International Journal of Medical Informatics 129 (2019) 154–166

Contents lists available at ScienceDirect

International Journal of Medical Informatics

journal homepage: www.elsevier.com/locate/ijmedinf

Review article

The emerging role of cognitive computing in healthcare: A systematic literature review

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ARTICLE INFO

Keywords:
Cognitive computing
Cognitive computing in healthcare
Systematic literature review

ABSTRACT

To assist medical professional in better treatment of diseases, and improve patient outcomes, healthcare has brought about a cognitive computing revolution. The cognitive computing system processes enormous amounts of data instantly to answer specific queries and makes customized intelligent recommendations. Cognitive computing in healthcare links the functioning of human and machines where computers and the human brain truly overlap to improve human decision-making. In regard to this convergence, this systematic literature review (SLR) provides comprehensive information of the prior research related to cognitive computing in healthcare. The SLR focused on methods, algorithms, applications, results, strengths, and limitation using different research articles collected from leading international databases using linear and citation chaining search. The main outcomes of the SLR include proposal on future research direction, challenges faced by researchers, capabilities and the impact of cognitive computing on healthcare outcome and a conceptual model, showcasing the better utilization of cognitive computing in healthcare domain. This study concludes with managerial implications, limitations and scope for future work.

1. Introduction

Digital healthcare has changed rapidly with an increase in the use of electronic health data produced by medical devices during clinical meetings or events [12]. But, this massive electronic health data remain largely underused and there is an urgent need to convert this raw data into meaningful, expressible and time-limited information [6–8]. However, there is lack of supply in data analysts and scientists, due to which, it cannot meet the demand of ever growing volume of this Big Data [45,55]. The possible solution is to train the computer systems to perform human work and to facilitate the management of large volume data, and cognitive computing is a possible alternative.

Cognitive computing is derived from cognitive science and Artificial Intelligence (AI) [2] and is the development of computer systems modeled on the human brain [59]. Cognitive computing embodies major brain behaviors of natural intelligence, including perception, attention, thought, etc., and has the characteristic of integrating past experiences into itself as an emerging paradigm of intelligent computing methodologies [60]. Cognitive learning is the function used to simulate cognitive processes such as thinking and remembering operations and can be regarded as a mathematical tool for cognitive computing [62]. By analyzing the cognitive mechanism, building cognitive computing system, and performing cognitive processes, cognitive operators allow human thought processes to be simulated (e.g. perception, attention, and remembering something) [61]. Cognitive computing systems in healthcare collect individual, clinical and social data from different healthcare sources to improve patient engagement [3] and the multidisciplinary combination of technologies such as Machine Learning (ML), Big Data Analytics (BDA), AI, Natural Language Processing (NLP), Data Visualization (DV) and Deep Learning (DL) allows such systems to figure the type and symptoms of a disease from data [1]. In such systems [4,5], the cooperation between machine and human beings is intrinsic and ensures that healthcare receives more data which can be used to solve complex issues. Cognitive computing enables healthcare professionals to acquire the best judgments from worldwide renowned medical practitioners and reach to the remote locations and save clinical studies to match more patients to life and its promising value in healthcare has generated an increasing interest of researchers from academia and industry [63].

Cognitive Informatics (CI) is a trans-disciplinary investigation of computer science, information science, cognitive science, and intelligence science that investigates the brain and natural intelligence's internal information processing mechanisms and processes, as well as their cognitive computing engineering applications [57]. Studying

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https://doi.org/10.1016/j.ijmedinf.2019.04.024
Received 17 February 2019; Received in revised form 20 April 2019; Accepted 27 April 2019
1386-5056/

Table 1
Difficulties experienced in healthcare.

Sr #	Difficulty	Description
1	Incomplete digital platform	[22] Despite the use of optical character reorganization, the digital system still has no access to all relevant data because not all of it is in a digital and readable format.
2	Lack of cloud-adoption	[22] Vendors such as Amazon, IBM, Microsoft, and Google are known to provide the best cloud-based service. However, there are still some healthcare organizations that are reluctant to transfer their data to the cloud and, instead, resort to on-site solutions which may have limited abilities and are potentially more complex.
3	Ever changing and evolving regulatory requirements	Healthcare is highly regulated industry where regulatory and reporting requirements continue to increase and evolve with government policy. Such requirements need quality reports around measurement like readmission, safety, and patient experience, and heavily influence pricing and financial information to the public [23]. Such government-imposed regulations only add burden.
4	Inconsistent variable definition	[24] Many clinicians from different groups may have inconsistent views of treatment for the same condition. Such treatment may not always lead to personalized treatment and personalized care plans.
5	Privacy and security	Medical records are normally targeted by cyber thieves and the stealing of such health or identity data costs companies or individuals [25] and causes potential damage.
6	Limited use	[22] The most popular application in healthcare tends to be advanced image processing and predictive analysis. However, much more can be offered by the digital system. Interactive bots, NLP, ML and DL are just a few examples in which only a limited number of hospitals participate.

human intelligence and its problem solving applications is a topic covered in many disciplines, including philosophy, math and logic, neuroscience, psychology, cognitive science, computer science, etc., and CI and granular computing (GC) are two studies with different emphases on human intelligence and human-inspired problem solving, wherein CI is the study of natural intelligence and its mechanisms for processing information and GC explores various levels of granularity in human-centered perception, problem solving, information processing, as well as their implications and applications in knowledge-intensive intelligent systems design and implementation [56]. In CI, objects/attributes are regarded as synapse-connected neurons, and the relationship represents the synapse in CI, and the brain generates new synapse or relationship between the existing neurons to represent new information [58].

Application of cognitive computing in healthcare is still in its infancy stage as there have been only a few literature reviews, but none of them have provided any crucial insights on this emerging domain. As a consequence, it becomes difficult and confusing to understand and apply the potential value of cognitive computing on improving the quality of patient care. In addition, researchers may find it challenging to track and use, such as its capabilities or impact on healthcare. An SLR is, therefore, conducted to capture relevant literature from diverse sources with the aim: i) to present the published academic research work on cognitive computing in terms of method, algorithms, applications and results used in the healthcare industry; ii) to explore the emerging areas of cognitive computing in healthcare; iii) to present the future direction of cognitive computing research in healthcare; and iv) to propose a conceptual model to understand the impact of cognitive computing on healthcare organizations' performance.

The review paper is structured as follows: Section 2 discusses the background and motivation for this study. Section 3 discusses the methodology used to carry out this review of literature. Section 4 focuses on analysis and discussion. Section 5 concludes the study with the managerial implication and limitations. Table A1 in Appendix captures the selected papers considered for the review. Table B1 in Appendix refers to the categorization of research articles and Table B2 in Appendix refers to the current research on methodology, algorithms, applications, and results.

2. Background and motivation

There have been three areas of computing, namely: i) tabulating era, ii) programmable era and iii) cognitive computing era [11,19]. The tabulating era was the first era of computing, wherein data were fed into mechanical systems and the computing was primarily performed by calculators, tabulating machines, and vacuum systems [20]. This era started in 1900 and ended in 1950. The programmable era was the second era of computing and was completely controlled by the programming, as inflected on the system [20]. It was a paradigm shift from mechanical systems to the electronic systems wherein enormous improvement happened in storage and performance benchmarks. Such computing is primary performed by mainframe, personal computer, and smart computer machines. This era started in 1950 and is still existence to date. The cognitive computing era evolved in 2011, wherein systems were developed to understand the way humans operate, through senses, learning and experiences. The main driver of this era was the sudden exponential increase in the amount of unstructured data, and then understanding, learning and communicating with people in natural language rather than software code, and being able to extract meaning and learn from large amounts of unstructured visual, verbal and numerical information and help people make complex decisions based on them [20]. This era led to the establishment of automated IT systems that can solve problems without the need for human assistance.

A cognitive computing environment requires sufficient data to detect patterns or anomalies and to ensure that the analytical results are reliable and consistent [18]. The discussions about cognitive computing always refer to Big Data (BD) and predictive analytics. BD facilitate the storage of large amounts of data, and predictive analysis gives the ability to predict what will happen, whereas, in comparison, cognitive computing gives the ability to learn from further interactions and suggest best actions. In short, cognitive computing is a technology that carries three core traits, i) NLP, ii) assertion and recommendations, and iii) continues to learn.NLP focuses on enabling computers to understand and process human languages, bringing computers closer to understanding language at a human level. Organizations can deploy cognitive solutions for item or product recommendation with continuous learning and continuous improvements.

Despite the development of digital technology, the healthcare industry is experiencing major difficulties as presented in Table 1.

In recent years, cognitive computing has been one of the most popular trends in healthcare technology [13] and plays a significant role in improving communications between people, and machines and has prompted the development of new models for human-machine interactions; the objective is to transform data into time-bound actionable insights for improved healthcare outcome throughout the patient's endways journey [21]. Another prospective benefit is the magnifying of trust in people in that computing devices can provide truthful responses within an acceptable trust range [14]. Rapid development of BD, ML, DL, and NLP techniques and the ability to handle large amounts of structured, unstructured, semi-structured data from heterogeneous sources makes cognitive computing a low complex task [15], for instance healthcare [16]. As a result, in future engineering systems, cognitive computing and relevant technology will play an important role [17]. Cooperation between humans and the machine is innate in a

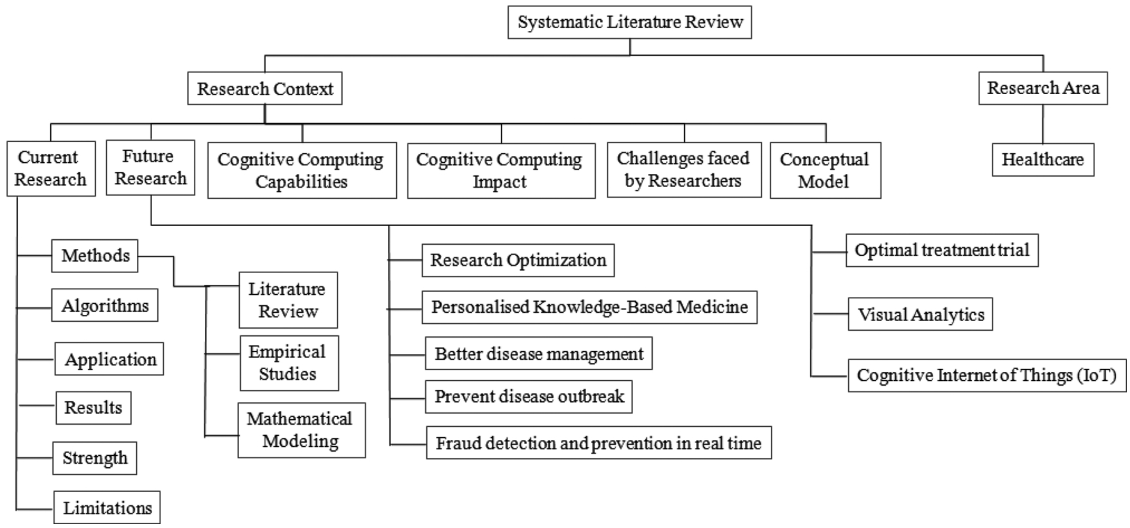

Fig. 1. SLR Map. (Source: self-compilation by authors).

cognitive system, which allows healthcare to gain greater value for solving compound problems from data [37–39].

3. Research methodology

The methodology for performing SLR is presented in Fig. 1. It is broadly classified into i) research context, and ii) research area. The research context covers i) current research by providing information in terms of methods, algorithms, application, results, strength, and limitations using different research articles. Three types of articles were examined, namely, literature review, empirical studies and mathematical modeling in the digital databases using linear and citation chaining search, ii) future research direction, iii) cognitive computing capabilities, iv) cognitive computing impact in healthcare, v) challenges currently faced by researchers, and vi) conceptual model. Future research directions are based on the following perspectives: research optimization, personalized knowledge-based medicine, better disease management, prevention of disease outbreak, fraud detection and prevention in real time, cognitive Internet of Things (CIoT), optimal treatment trial and visual analytics. The research area is on healthcare.

An SLR collects empirical data using a formal protocol [46–48] and is typically the collection of research studies in a variety of fields [49–51] to provide the reader with a broad spectrum of knowledge on underlying study of current research. The current study conducts SLR on the basis of the guidelines outlined by [9,10]. There are three different stages, expressly: i) planning the review, ii) conducting the review, and iii) reporting the review. Each stage is divided into several steps and the process is presented in Fig. 2 from which the tasks from each stage can be easily comprehended.

3.1. Planning the review

3.1.1. Research question

Gather current research in terms of method, algorithms, and applications in cognitive computing with application in healthcare and then present the results.

3.1.2. Inclusion criteria

The inclusion criteria (IC) used to select the literatures to be included in the review is presented in Table 2.

3.1.3. Exclusion criteria

The exclusion criteria (EC) used to determine literatures for exclusion in the review is presented in Table 3.

3.1.4. Digital database

The digital databases used to collect the data for the review of papers are i) Scopus, ii) DBLP, iii) PubMed, iv) ScienceDirect, v) Springer, vi) Sage vii) Taylor & Francis, and viii) Emerald.

3.1.5. Review protocol development

Scopus was first considered to extract data from these digital databases as: i) compared to other digital databases, the extensive number of studies in connection with this study are indexed, ii) it is the leading digital literature database reviewed by peers, and iii) it has extensive scientific and interdisciplinary information. DBLP, PubMed, ScienceDirect, Springer, Sage, Taylor & Francis, and Emerald have also been browsed for the papers and included those that are not referred to in Scopus. Furthermore, additional relevant papers matching to the context of this study were included on the basis of full text with citation chaining search. Citation chaining included relevant papers using both backward and forward approach in the literature studies from the above digital databases.

3.1.6. Review protocol evaluation

With a view to support the criteria of inclusion, and exclusion, and the selection of research data, it is vital to examine and evaluate the quality of studies. Indeed, the objective of quality assessment is to make sure that the results of the study are suitable and impartial [52]. Thus, a number of quality evaluation (QE) questions were identified in order to improve this study. Previous SLRs [52–54] inspired the design of this review. An exclusion criterion, i.e. EC 2 is the composition of QE questions and is presented in Table 4.

To ensure the efficiency of this study's results, the quality score is considered a norm for exclusion and, consequently, only the appropriate studies have been selected with a quality score of meeting or exceeding fifty percent of the ideal score of 9. Table A6 of Appendix provides a complete list of the selected studies with quality evaluation score.

In Fig. 3, various stages for data selection are presented, where Si, $1 \le i \le 6$ represents sequential stages and the description of each stage can be easily comprehended from it. Oval callouts linked to each stage are the applicability of respective inclusion criteria(s) and exclusion criteria.

3.2. Conducting the review

3.2.1. Search syntax

Table 5 shows the search syntax that was utilized in the SLR for

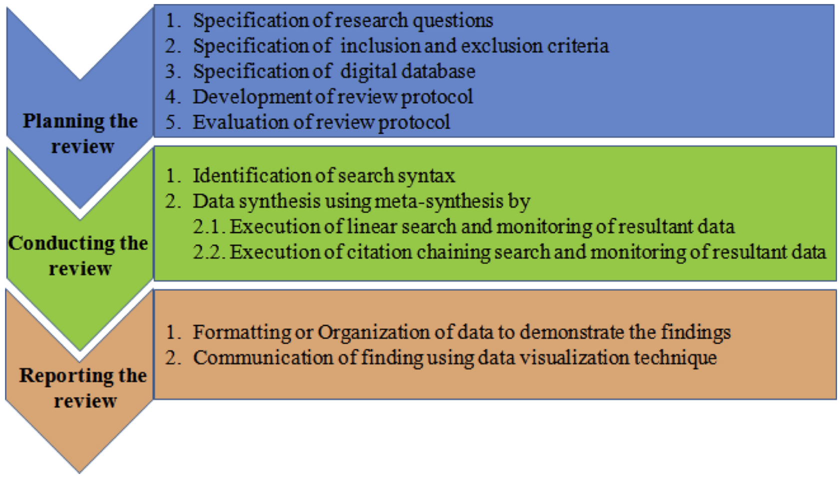

Fig. 2. SLR organization. (Source: self-compilation by authors).

Table 2
Inclusion criteria for selection of literatures.

IC#	Description
IC 1	The used keywords are: “Cognitive Computing”, “Cognitive System”, “Cognitive Informatics” and Healthcare, “Health care”. The operators of search syntax are OR, AND.AND operator signifies that both keywords must be present in the search queries and OR means that at least one keyword must be present in the queries searched.
IC 2	Studies published before December 2018.
IC 3	Studies published in English.
IC 4	Studies limited to document type of journal articles.
IC 5	Include abstract-based studies.
IC 6	Include full-text-based studies.

selecting the research papers.

The various attributes of the search syntax are: Scopus:(i) TITLE-ABS-KEY: the keywords selected are searched for in the title, abstract and keywords of the paper, (ii) AND: operator that means that both keywords in the searched item should be present, (iii) OR: operator that means that one of the keywords in the searched item should be present, (iv) LANGUAGE: papers written in English are addressed in this study, (v) LIMIT-TO(DOCTYPE): for this study, only journals were considered. Here, 'ar' stands for article in the journal, 're' stands for article in the review,' ip' stands for article in the press (vi) LIMIT-TO (EXACTKEYWORD): include the papers matching to the exact keyword, and (vii) * is the wildcard character that represents one or more character. The search syntax for others can be easily seen from Table 5.

3.2.2. Data synthesis

A qualitative meta-synthesis technique is used so as to gain in-depth understanding of method, algorithms, applications, results, strengths, and limitations of current research. Fig. 4 presents the output of the meta-synthesis technique. The figure depicts i) search strategy, including literature linear search and citation chaining search, ii) number of studies at each stage of the process, and iii) the summary of studies selected for synthesis.

In stage 1, a total of 16,631 papers have resulted, out of which 224 were from Scopus, 5 from DBLP, 13 from PubMed, 840 from ScienceDirect, 11,197 from Springer, 2,111 from Sage, 2,112 from Taylor & Francis, and 129 from Emerald with the selected keywords, English language and restricted till December 2018. The other numbers pertaining to each stage can be easily understood from Fig. 4. Thirty-two of the papers were found to be relevant to this study. The list of selected papers considered for this study is shown in Table A1 of Appendix; the details of the selected papers are given in Table A2 of Appendix; the breakdown of selected papers considered for review by year and digital database is given in Table A3 of Appendix; the breakdown of the selected papers' source H-Index is shown in Table A4 of Appendix; and the breakdown of the selected papers' source % of international collaboration is presented in Table A5 of Appendix. It can be observed from: 1) Table A1 that the study by S26 in Appendix has the maximum number of citations followed by the study by S32 in Appendix; 2) Table A2 shows that 2018 contributed the maximum number of papers followed by 2017; 3) Table A3 shows that Scopus leads the indexing database followed by ScienceDirect; 4) Table A4 shows that the study by S3 Appendix leads H-Index followed by the study by S24 in Appendix; and 5) Table A5 shows that average international collaboration leads by *ACM Transactions on Internet Technology* and is followed by *OMICS: A Journal of Integrative Biology*.

3.3. Literature review reporting

This section presents the results of this study.

3.3.1. Data formatting/organization to demonstrate finding

A search comprising of literature linear and citation chaining was performed in digital databases, as shown in Fig. 3. These papers were thoroughly analyzed to select only the most relevant articles and, finally, thirty-two articles were included in the study. QEs were applied to the studies to evaluate the quality of the selected papers on the basis of full texts. Data of such articles were classified, organized and formatted to demonstrate the finding.

3.3.2. Communication of finding

Fig. 5(a) shows the word cloud on selected studies keywords and Fig. 5(b) shows the word cloud on selected studies article title. The

Table 3
Exclusion criteria to omit literatures.

IC#	Description
EC 1	Eliminate duplicate studies with matching title and/or Digital Object Identifier (doi)
EC2	Eliminate studies based on quality evaluation questions and which is discussed in the Review Protocol Evaluation stage.

Table 4
Composition of QE questions.

QE#	Description
QE 1	The study contains evidence which is quantitatively or qualitatively analyzed. The probable answers are: "quantitative research (+2)", "qualitative research (+1.5)" and "no evidence (+0)".
QE 2	The study unequivocally examines the benefits and limitations. The probable answers are: "yes (+2)", "no (0)" and "partially (+1)". The score is partial if only one of the study's advantages or challenges is reported.
QE 3	The output of the study is justifiable. The probable answers are: "yes (+2)" and "no (0)" and "partial (+1)". The score is partial if only very limited techniques are explained or one of the techniques used is not detailed.
QE 4	The study was published in a reliable and recognized source. The probable answers are as follows: (+2) if the summation of citations number and H Index is exceeding 100 (+1.5) if the summation of citations number and H Index is exceeding lying between 50 and 99 (+1.0) if the summation of citations number and H Index is exceeding lying between 1 and 49 (+0) if the summation of citations number and H Index is 0
QE 5	The study compares the proposed method with other methods and the probable answers are: "yes: + 1," "no: 0".

keywords word cloud gives an overview of the keywords of the selected articles and the article title word cloud gives an overview of the titles of the selected articles. Fig. 5(a) and (b) depicts that "cognitive computing" had been closely associated with health and indicates that this study is unbiased, and trustworthy.

The paired word analysis had been applied over the keywords to better understand which keywords are being used together mostly. The analysis depicts the words that have been used often are: i) cognitive computing with thirteen repetitions, ii) health care or healthcare with six repetitions, iii) artificial intelligence with five repetitions, iv) Big Data with four repetitions, and v) cognitive systems engineering, machine learning, personalized medicine with three repetitions each. Thus, this indicates that cognitive computing and healthcare are strongly connected and this study is unbiased, and trustworthy.

Fig. 6 depicts the distribution of articles by 1st author's country and it indicates that the United States has contributed the highest number of articles by 1st author among other countries.

Fig. 7 showcases the distribution of papers by year of publication and digital databases, and it indicates 2018 has recorded the highest number of articles, and Scopus has the highest number of articles for this study.

Fig. 8 showcases the distribution of articles by subject area and it indicates the majority are from medicine, computer science, and engineering.

Fig. 9 showcases the citation count of the selected articles over the publication year and it indicates that 2017 is leading in terms of the quality of citations. However, the quality of citations of 2018 and the other years may lead to growth in the days to come.

Fig. 10 showcases the distribution of papers by study type. Four study types, namely experimental, conceptual, review and theoretical, are considered to categorize the articles.

4. Analysis and discussion

Cognitive computing can investigate a variety of different data types and their interpretation to generate rich insight [26]. Cognitive computing includes a variety of tools and techniques, including BD, Predictive Analysis, IoT, ML, NLP, Probabilistic Reasoning and DV [27]. Some of the cognitive system's key features are: learning skills, knowledge improvement without reprogramming, development and hypotheses analysis. These processes can be categorized as: i) observation, ii) interpretation, iii) evaluation, and iv) decision [28].

The healthcare industry involves many different players who support patient wellbeing and treatment. The data managed and used by various healthcare players are presented in Table 6.

Core profile comprises of i) demographics like name, address, date of birth, contact number, and marital status, etc.; ii) life changes like employment, divorce, and marriage, etc.; iii) family relations like spouse, daughter/son, and grandchildren. Health profile comprises of medical report and biometric data. Lifecycle profile comprises of health habits, hobbies, obesity, etc. Social profile comprises of wellness activities, social interactions, chaplain visit, social services, etc.

It can be easily made out and understood from Fig. 12 that all the players have access to different data sources and the government primarily controls and manages the regulatory requirements.

Fig. 13 represents a conceptual model showcasing the better

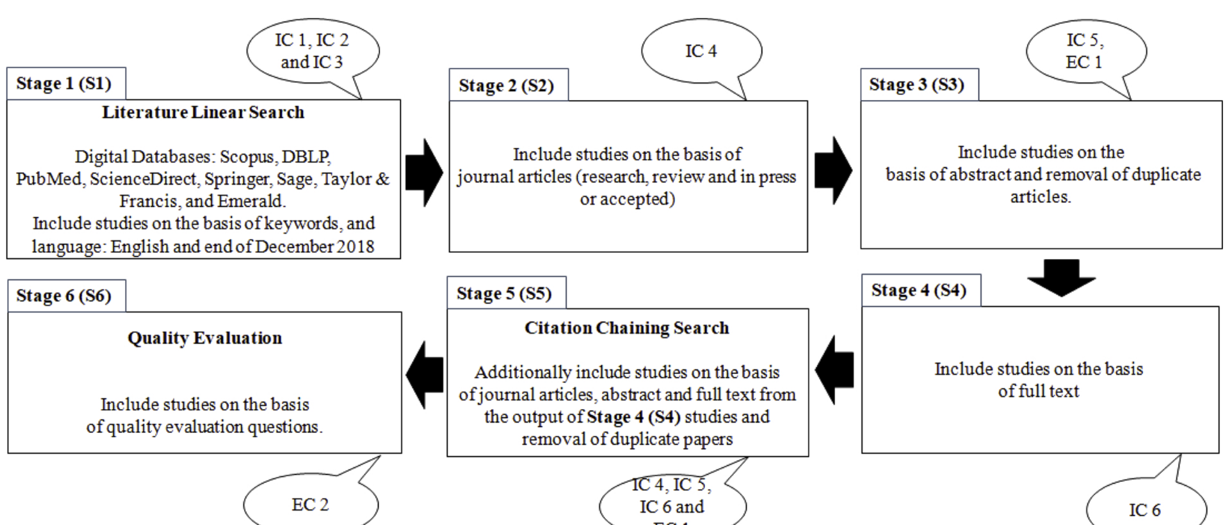

Fig. 3. Research Data Selection Process (Source: self-compilation by authors).

Table 5
Search Syntax of the selected research papers.

Data Source	Search Syntax
Scopus	(TITLE-ABS-KEY ("cognitive computing*")ORTITLE-ABS-KEY ("cognitive system*")ORTITLE-ABS-KEY ("cognitive informatics*") AND(TITLE-ABS-KEY ("health care *")ORTITLE-ABS-KEY ("healthcare *") AND(LIMIT-TO (LANGUAGE, "English") AND(LIMIT-TO (EXACTKEYWORD,"Cognitive System*")ORLIMIT-TO (EXACTKEYWORD,"Cognitive Computing")ORLIMIT-TO (EXACTKEYWORD,"Health Care")ORLIMIT-TO (EXACTKEYWORD, "Healthcare*") AND(LIMIT-TO (DOCTYPE,"ar")ORLIMIT-TO (DOCTYPE,"re")ORLIMIT-TO (DOCTYPE,"ip")
DBLP	cognitive system* and healthcare type:Journal_Articles: cognitive computing* and healthcare type:Journal_Articles: cognitive Informatics and healthcare type:Journal_Articles:
PubMed	(Cognitive Computing[Title/Abstract] OR Cognitive System[Title/Abstract] OR Cognitive Informatics[Title/Abstract]) AND (healthcare[Title/Abstract] OR health care[Title/Abstract])
ScienceDirect	("cognitive computing" OR "cognitive system" OR "cognitive informatics") AND (healthcare OR "health care")
Springer	(Cognitive Computing* OR Cognitive System* OR Cognitive Informatics*) AND (healthcare OR health care)
Sage	"cognitive computing" OR "cognitive system" OR "cognitive informatics" AND health*
Taylor & Francis	("Cognitive Computing" OR "Cognitive System" OR "Cognitive informatics") AND Health*
Emerald	("cognitive computing" OR "cognitive system" OR "cognitive informatics") AND health*

utilization of cognitive computing. In the conceptual model, healthcare data generated by different players are in structured, unstructured and semi-structured form and hosted in cloud with data-as-a-service offering.

Different components of the conceptual model are shown in Table 7.

4.1. Feasibility analysis

A huge volume of data, such as digital images from CT scans and MRIs, medical device reports, patient medical records, clinical trial results, and billing records, are created and managed by the healthcare ecosystem. Such data exist in a variety of formats ranging from manual paper records and spreadsheets to unstructured, semi-structured, structured, and streaming data format. Some of them are well-integrated, but most of them are not. As a result, significant challenges are posed due to the vast amount of generated data and their analysis. Therefore, cloud computing and a distributed architecture is the basic model needed to make cognitive computing operational on a large scale in a cost-effective manner. The need to find patterns and outliers in structured, semi-structured and unstructured data can help to improve patient care, which is one of the persistent challenges. Additionally, the healthcare professionals get the required insights from all types of data to act confidently and optimize their decision-making using different analytics, such as descriptive, diagnostics, prescriptive, etc., with a continuous self-learning process by combining different technologies such as BD, ML, AI, DL, NLP, etc., thereby enabling significant improvements in outcomes.

4.2. Current research areas

Research articles from digital databases are categorized and presented in Table B1 of Appendix. Dimensions used for categorization of

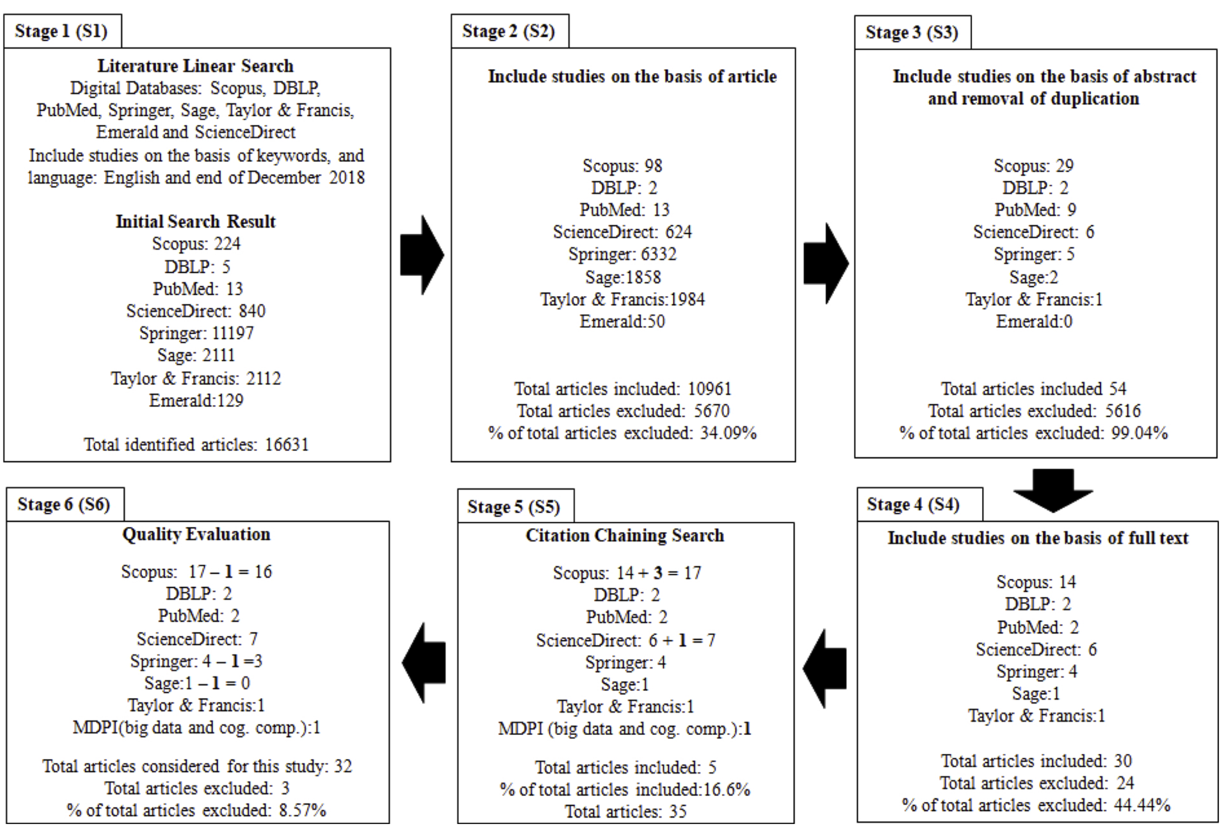

Fig. 4. Output of qualitative meta-synthesis technique (Source: self-compilation by authors).

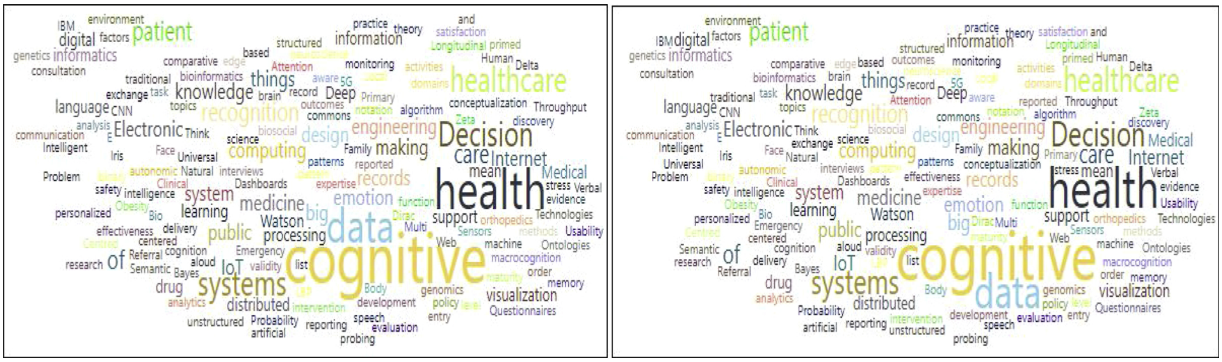

Fig. 5. (a)Word cloud on selected studies keywords; (b) Word cloud on selected studies article title.

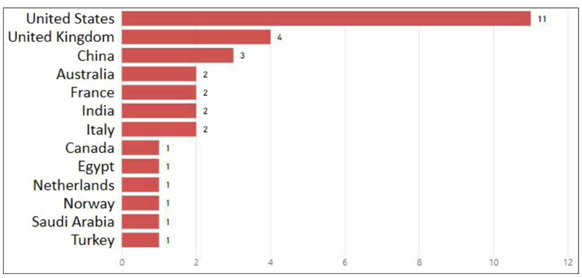

Fig. 6. Distribution of paper authors by country.

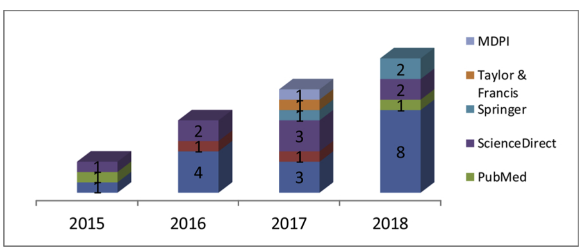

Fig. 7. Distribution of papers by year of publication and digital database.

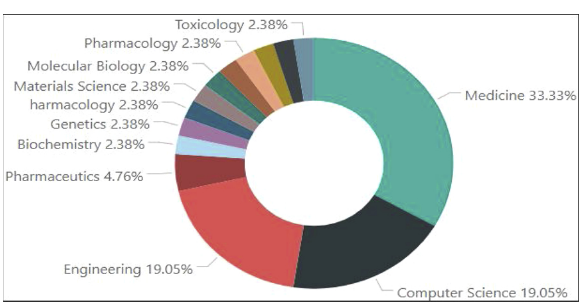

Fig. 8. Distribution of papers by subject area.

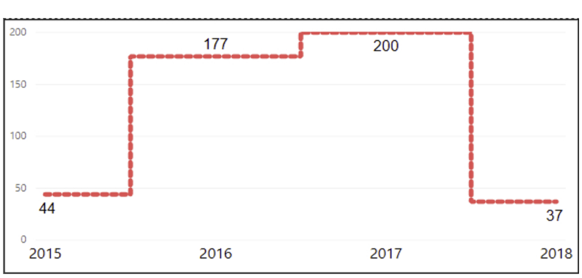

Fig. 9. Quality of citations of the selected articles for this study.

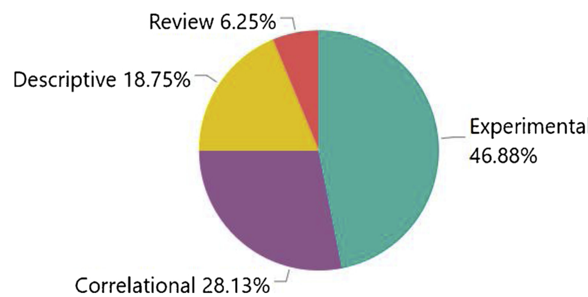

Fig. 10. Distribution of articles by study type.

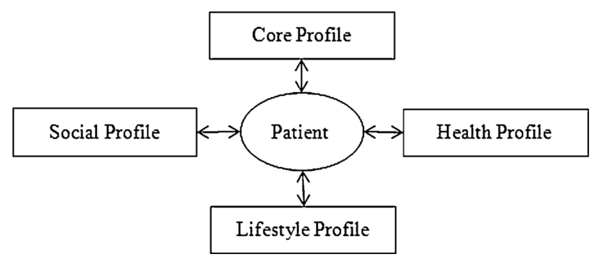

Fig. 11. Patient personal identifiable information profile.

the journal articles are presented in Table 8.

Current research in terms of method, algorithms, applications, results, strength and limitations are presented in Table B2 of Appendix at an abstraction level. From the current research, the conclusion can be drawn that cognitive computing in healthcare is an encouraging topic and is used to mend doctor-patient gaps.

The authors' opinions of cognitive computing system in healthcare are that: i) it is a data driven approach and can offer a better user Quality of Experience (QoE) in an emergency case; ii)it holds the possibility of accurate, problem-list-centric patient record summarization, conceivably leading to greater efficiency, better support for clinical decisions and improved patient care quality; iii) historical data analytics can be used by clinics and hospitals to optimize the allocation of resources and workflows; iv) it improves usefulness and enhanced usability of orders for electronic consultation; v) it affords intelligent decision-making and decision support; vi) it relies on tried-and-tested ML and DL algorithms; vii) it adopts to a cognitive system engineering process approach; viii) it has cost-effectiveness, i.e. lower costs at the same quality of care or increased costs and improved quality of care at an acceptable incremental cost per incremental unit of quality of care; ix) it affords a cultural change in the practice of medicine, i.e. physicians and intelligent recommendation to facilitate on how patients are to be medicated; x) it assists in the creation of individual treatment plans and, thus, improves the experience of patients and doctors; xi) it helps tired radiologists to find anomalies of interest in images quickly.

Table 6
Different players in healthcare and data management role.

Sr #	Player	Description
1	Patient	Produces health data such as personally identifiable information, test results, and previous medical history in non-digital format.
2	Healthcare providers	Person or companies provides healthcare services and produces a) patient medical records, b) data from medical devices and sensors, c) records of hospital admissions, d) books of medical text, e) medical journals articles, f) clinical research studies, g) regulations reports, h) billing, and i) cost data.
3	Pharmaceutical firms	Data to support pharmaceutical research, clinical trials, drug efficacy, healthcare provider's prescriptions.
4	Healthcare payers	Institutions that pay healthcare providers, including insurance companies, private employers, the government and individuals, and generate data on billing and usage review.
5	Government regulatory services	Produce regulatory data.
6	Healthcare data service providers	Produce data on the use and effectiveness of prescription drugs, health terminology taxonomies and software solutions for the analysis of health data.
7	Healthcare information service	Individuals or companies providing health-related advice or reports for the betterment of society
8	Healthcare research center	A group of researchers which works or leads independent research and development of healthcare projects in a variety of topics and produces research and reports data
9	Medical device manufacturer	Produces reports and research data. A patient's personally identifiable information can be characterized by the profiles a) core profile, b) health profile, c) lifestyle profile, and d) social profile having full access to records. This limits the information the system can see and causes the medical record to be incomplete and is presented in Fig. 11.

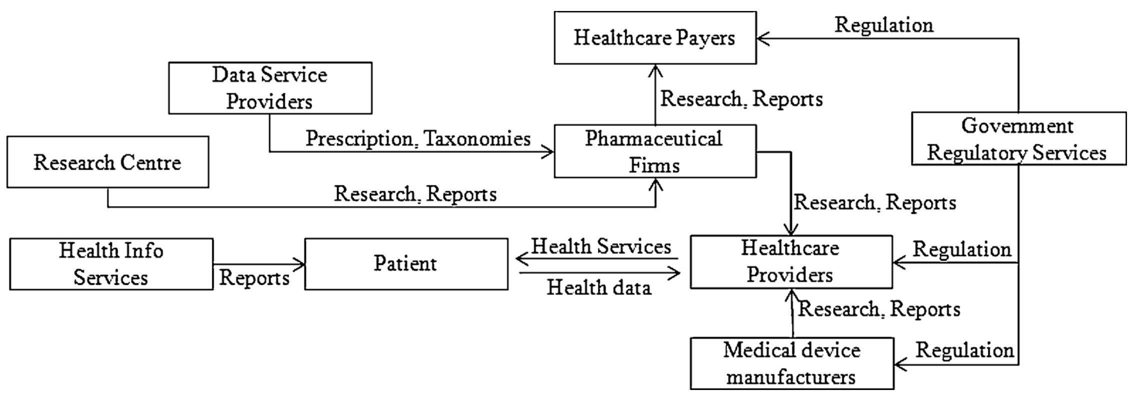

Fig. 12. Access to data by different players of healthcare industry.

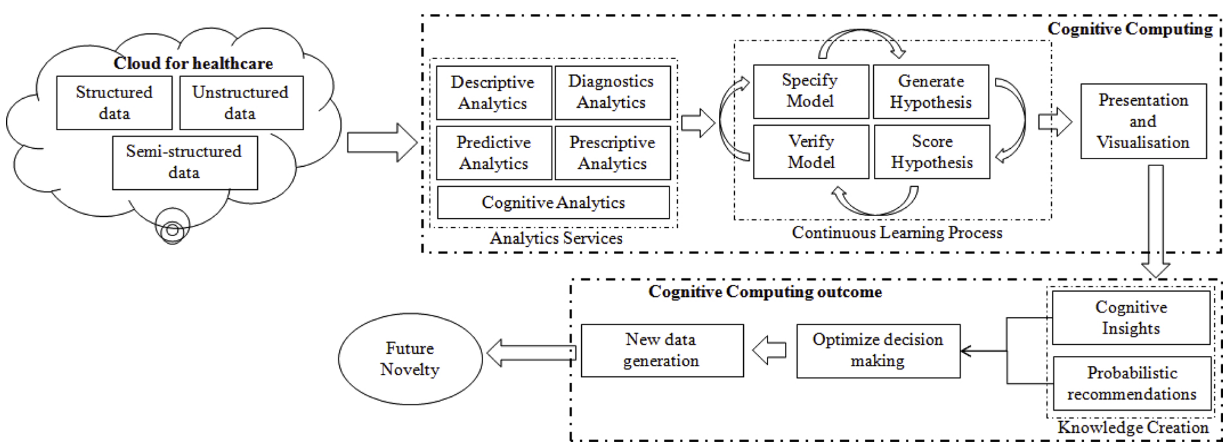

Fig. 13. Conceptual model for better utilization of cognitive computing.

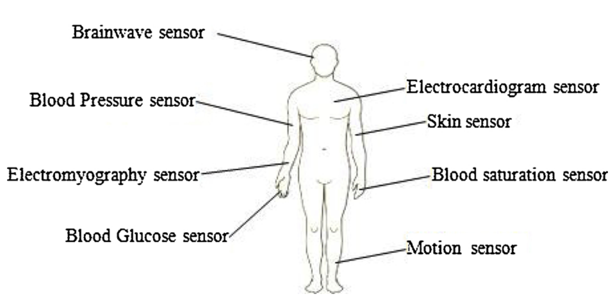

Fig. 14. Common human body sensors layout.

4.3. Future direction of research

Cognitive computing has huge potential to transform the entire value chain of healthcare, from discovery of drug to personalization of patient, improved clinical outcomes, more efficient management of public health, and more wide-ranging recompense of care. It is exciting to perceive how cognitive computing can further improve and expedite the union between clinicians, policy makers, players and researchers for cost optimization, reduction of risks and improvement of personalized care. The future directions are presented in Table 9.

Table 7
Conceptual model components.

Component	Description
Analytics services	Services such as a) descriptive analytics, b) diagnostics analytics, c) predictive analytics, d) prescriptive analytics, and e) cognitive analytics describing what the best action is.
"Continuous learning processing" process with distinct task	The distinct tasks are a) model specification, b) hypothesis generation, c) hypothesis scoring, and d) model verification. The model has to learn continuously.
Presentation and visualization of information	The advantage of cognitive computing is that the healthcare professional gets cognitive insights from all these types of data more easily and acts confidently and optimizes their decision-making to generate new data, leading to future innovation.

Table 8
Journal articles categorization.

Category	Category Details
Settings	Clinical–studies were conducted in real-world clinical setting. Simulated – studies were conducted with simulated settings
Data collection methods	One or more of the methods, such as surveys, interview or observation, etc.
Participants	Doctors, nurses, patients or other staff
Output	What has been proposed by the authors, e.g. system or framework or functional prototype or strategic solution, etc.

Table 9
Future directions.

Sr #	Research direction	Description
1	Research Optimization	Researchers from both industry and academia can a) predict disease trends in modeling future demand and costs; b) improve the design and analysis of clinical trials, accelerate research times and the accuracy of results; c) enable drug developers to reduce the risk of new drug products and to translate research results into industry and regulatory practices methods and technologies.
2	Personalized Knowledge-Based Medicine	Researchers can explore a) medical treatment tailored to the individual medical attributes of each data-rich patient record and then examine the links between genetic variation, predisposition to disease and specific drug responses, which will allow early detection and diagnosis before the symptoms and reduce complication; b) adjust the use of genetic variation therapies and adjust medicine doses to reduce side effects.
3	Better disease management	Researchers can explore on a) integrating personalized knowledge-based medicine and evidence-based care to better manage the disease; b) remote monitoring of patient in real-time to monitor adherence to prescription and improve future treatment options; c) use advanced analytics in patient profiles to detect anomalies and identify high risk patients with a specific disease.
4	Prevent disease outbreak	Researchers can explore in data patterns to determine possible outbreaks of infectious diseases and the efficacy of vaccination programs, trends, such as alcohol-related emergency room visits and accident injuries at home, that are typically more difficult to analyze.
5	Fraud detection and prevention in real time	Researchers can investigate in real-time fraud, anomalies in the system of refunds and regulatory breaches.
6	Cognitive Internet of Things (CIoT)	IoT-based systems that implement real-world applications are constantly evolving and generating startling requirements, [40] requiring coordination of management processes and interaction with people to learn from their intelligence and present more precise analytics. As a result, a new IoT era named "Cognitive IoT" [41] was announced. Because mobile health applications and wearable devices are increasingly used in daily lives [42,43], Cognitive IoT is becoming one of the most popular trends. Researchers can explore on common Cognitive IoT sensor of human body for real-time sensing of body signals and how it can helpful for the doctors for real-time diagnosis and treatment service. [2] common Cognitive IoT sensors are i) brainwave sensor- such sensor is placed on the scalp to detect brainwaves; ii) blood pressure sensor–a non-invasive sensor designed to measure systolic, diastolic and mean arterial blood pressure utilizing the oscillometric technique; iii) electromyography sensor- measures the electrical activity of muscles; iv) blood glucose sensor – measures the level of glucose in the interstitial fluid and changes it into an electrical signal. The signal represents the amount of sugar in the blood; v) electrocardiogram sensor- detects the electrical and muscular functions of the heart; vi) skin sensor- measures a pertinent parameter of the skin (e.g. moisture, sebum); vii) blood saturation sensor–monitors the oxygen saturation of patient's blood; and viii) motion sensor- detects movement alerting medical staff to the patient's movement in the hope that the patient will not fall. Fig. 14 represents the layout of common human body sensors, which can be especially applicable to the elderly and patients with chronic diseases. [44] Consumers can even use IoT fitness trackers to monitor patients with health problems, such as cardiological and oncological patients.
7	Optimal treatment trial	Researchers can explore different ways to increase the transparency of different services and drugs due to the wide existence of different healthcare providers' practices, results and costs. This can be done by analyzing the results of a wide range of patients and then comparing the effectiveness of various interventions and, thus, reducing the effects of over-treatment and under-treatment. This will also enable patients to interact and make the best decisions with clinicians.
8	Visual Analytics	Researchers can explore a) modernistic techniques for visualizing data and its application to healthcare data; b) areas and healthcare players that require more attention to patients, clinicians and researchers; c) how storytelling can be applied by making a two-part effort to obtain valuable insights. The data that feed the chart, graph or interactive dashboard must first be timely, detailed and completely reliable, and, secondly, the visualization must present the information in a clear, attractive and intuitive manner while adhering to the best practices of cognitive computing, dashboard and scoring methodology.

Table 10
Challenges faced by researchers.

Sr #	Description
1	[18] Cognitive computing system builders need to collect sufficient relevant knowledge to be useful and to represent it in a sense that adds to the knowledge of the system. To capture and represent the knowledge of healthcare, experts who know vocabularies and rules of healthcare are required; furthermore, they need to explain the codification of machine learning and deep learning. In order to build the cognitive computing system, taxonomies and ontologies with focus on a specific area of knowledge should be defined. However, they argue that it is not possible to acquire enough knowledge to design a cognitive computing system that replicates the healthcare industry, not even with the assistance of healthcare industry experts.
2	[31] To succeed with deploying cognitive computing applications, it is essential to have clarity regarding responsibilities between human users and the cognitive computing application. Although a cognitive computing system assumes some prior responsibilities, it also creates new tasks for humans, such as training and sustaining the cognitive computing application. Without supervision, a cognitive computing system will lose relevance over time and be able to handle fewer of its assigned tasks successfully since healthcare products and customers change with time and new policies and rules for business might be required. Thus, healthcare encounters the challenge of ongoing supervision of the cognitive computing system, to monitor the performance and regularly recalibrating it to result in correct outputs. Supervision is necessary to maintain and manage the quality, as well as to ensure that the cognitive computing system retains its accuracy and relevance.
3	[32] Explains that cognitive computing systems need to be provided with related dictionaries and thesauruses to enable language understanding. Interpretation implies the ability to understand data, to derive the significance of sentences and paragraphs in a language that goes beyond the definitions of terms. Cognitive computing systems differ from keyword search and text analysis by being able to understand verbs, adjectives and prepositions, allowing them to understand what language actually means rather than just what it says
4	The language makes possible [33] for cognitive computing systems to help to understand the world better, as well as to engage with us. But language in this case is not as simple as, for example, English or Chinese. The special language in healthcare can consist of chemical symbols, medical images, or be embedded in legal terms. The challenge is to teach systems structure, vocabulary of spoken and written languages, as well as business-specific words and concepts.
5	A cognitive computing system can show [34] its full capability only through sufficient training. To do this, question-answer pairs needs to be produced in natural languages. Producing a sufficient number of question-answer pairs requires a lot of work. Training cognitive computing system can be tedious and not effective if certain guidelines are not observed.

Table 11
Cognitive Computing Capabilities.

Sr #	Capability	Description
1	Understand	Similar to humans, cognitive computing systems understand medical images, natural languages, and other unstructured data, in addition to structured data like hospital EMR and claims/reimbursement.
2	Reason	Cognitive computing systems can reason, grasp underlying concepts, form hypothesis, and infer and extract ideas.
3	Learn	With each data point, interaction and outcome, a cognitive computing system develops and sharpens expertise, so it never stops learning.
4	Interact	With the abilities to see, talk and hear, cognitive computing systems naturally interact with humans.

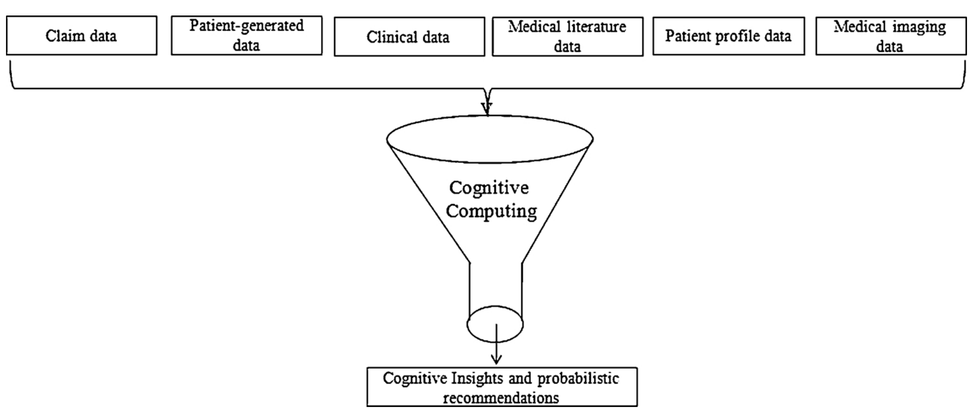

Fig. 15. Impact of cognitive computing systems on healthcare.

4.4. Challenges faced by researchers

The challenges faced by the researchers are presented in Table 10.

4.5. Cognitive computing capabilities

Cognitive computing systems can help us to overcome our limitations in many situations [33]. Even if we are in the early stages of cognitive computing, the next decade will stretch the limits of what is possible with new software and innovations [18]. The possibilities of cognitive computing systems are almost endless, its ability to handle complex tasks such as NLP, data mining, classification, and knowledge management enables the cognitive computing system to make very sophisticated tasks and answer complex questions [35].Through implementing cognitive computing, healthcare personnel can focus on more important business-oriented or strategic initiatives and save hours of staff time and also reduce the actual detection and resolution time [36].The different capabilities that [29]differentiate cognitive computing systems from traditional programmed computing systems are presented in Table 11.

4.6. Cognitive computing systems' impact on healthcare

Cognitive computing systems process massive amounts of data to understand, reason and then learn from it and interact with the healthcare providers to develop enhanced treatment or care plan for the patients. Fig. 15 represents the impact of cognitive computing on healthcare. Such system takes various forms of data input, such as claim, patient-generated, clinical, medical literature, patient profile, medical imaging and, after processing, produces cognitive insights and probabilistic recommendation.

The impacts in terms of cognitive insights and probabilistic are

Table 12
Cognitive Computing Impact.

Sr #	Impact
1	Provide timely insights for individuals.
2	Proactively identifies at-risk patients.
3	Predicts patient health needs and cost care.
4	Supports personalized medicine and clinical decision-making.
5	Recommends intervention based on probability of success.
6	Improves patient engagement and communication across care settings through the use of technologies like mobile health app and wearable sensors.
7	Through the use of NLP technology, correlates relevant clinical studies for knowledge-driven and data-driven support.
8	Helps healthcare players to better understand the population.
9	Help researchers to analyze genomic data.
10	Help researchers to tie makers of certain diseases to many environmental and personal factors that affect an individual's health.
11	Guides physicians to provide precision medicine that varies with each patient.
12	Merges advanced image and textual processing with visual reasoning abilities that can identify the relevant information in the image.
13	Leads to innovate ways of using intensive care unit (ICU) data and to integrate mobile monitoring data with EHRs while giving feedback to students.
14	Improves predictive modeling used in health risk stratification and health financial risk management.
15	Helps patients to optimize their help through personalization information and social support.
16	Converts unstructured documents into structured data, which helps to improve communication in care settings.

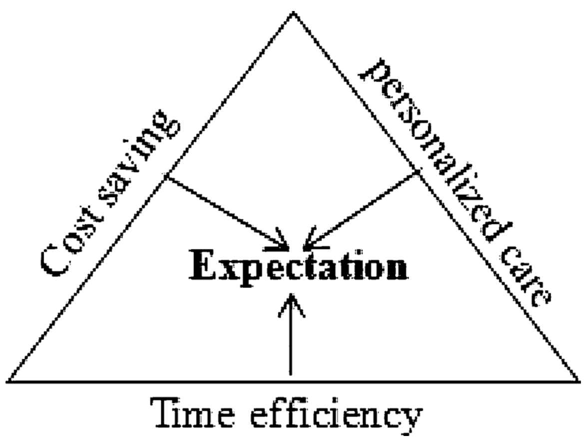

Fig. 16. Iron triangle representing the impact of cognitive computing in healthcare.

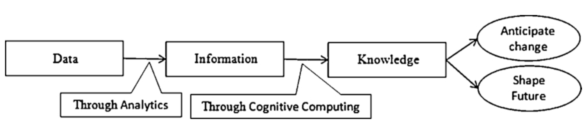

Fig. 17. Progression of data to knowledge through analytics and cognitive computing.

presented in Table 12 and are based on the study [30].

The impact success can be measured by plotting an iron triangle wherein one side of the triangle represents efficiency in time of treatment or diagnosis, another side represents cost saving and the final side represents the personalized care. The three sides of the iron triangle should focus on managing and exceeding patient expectation. The iron triangle is presented in Fig. 16.

5. Conclusion

This paper analyzes the existing academic literature in the field of cognitive computing and healthcare. We followed the systematic literature review approach in this study and used digital databases such as DBLP, PubMed, ScienceDirect, Springer, Sage, Taylor & Francis and Emerald to extract the information. The SLR discussed methods, algorithms, applications, results, strengths, and limitations of thirty-two articles using linear and citation chaining search.

The review of prior literature shows that cognitive computing is the buzzword in healthcare and can be seen alongside of AI, ML, DL, BD, and BDA. As a result of an explosion in data creation, it is virtually impossible for a human to keep a tab on all the latest developments for decision-making processes. Cognitive computing deals with complex situations characterized by uncertainty and ambiguity, i.e. deals with problems of a human nature. Cognitive computing systems often weigh conflicting evidence and propose a response that can be considered best instead of right. From this summary, it can be argued that cognitive computing in healthcare is promising. Cognitive computing systems are capable of capturing the process of human thinking and then learning from the errors when they are committed by the system.

The study presented the future research directions, challenges faced by the researchers, capabilities of cognitive computing and its impact on healthcare. The domain of cognitive computing in healthcare will be incomplete without harnessing the benefits of cloud adoption. A conceptual model has been proposed in this study that needs to be tested and verified to validate this model.

The key findings for researchers from this study are: 1) Academic literature has been present in this combined field of cognitive computing and healthcare since 2013, but the emphasis has been on the year 2015. 2) While the future for cognitive computing may be very promising, some significant hurdles still need to be overcome. 3) To date, international collaboration has hardly existed and is needed to highlight the contexts and trade-offs in such research explorations between localization versus globalization. 4) Most of the experiences reported come from the United States, where the healthcare system is organized in a peculiar way, which is quite different from most other countries.

5.1. Managerial implication

For the past few years, healthcare industry leaders have understood that, if unique data are captured before the competitors find it, they can have competitive advantages. Slowly, the industry has started integrating data across silos such as claims, patient-generated health assessments, clinical, and the most important medical literature. The leaders of the industry understand that, if a meaningful relationship or patterns are extracted from such data, information can be turned into knowledge to anticipate the change and to shape the future. In Fig. 17, such progress is presented with a technology driver. Progression from data to information occurs through analytics and the progression from information to knowledge occurs through cognitive computing. In reference to healthcare, the anticipated changes might be the implementation of emergency department (ED) improvement strategies anticipating challenges and, then, taking steps to prevent them. In relevance to ED, the future can be shaped better with better patient care by not operating on a 'first come, first served' basis, rather with patients being categorized and attention given to the patients who need urgent help first.

By means of advanced analytical algorithms and by combining diversified healthcare data, cognitive computing systems uncover insights that were earlier beyond computational capabilities. Without cognitive computing, people required to discover patterns and insights manually. Even with plenty of time, researchers may miss the patterns and insights in health records. By contrast, if such large data are processed using a cognitive computing system, the knowledge that an army of resources would have required can be gained.

Cognitive computing systems facilitate sharing of knowledge through open question answering (Open QA) system. It solves the situation in which ambiguity and uncertainty exist and attempts to imitate the human brain's mechanism.

There are many limits to traditional analytics - problems need to be predefined, there's no capacity for handling ambiguity, semantics for structured and unstructured data must be known, and interaction with the end user is through formal digital means. Cognitive computing, however, opens up possibilities where machines can learn new problem domains, reason through hypotheses, resolve ambiguity, evolve towards more accuracy, and interact in natural means. This creates vast opportunities for complex problem solving across all players and reduces medical treatment cost. It allows doctors to better understand what tests are to be performed to better understand the patient's health problem, diagnose further problems and diseases, find appropriate solutions and provide the best possible care. Hospitals can determine which patients are more likely to develop a certain disease or disease. Post-discharge results may be controlled and the number of readmissions significantly reduced.

5.2. Limitation

The different limitations of cognitive computing in healthcare are: First, limited risk analysis: whereas unstructured data are criticized for their lack of organization and difficulty in translating into electronic health records, cognitive computing systems fail to analyze the risk that such data lacks. This includes socioeconomic, cultural, political, and human factors, e.g. children in lower incomes households are more likely to develop chronic problems, and taking all children with chronic problems, poor children are more likely to have adverse health outcomes. In such cases, for complete risk analysis and final decision-making, human intervention is necessary. Second, meticulous training process, i.e. initially, cognitive computer systems need training data to fully understand and improve the process. The painstaking process of training cognitive computing systems is most likely the reason for its slow adoption. In addition, it is made even worse by the complex and costly process of using cognitive computer systems. Third, lack of automated critical decision: cognitive computing systems complement individual intelligence and analysis but depend on humans in taking vital decisions, and are lacking an automated critical decision-maker.

Authors' contributions

Author RB was responsible for the study conduction; Authors RB, AD, and PB reviewed the literature and assessed the quality of the included studies; RB synthesised the literature according to the described methodology; RB wrote a first draft of the manuscript and all other authors contributed to the final version. AD provided several suggestions to improve the quality of the systematic literature review. All authors have read and agreed to the paper being submitted in the present form.

Conflicts of interest

The authors of this manuscript declare no conflicts of interest.

Appendix. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ijmedinf.2019.04.024.

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