Use of Internet of Things for Chronic Disease Management: An Overview

Abstract
Most of the countries with elderly populations are currently facing with chronic diseases. In this regard, Internet of Things (IoT) technology offers promising tools for reducing the chronic disease burdens. Despite the presence of fruitful works on the use of IoT for chronic disease management in literature, these are rarely overviewed consistently. The present study provides an overview on the use of IoT for chronic disease management, followed by ranking different chronic diseases based on their priority for using IoT in the developing countries. For this purpose, a structural coding was used to provide a list of technologies adopted so far, and then latent Dirichlet allocation algorithm was applied to find major topics in literature. In order to rank chronic diseases based on their priority for using IoT, a list of common categories of chronic diseases was subjected to fuzzy analytic hierarchy process. The research findings include lists of IoT technologies for chronic disease management and the most-discussed chronic diseases. In addition, with the help of text mining, a total of 18 major topics were extracted from the relevant pieces of literature. The results indicated that the cardiovascular disease and to a slightly lesser extent, diabetes mellitus are of the highest priorities for using IoT in the context of developing countries.

Keywords: Chronic disease in developing countries, chronic disease management, Internet of Things for chronic disease, Internet of Things for health care, latent Dirichlet allocation, smart health care

Introduction
Internet of Things (IoT) offers a wide range of solutions, which can be used to enhance the quality of health care at even lower cost,[1] thereby serving as a key enabler to sustain health-care delivery.[2] IoT refers to a network of interconnected smart things (e.g., sensors, smartphones, and RFID tags) that allow people and things to interact at virtually any time/anywhere to provide the desired services.[3,5] IoT contributes to efficient and effective treatment by revolutionizing the traditional health-care systems through providing a continuum of care and precise prognosis, sharing effective health strategies between various regions, checking patients’ compliance with the treatment, offering effective and customized treatment planning, and getting insight from the collected information. IoT provides a more comprehensive approach to health care, especially for patients with chronic conditions.[6] The benefits of utilizing the IoT for chronic disease management highlight the need for developing the technology for this special application. This has been further reflected in the literature on chronic disease management. The rate of incidence of chronic diseases is increasing throughout the world, threatening the developing countries in particular.[7] According to the World Health Organization (WHO), the rate of chronic diseases and resultant fatalities in the low- and middle-income countries is anticipated to increase until 2030.[7,4] Abegunde et al. inspected a total of 23 low- and middle-income countries in 2005 and concluded that some 84 billion dollars of economics production will be lost during 2006–2015 if no action is taken against the chronic diseases in these countries.[9] Given the costs and fatalities incurred by chronic diseases, it is necessary to take action for decreasing the respective damages.[7] In the meantime, new technologies (e.g., IoT) can provide promising comprehensive solutions for enhancing health-care quality at even lower costs.[1,6]

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Despite the presence of a number of literature reviews on the use of IoT for improved health care in general\cite{10,11} and the fact that a review on the relevant literature confirms the presence of efforts toward using the IoT for chronic disease management, compilation of the achievements of the research works focusing on the use of IoT for chronic disease management in a neat and integrated report is yet lacking. Describing different chronic diseases and technologies used for particular purposes so far, such an overview would help other researchers who are planning to work on the use of IoT for chronic disease management. Given the required time and budget for implementing IoT for chronic disease management, it is also necessary to prioritize different chronic diseases for using IoT in the developing countries.

The present article aims to not only compile an overview on the literature discussing the use of IoT for chronic disease management, but also prioritize chronic diseases for the use of IoT. Section 2 sets out the methodology adopted in the current study, while Section 3 describes the findings and Section 4 presents a discussion on the presented works and draws some conclusions.

**Research Methodology**

In order to provide an overview (mainly by using text mining) on literature discussing the use of IoT for chronic disease management, a number of articles on literature analysis and applications of IoT for chronic disease management were reviewed to determine the dimensions that help provide an overview on the available literature.\cite{10,12-17} Finally, the present research questions (RQs) were developed based on the identified dimensions.

**Research questions**

The followings are the RQs investigated in this work:

**RQ1.** Which technologies are engaged in the use of IoT for chronic disease management?

**RQ2.** What chronic diseases are most discussed?

**RQ3.** Which topics are usually appeared in the literature?

**RQ4.** How is the distribution of documents among the mentioned topics?

**RQ5.** Which chronic disease(s) has higher priority for using IoT?

The following three methodologies were used to address the RQs: structural coding, latent Dirichlet allocation (LDA), and fuzzy analytic hierarchy process (FAHP). Indeed, structural coding was used to provide answers to RQ1, while RQ2 was addressed using quantitative analysis of textual data (quanteda), and LDA was devised to investigate RQ3 and RQ4. Finally, RQ5 was surveyed using FAHP. The required data for RQ1–4 will be collected by literature searching and RQ5 will be answered by the collected data from the survey.

**Structural coding**

In an attempt to identify technologies engaged in the use of IoT for chronic disease management, one should search for related pieces of literature followed by having them analyzed. This study uses the keywords Internet of things + chronic disease, IoT + chronic disease, and wireless sensor + chronic disease to find relevant literature. The search was done in the Google Scholar where most academic journals, books, and proceedings are indexed.\cite{18} The term “wireless sensor + chronic disease” was used because most applications of wireless sensor network for chronic disease management have potentials for IoT implementation given that wireless sensor networks have been an important element of the IoT\cite{19} and played a key role in the evolution of IoT.\cite{20} The search process was done on February 18, 2019, without applying the publication year filter on the search results to cover the indexed contributions published until that date. The top 1000 search results for the first and second searched terms and the top 400 search results for the third searched term were analyzed as the next search results were seemingly irrelevant. Some search results were common between different key terms, especially the first and second ones (Although the IoT is the acronym for Internet of things, the searches for the two-term led to different results [at least in the order of appearance]. Hence, both of the key terms were searched for to enhance reliability.) Moreover, some literature reviews appearing in the search results were selected as those contained lists of cases where IoT was used.

Following the search strategy described herein, we ended up with a total of 161 contributions. As a supplementary source of information, the list of chronic diseases by the WHO (WHO, 2001 as cited in Patra et al., 2007) was used as a checklist. All of the 161 papers were scanned to identify the chronic disease(s) discussed in each of them. In cases where the number of contributions discussing a particular chronic disease was turned out to be few or equal to zero, the Google Scholar was searched for the chronic disease along with the term “Internet of things.” Should such a search strategy failed to return acceptable number of results, the name of the chronic disease was further searched for in combination with the term “wireless sensor network” to cover as much of relevant studies as possible. The search process was stopped once the search results seemed irrelevant or an acceptable number of relevant studies were found. Although no upper limit was set for reviewing the search results, one to four relevant contributions were selected for each search to keep the number of considered contributions manageable in the terms of time and effort. For the chronic diseases for which the Google Scholar returned no result on the use of IoT, the main Google search engine was adopted to find relevant studies, if any. This auxiliary search step led to the identification of 25 more relevant contributions, increasing the total number of relevant contributions to 186 [Appendix 1 and Figure 1].
In this research, structural coding of the literature was utilized to identify the IoT technologies customized for chronic disease management. The structural coding provides a tool for quick identification of the specific part(s) of a text relating to a particular RQ. It is useful when encountering large datasets generated from semi-structured methods. For this purpose, one should begin with coding the questions and respective answers before consolidating and extracting the relevant data from the entire text. Indeed, structural coding undertakes data coding and categorization to enable identification of commonalities, differences, and relationships. Acting as an indexing system, it allows researchers to focus on relevant data to a specific analysis out of a large dataset.[21-26]

By using structural coding, different parts of each article relating to assistive technologies were identified and compiled for future coding and analysis. RQDA, a qualitative library for R software,[27,28] was utilized to simplify the coding task. In fact, the RQ1 could be addressed by merely reading the selected articles rather than going through structural coding. However, considering the uncertainty resulted from failure to clearly indicate the used technology in the considered articles, a coding strategy was adopted to simplify this process.

Making a literature review, Guest et al. introduced techniques for enhancing the validity and reliability in qualitative research.[21] Some of these techniques were used in this work, including team-based research instrument design, team training for data collection, real-time data monitoring, intercoder agreement (coding the data by two researchers and comparing the results), and external review (having the data and related interpretations reviewed by an external researcher).

**Quanteda technique**

Various computer-assisted tools have been developed for qualitative data analysis.[29] In the current work, the Quanteda, an R package for quantitative analysis of text data,[30,31] was used to identify the most-discussed chronic diseases. To do that, the list of chronic diseases released by the WHO was used as a reference.[32] In the first step, contents of all of the 186 contributions were fed, in plain text format, to the R software followed by searching for the chronic diseases on the WHO list by using the tutorials[31,33] to identify the articles discussing on each disease (we used the available codes in tutorials with some editions). An essay containing 60 words before and 60 words after the reference to the chronic disease was extracted for each contribution. The results were manually inspected to ensure that the reference was made in the scientific content of the contribution rather than the meta data such as researchers’ affiliations, title of conference, journal names, and citations. Without such strategy, affiliation of an author working at a cancer center, for example, would mistakenly recognize the contribution as the one discussing on cancer.

The method used for finding the most-discussed chronic diseases came with three important flaws. First, the contributions that even briefly introduced a particular chronic disease would be recognized as the ones discussing on that chronic disease. Second, there might be cases where the solution provided in a particular contribution was of help for more than one chronic disease, but the authors failed to refer all chronic diseases which could be covered by the solution. And third, the WHO-provided list of chronic diseases is not inclusive of all chronic diseases in each category, but rather uses an “other diseases” item on the list of each category. Investigating the three flaws, it was found that their impacts on the results are not significant because of three main reasons: (1) if a chronic disease was really noteworthy, the authors would indicate its name throughout their papers; (2) the brief introductions to chronic diseases were generally too rare and limited to place a chronic disease on the most-discussed list (however, the results were manually inspected to avoid such problems); and (3) the fact that the instances of the main categories were searched for implies that the instances of possible diseases that were not listed by the WHO were ignored; this may be interpreted as a limitation of the present research, but one may reason that the WHO would list such chronic diseases if those were significant. Nevertheless, the missed most-discussed diseases, if any, might appear in the results of LDA.

**Latent Dirichlet allocation**

An objective of the present study has been to evaluate major topics in the selected pieces of literature (RQ3 and RQ4). The so-called LDA was applied for this purpose. Before this algorithm could be implemented, the collected data must be prepared by having them converted to plain text, to facilitate cleanup and other processes on the data, checking the converted text files for a list of stop words, transforming all letters to lower case, and removing punctuations, numbers, stem words, and special characters (e.g., @). In the relevant research works, the prepared data for LDA algorithm are usually referred to as “clean data.” Interested readers may refer to Sherman’s book for more information.[37]

Introduced by Blei et al., LDA provides a probabilistic generative model for text collection. The main idea behind LDA is the assumption that each essay is a mixture of latent topics, with each topic being defined as a particular distribution of related words.[38] The LDA has been widely used for topic modeling and literature analysis.[39-42] In this article, LDA was utilized to identify major topics in the selected contributions [Figure 1] using a statistical tool called R Software.[25] In this regard, available tutorials about applying LDA by using R and analyze data have been used (we used available codes in tutorials with some editions).[34,35,43,44] For this purpose, word clouds were extracted based on the selected pieces of literature, optimal
number of topics were identified, top ten keywords for each topic were identified, and distribution of the documents among different topics was evaluated.

**Fuzzy analytic hierarchy process for prioritizing chronic diseases for Internet of Things**

In order to prioritize the chronic diseases based on their priority for using IoT (RQ45), FAHP was used. AHP, introduced by Thomas Saaty, works by weighting a list of alternatives based on selected criteria.\[45\]–\[47\] The uncertainty associated with the decision environments justifies the use of FAHP to rank the chronic diseases.\[48\],\[49\] Chang developed a FAHP as an extent analysis method,\[50\] which later on became the most popular FAHP technique and was frequently used for pair-wise comparisons, as is the case in the present work.\[51\]

In the current study, the most-discussed categories of chronic diseases in the developing countries were used as the alternatives for the FAHP model. The categories were identified based on a review on the studies discussing chronic diseases in the developing countries. These included malignant neoplasms, diabetes mellitus, cardiovascular diseases, and respiratory disorders.\[7\],\[9\],\[32\],\[52\],\[53\]

Here, we used the categories of chronic diseases rather than particular diseases to keep the number of alternatives reasonable. The criteria for a FAHP model can be defined by researchers or based on the relevant literature. As mentioned in the *Introduction* section, chronic diseases incur both costs and fatalities, thus “cost reduction” and “death prevention” were herein selected as the criteria to weight different categories of chronic diseases for using IoT. Figure 2 shows AHP model for prioritizing different categories of chronic diseases for using IoT.

To ensure consistency of the result, various consistency indexes and approaches exist.\[54\] In this research, the method proposed by Gogus and Boucher was used. According to this method, a matrix is recognized as consistent if the value of two consistency rates (CR), namely $CR^u$ and $CR^g$, are equal to or lower than 0.1 for each comparison matrix.\[55\]

**Results**

This section presents the results obtained upon applying each of the used methods. We distinguish between findings of different methods to better understand the results, but this does not mean that these findings are independent of one another. The entire set of findings provides an overview on the literature.

**Engaged technologies and most-discussed chronic diseases**

Based on the structural coding task and related analysis, IoT technology and sensors, big data, cloud computing, fog computing, robotics (Robots can also be considered as IoT-enabled devices), web-based technologies, blockchain, and semantic technology were identified as the main assistive technologies for IoT-based chronic disease management. Different cases may use a different combination of these technologies to provide desired services. IoT-equipped sensors have been used to gather...
data from the surrounding environment or measure patient’s vital parameters. These could be further developed to process such data and take actions autonomously. For example, Li et al. proposed a pervasive monitoring system for measuring physical signs of the patient, for example, blood pressure, electrocardiogram, SpO2, and heart rate, and his/her location and send them to a remote server. Continuously sensing the subject and generating data, an IoT device produces huge amounts of data (i.e., big data) that can be processed to provide valuable pieces of information for disease detection or development of smarter solutions. Gachet Páez et al. discussed the use of big data and IoT for chronic disease management.

Cloud computing provides portability for the use of IoT for patient monitoring. It stores the data collected through IoT devices on the cloud where the required computation can be done. In their study, Sinnapolu and Alawneh developed an iOS application for heart rate monitoring by using a wearable sensor. In emergencies (i.e., critical conditions occurring to the patient), the application could route the nearby hospitals for the drive or take other actions such as pulling over for assistance. In cases where real-time data analysis is required and common delays with cloud computing cannot be tolerated, fog computing can be of help. Cisco developed the fog or edge computing as an extension to the cloud computing. Here, the fog refers to an intermediary between the user and the cloud, which acts to reduce the latency by performing real-time data analysis rather than sending such huge amounts of data to the cloud for processing.

Blockchain refers to a network of publicly distributed systems that transmit records of transactions in a way that cannot be falsified after the event. It uses an asymmetric encryption method with different keys for encrypting and decrypting a message or transaction. Saravanan et al. developed a secure mobile device for diabetes monitoring, wherein the blockchain was used to ensure the security of and trusted access to the collected data.

As of present, the semantic technology is usually used for inference purposes. It creates an ontology model to define relationships between different concepts. An ontology model provides a framework for describing the knowledge about a particular subject by considering different concepts and their relations. For example, Jara et al. presented a system for drug identification and delivery using the ontology and IoT, wherein the ontology described the drug concepts and patient’s information, while the IoT helped identify drugs using radio-frequency identification (RFID), near-field communication (NFC), or similar technologies.

The identified technologies can be used in general patient monitoring systems not only systems for chronic diseases management. In other words, the use of IoT for chronic disease management describes a special case of the use of IoT in the scope of general health care, and this is why there are common technologies that can be applied in both contexts.

Based on the analysis results and the existing studies, Figure 3 shows the interaction among several technologies adopted for smart chronic disease management, including IoT, big data, cloud computing, and fog computing, for a case where all of the four technologies were engaged. Sensors and IoT devices gather data from patients. Fog computing does real-time analysis on the data, and cloud computing serves as the main storage for the collected and processed data. In a hospital or a research center, analytical tools and methods can be used to recognize patterns in the data or develop new applications. Doctors and professionals in the hospital can monitor patients remotely and assist them in emergencies. This model is not exclusive to chronic disease management, but rather general IoT-based patient monitoring systems may utilize the same interaction schemes among related technologies.

Development of each of the mentioned technologies (or any combination of them) to provide new IoT applications or improve the available solutions for chronic disease management provides topics for future research in this domain. Some researchers elaborated on the security and privacy challenges associated with the use of IoT in health-care domain. In this respect, blockchain has been recognized as a promising technology for ensuring the security and privacy of the data collected through IoT for health-care applications. Further development of blockchain into smart chronic disease management and health-care systems can be investigated in future research works.

Produced by Quanteda and R package, Table 1 shows statistical information about the contributions discussing each chronic disease. The first column (Column A) in this table lists the chronic diseases. The second column indicates the keywords searched for each chronic disease. The third column (number of studies) refers to the number of contributions wherein the respective key term has been mentioned at least once. An attempt was made to set the key terms in such a way to have as wide range of results as possible, followed by manual inspection of the results.

The fundamental question to address in this step is whether a higher frequency of reference to a particular chronic disease in the literature can recognize the diseases as a most-discussed one? To answer this question, diabetes and cardiovascular diseases, as the two most-cited chronic diseases, were manually investigated; indeed, these were candidates for most-discussed chronic diseases, with the results confirming that diabetes and cardiovascular diseases were the most-discussed chronic diseases in the studied literature.

Based on related analysis, there were studies discussing the actual or potential applications of IoT for supporting the patients engaged with chronic disease such as cancer, diabetes, depression, dementia, cardiovascular diseases, and asthma. The level of support varied from simple data collection via an IoT-enabled device to highly sophisticated
levels. In addition, some of the studies provided no more than brief explanations on the possibility of using IoT or wireless sensors for a specific chronic disease rather than presenting comprehensive solutions. Future research works may focus on the formulation of IoT for the management of the chronic diseases for which IoT has either not been applied yet or been applied partly or at lower levels of maturity. In their work, Dadkhah et al. identified different stages of IoT development and indicated possible contributions of health-care professionals to the IoT body of knowledge.[66]

IoT-enabled devices usually use sensors to measure one or more specific parameters of the patient’s body to monitor a particular chronic disease. Figure 3 demonstrates some of these parameters based on the work by de Morais and AdeAquino.[10] With the advance of medical science, new parameters may become necessary for monitoring particular chronic diseases, necessitating special sensors and IoT devices for measuring them. Accordingly, future research work may also focus on the development of new sensors.

As discussed in the Introduction section, IoT promotes health-care quality at even lower cost.[1] It can revolutionize the health care by providing effective and efficient treatment and new capabilities, especially for chronic disease management.[10] Before adopting IoT, managers need to delineate their goal and then decide about the specific IoT application(s) that may render helpful regarding the considered chronic disease and the ultimate goal. Customizing IoT strategies for various countries can be undertaken in future works.

The content and structure of this section and Figure 3 were adopted from other research works.[10,11]

**Major topics in the literature and their distribution**

As mentioned in Section 3, findings of the present section are based on text mining on clean data.[34‑36,43,44] Figure 4 shows the word clouds extracted from the literature. As shown in this figure, patient, data, system, sensor, use, health, technology, and monitor were most frequently mentioned in the considered contributions. One may combine these keywords into a phrase: patient monitoring using different sensors and gathering related data. These keywords represent the main concepts on which the literature about the use of IoT for chronic disease management elaborate. The size of each keyword in Figure 4 represents its frequency of appearance.

For LDA analysis, one must begin with defining the number of topics to be extracted. In other words, LDA cannot calculate the optimum number of topics by itself and rather the user must set the number of topics as an input parameter. Different studies have presented various methods for determining the optimum number of topics for a LDA analysis.[67‑70] Nikita Moor designed a library for R package: “ldatuning;” this library could be devised to draw graphs based on the available data and help researcher find the optimal number of topics for LDA analysis.[43,71] Accordingly, she used four metrics, namely Arun2010, CaoJuan2009, Deveaud2014, and Griffiths2004. Based on the output graphs of the mentioned library, researchers should find extremums, i.e., to find a range of topics for which Arun2010 and CaoJuan2009 are minimized, while Deveaud2014 and Griffiths2004 are maximized.[43]
<table>
<thead>
<tr>
<th>n</th>
<th>Chronic diseases*</th>
<th>Searched keywords</th>
<th>Number of studies which mentioned to a chronic disease</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Nutritional deficiencies</td>
<td>Nutrition, malnutrition, Iodine, Vitamin, Anaemia</td>
<td>Malnutrition=1</td>
</tr>
<tr>
<td>2</td>
<td>Malignant neoplasms</td>
<td>Neoplasms, Cancer, Lymphomas, Myeloma, Leukaemia</td>
<td>Cancer=23</td>
</tr>
<tr>
<td>3</td>
<td>Diabetes mellitus</td>
<td>Diabetes</td>
<td>Diabetes=83</td>
</tr>
<tr>
<td>4</td>
<td>Endocrine disorders</td>
<td>Endocrine</td>
<td>Endocrine=0</td>
</tr>
<tr>
<td>5</td>
<td>Neuro-psychiatric conditions</td>
<td>Neuro, Psychiatric, Depression, Bipolar, Epilepsy, Alcohol, Dementia, Parkinson, Sclerosis, Drug use, Post-traumatic stress, Obsessive, Panic, Sleep disorder, Migraine, Retardation</td>
<td>Depression=23, Bipolar=4, Epilepsy=10, Alcohol=11, Dementia=22, Parkinson=8, Sclerosis=4, Obsessive=0, Panic=1, Sleep disorder=5</td>
</tr>
<tr>
<td>6</td>
<td>Sense organ diseases</td>
<td>Sense organ glaucoma, Cataracts, Presbyopia, Deafness</td>
<td>Glaucoma=4</td>
</tr>
<tr>
<td>7</td>
<td>Cardiovascular diseases</td>
<td>Cardiovascular, Rheumatic, Hypertension, Ischaemic, Cerebrovascular, Inflammatory heart</td>
<td>Cardiovascular=47, Rheumatic=1, Hypertension=37, Ischaemic=1, Cerebrovascular=5</td>
</tr>
<tr>
<td>8</td>
<td>Respiratory diseases</td>
<td>Chronic obstructive pulmonary disease, Asthma</td>
<td>Chronic obstructive pulmonary disease=18, Asthma=24</td>
</tr>
<tr>
<td>9</td>
<td>Digestive diseases</td>
<td>Digestive diseases, Peptic ulcer, Cirrhosis of the liver, Appendicitis</td>
<td>All equal to zero</td>
</tr>
<tr>
<td>10</td>
<td>Genitourinary diseases</td>
<td>Genitourinary, Nephritis, Nephrosis, prostatic hypertrophy</td>
<td>Nephritis=2, Nephrosis=1</td>
</tr>
<tr>
<td>11</td>
<td>Skin diseases</td>
<td>Skin disease</td>
<td>Skin disease=2</td>
</tr>
<tr>
<td>12</td>
<td>Musculo-skeletal diseases</td>
<td>Musculo diseases, Skeletal diseases, Arthritis, Osteoarthritis, Gout, Low back pain</td>
<td>Arthritis=13, Osteoarthritis=4, Gout=1</td>
</tr>
</tbody>
</table>

Contd...
Dadkhah, et al.: Internet of things for chronic disease management

<table>
<thead>
<tr>
<th>n</th>
<th>Chronic diseases*</th>
<th>Searched keywords</th>
<th>Number of studies which mentioned to a chronic disease</th>
</tr>
</thead>
</table>
| 13  | Congenital anomalies | Congenital anomalies  
Abdominal wall defect  
Anencephaly  
Anorectal atresia  
Cleft lip  
Cleft palate  
Oesophageal atresia  
Renal agenesis  
Down syndrome  
Congenital heart anomalies  
Spina bifida | Spina bifida=1 |
| 14  | Oral conditions   | Dental caries  
Periodontal disease  
Edentulism | Periodontal disease=1 |

*This column has been adapted[32]

Table 2 shows the labels assigned to each topic. As shown in this table, some topics were broader than the others and vice versa. Each contribution might include multiple topics. Figure 4 illustrates the distribution of the contributions among different topics on a scatter plot. As shown in this figure and Table 2, the broader topics (e.g., topics 1 and 17) were discussed in more contributions (i.e., corresponding to higher gamma value). Data collection in IoT (topic 17) was the most widely covered topic; this makes sense because most of the discussions on the use of IoT for chronic diseases are kind of data-collecting process using sensors and devices.

Prioritization of chronic diseases for the use of Internet of Things

Prioritization of chronic diseases for the use of IoT was done by performing a survey among experts of chronic disease management. The questionnaire was made up of three questions about ranking criteria and alternatives for each criterion. In order to prepare the participants for the survey, they were provided with adequate deals of information about the research goal, IoT, and categories of chronic diseases. Ultimately, out of the distributed and collected questionnaires, six ones were filled validly. According to consultations with analytic hierarchy process (AHP) experts and based on available literature,[78] this number of forms was found to be adequate for further analysis. Applying the CR proposed by Gogus and Boucher, the participant was asked to revise his/her answer if the rate exceeded 0.1. Based on the experts’ opinions and the method presented in methodology section, different criteria and diseases were ranked, as tabulated in Tables 3-6.

Results of the current study indicated that fatality prevention has higher priority over cost reduction so that managers must base their decisions about the use of IoT for chronic disease management on the fatality prevention rather than cost reduction. However, considering either of cost reduction or fatality prevention as a criterion, cardiovascular diseases and diabetes mellitus were found...
to be of higher priority than the other diseases such as respiratory diseases or malignant neoplasms. This opinion holds equally whether fatality prevention, cost reduction, or a combination of both is selected as the criterion.

Discussion and Conclusion

The literature on the use of IoT for chronic disease management was overviewed. The main technologies engaged in the IoT-based chronic disease management were discussed, major topics in the literature were presented, and chronic diseases were prioritized for using the IoT.

Based on the results of LDA analysis, the most-discussed topics in the literature were identified [Figure 6]. In Figure 6, the dots show contributions of articles on respective topics, with the dots with higher values of gamma showing the domination of the respective topic in the literature. Represented by dots of the highest gamma value, topic 17 (data collection in IoT) is the dominant topic in the literature, possibly because of its broadness given that most applications of IoT in chronic disease management represent special cases of a data collection using sensors and devices. Relatively similar results were found for other broad topics, such as smart health-care services. Some topics exhibited low values of gamma...
Table 4: Ranking of the chronic diseases based on their priority for using Internet of Things by considering cost reduction as a criterion

<table>
<thead>
<tr>
<th>Chronic disease category</th>
<th>Weight</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Malignant neoplasms</td>
<td>0.000</td>
<td>3</td>
</tr>
<tr>
<td>Diabetes mellitus</td>
<td>0.303</td>
<td>2</td>
</tr>
<tr>
<td>Cardiovascular diseases</td>
<td>0.697</td>
<td>1</td>
</tr>
<tr>
<td>Respiratory diseases</td>
<td>0.000</td>
<td>3</td>
</tr>
</tbody>
</table>

Table 5: Ranking of the chronic diseases based on their priority for using Internet of Things by considering fatality prevention as a criterion

<table>
<thead>
<tr>
<th>Chronic disease category</th>
<th>Weight</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Malignant neoplasms</td>
<td>0.000</td>
<td>3</td>
</tr>
<tr>
<td>Diabetes mellitus</td>
<td>0.363</td>
<td>2</td>
</tr>
<tr>
<td>Cardiovascular diseases</td>
<td>0.637</td>
<td>1</td>
</tr>
<tr>
<td>Respiratory diseases</td>
<td>0.000</td>
<td>3</td>
</tr>
</tbody>
</table>

Table 6: Overall ranking of chronic diseases based on their priority for using Internet of Things

<table>
<thead>
<tr>
<th>Chronic disease category</th>
<th>Weight</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Malignant neoplasms</td>
<td>0.00000</td>
<td>3</td>
</tr>
<tr>
<td>Diabetes mellitus</td>
<td>0.35034</td>
<td>2</td>
</tr>
<tr>
<td>Cardiovascular diseases</td>
<td>0.64966</td>
<td>1</td>
</tr>
<tr>
<td>Respiratory diseases</td>
<td>0.00000</td>
<td>3</td>
</tr>
</tbody>
</table>

(e.g., epilepsy management using IoT and semantic IoT data modeling), indicating limited extent of studies on these topics. Topics 10 and 12 discuss the application of IoT in a similar domain, however these topics are different.

Based on the experts’ opinion, cardiovascular diseases followed by diabetes mellitus were of the highest priorities for using IoT in developing countries. The reason might be the inherent capabilities of IoT for the treatment of these diseases rather than malignant neoplasms and respiratory disorders. Moreover, knowing the significant contribution of lifestyle into the management of cardiovascular diseases and diabetes mellitus, IoT device works well for monitoring the patient’s lifestyle. Considering Table 1, a lot of research works, among the selected pieces of literature, have focused on cardiovascular diseases and diabetes mellitus. For the cardiovascular diseases, this is understandable based on the result of LDA analysis because topic 10 and 12 are related to the use of IoT for cardiovascular diseases. However, when it comes to diabetes mellitus, only one topic (i.e., diabetes management) is directly related to the use of IoT for diabetes mellitus. Moreover, Figure 6 shows that the number of contributions discussing this topic is moderate. Accordingly, it seems that researchers have well understood the potentials of IoT for cardiovascular diseases and to a lesser extent, diabetes mellitus in terms of cost reduction and fatality prevention, encouraging them to do more research works on these two diseases (not only in the developing countries, but around the globe). Figure 6 further indicates that the contributions on the use of IoT for respiratory disorders are limited, with no contribution found on the malignant neoplasms. Nevertheless, there is research which state that security of IoT is an important concern.

This work was supposed to focus on the use of IoT for chronic disease management in developing countries. Although the search strategy did not reflect such an attitude, the presented rankings were based on that. Future research works may consider the developed countries to prioritize the chronic diseases in such countries and delineate the most significant criteria.

Despite the current study which considered the chronic diseases in general, future research works may focus on a specific category of chronic diseases by introducing related sensors and corresponding platform(s), current status of research, and guidelines for future research.

This research presented multiviews to the existing literature on IoT for chronic disease management through the following three methodologies: structural coding, LDA, and FAHP.
This was done by identifying the technologies engaged in IoT-based chronic disease management, most-discussed chronic diseases, major topics in the literature, and priority of chronic diseases in the developing countries.

This research suffers from a number of limitations. There were chances of inaccurately labeled topics in the LDA. The F-AHP was based on the opinions of selected experts, and other experts may have different opinions. According to Figure 1, out of the 2400 contributions in which abstracts were scanned, only 186 articles were selected for further analysis. Later in the structural coding process, some of the selected contributions were recognized as irrelevant (upon analyzing their full texts) and hence excluded. However, the LDA and Quenteda library were applied on the entire set of the 186 selected contributions, i.e., these latter two techniques were applied on the results of the search strategy rather than the filtered data via structural coding. Some of the processes applied in this research were automatic or semi-automatic, making the susceptible to error, although the error was found to impose only insignificant impacts on the final results. Finally, the list of chronic diseases considered in this study is not comprehensive, but rather signifies the most-discussed diseases instead. Moreover, assistive technologies were identified based on the selected pieces of literature only, leaving the chances of the presence of other technologies in other studies.

For future read, interested readers are encouraged to read review articles elaborating on the use of IoT in the health-care domain.\textsuperscript{10,11,81}

### R Packages

The below R packages have been used in the current study:

- “tm”\textsuperscript{82,83}
- “SnowballC”\textsuperscript{84}
- “wordcloud”\textsuperscript{85}
- “RCOLORBrewer”\textsuperscript{86}
- “readxl”\textsuperscript{87}
- “ldatuning”\textsuperscript{88}
- “topicmodels”\textsuperscript{89}
- “tidytext”\textsuperscript{90}
- “ggplot2”\textsuperscript{91}
- “dplyr”\textsuperscript{92}
- “readtext”\textsuperscript{93}
- “quanteda”\textsuperscript{94}
- “summarytools”\textsuperscript{94}

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### Conflicts of interest

There are no conflicts of interest.

### References

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Appendix 1

List of 186 selected papers based on Figure 1


4. AL‑Jaf TG, Al‑Hemiary EH. Internet of Things Based Cloud Smart Monitoring for Asthma Patient. Paper Presented at the The 1st International Conference on Information Technology (ICoIT’17); 2017.


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43. Darshan K, Anandakumar K. A comprehensive review on usage of Internet of Things (IoT) in healthcare system. Paper Presented at the 2015 International Conference on Emerging Research in Electronics, Computer Science and Technology (ICERECT); 2015.
74. Jagadeeswari V, Subramaniyaswamy V, Logesh R, Vijayakumar V. A study on medical Internet of Things and Big Data in personalized
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119. Muriuki IM. Fuzzy Expert Based Real Time Monitoring System for Patients with Chronic Heart Failure through IOT. Strathmore University; 2018.


