other diseases and technological solutions. Thirdly, context of the tweets containing diseases and technological solution had not been considered.

The studies can be explore in terms of the single disease and technologies and deriving into how the technology is being evolved with respect to the social media discussions. The diseases discussions can be explored in terms of geographical location in further and exploring various application of the technology at the grass root level. In the sample collected, the tweets were posted by the technology companies, news channels, bloggers, medical professional and others, the discussions around technology can be differentiated with respect to professions of the author. The insights of the study reveals the technologies such as (a) wearable, internet of things, big data, deep learning, machine learning and artificial intelligence can be combined; (b) telemedicine, blockchain and internet of things can be combined for revolutionizing the health domain but how it is out of the scope of the study, future researchers can explore this, according to the actor network theory these clusters can be regarded as the black box of the social technical system in health domain.

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