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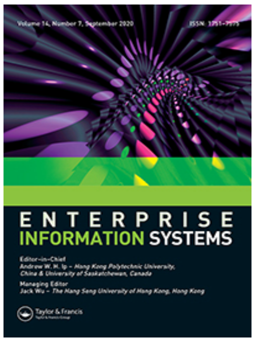

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REVIEW ARTICLE

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Big data analytics in healthcare: a systematic literature review

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ABSTRACT

The current study performs a systematic literature review (SLR) to synthesise prior research on the applicability of big data analytics (BDA) in healthcare. The SLR examines the outcomes of 41 studies, and presents them in a comprehensive framework. The findings from this study suggest that applications of BDA in healthcare can be observed from five perspectives, namely, health awareness among the general public, interactions among stakeholders in the healthcare ecosystem, hospital management practices, treatment of specific medical conditions, and technology in healthcare service delivery. This SLR recommends actionable future research agendas for scholars and valuable implications for theory and practice.

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Big data; analytics; big data analytics; healthcare; hospital management; medical informatics; personalised patient care; systematic literature review ; Covid-19

1. Introduction

Healthcare enterprises search for suitable technologies to streamline resources for the sake of improving the patient experience and organisational performance (Tang et al. 2019; Wang, Kung, and Byrd 2018; Tandon et al. 2020). Healthcare can be conceptualised as a system comprising three constituent parts: (a) core providers of medical care services, such as physicians, nurses, technicians, and hospital administrations (Boudhir, Ben Ahmed, and Soumaya 2017; Zhang, Simon, and Yu 2017); (b) critical services that are associated with medical care services, such as medical research and health insurance (Austin and Kusumoto 2016; Chandola, Sukumar, and Schryver 2013); and (c) beneficiaries of medical care services, i.e., patients and the public (Salomi and Balamurugan 2016; Weng and Kahn 2016). This study considers that a healthcare system includes contact-based and technology-based remote monitoring services extended by constituent service providers to promote, maintain, or restore the health of beneficiaries (George, Chacko, and Kurien 2019; Kaur, Sharma, and Mittal 2018). Big data analytics (BDA) has had a considerable influence across healthcare functions (Gu et al. 2017; Sáez and García-Gómez 2018), including clinical decision support, disease surveillance, and health management, among others (Raghupathi and Raghupathi 2014).

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BDA can be conceptualised as the analysis of detailed, dynamic, low-cost, massive, and varied data sets to deliver sophisticated solutions (Kamble et al. 2019; Kaur, Sharma, and Mittal 2018). The primacy of BDA has often been attributed to its ability to convert data-scarce decisions into data-rich decisions and to provide competent simulations for problems in various fields (Kitchin 2014). Numerous studies have probed the potential application of BDA in healthcare (Harerimana et al. 2018; Hussain et al. 2019; Palanisamy and Thirunavukarasu 2017). For instance, patient care, patient monitoring, disease diagnosis, treatment methods, and other areas may benefit from BDA applications (Kaur, Sharma, and Mittal 2018). Enhanced risk-profiling based on a Bayesian multitask learning approach has the potential to revolutionise clinical practices by helping to minimise failures and reduce delays in providing preventive interventions (Lin et al. 2017). Wang, Kung, and Byrd (2018) posited that the adoption of a strategic approach by healthcare organisations in deploying BDA may also produce business benefits. However, scholars have argued that the trade-off between harvesting efficient data-driven healthcare solutions and the associated privacy risks in the process is yet to achieve an equilibrium (Kim, Lee, and Chung 2017; Li et al. 2015).

A discussion on the use of BDA in healthcare has been developing recently in the literature (Galetsi and Katsaliaki 2019; Prasser et al. 2019). Consequently, the need to summarise the insights emerging from the discussions has gained prominence (Mehta and Pandit 2018; Zhang, Simon, and Yu 2017). In the quest to meet this need, prior research has followed two approaches to reviewing the literature. The first approach has been to review narrow areas within the literature on the use of BDA in healthcare. For instance, Zhang, Simon, and Yu (2017) highlighted the promising opportunities that BDA offers to advance research on Alzheimer's disease. Malik, Abdallah, and Ala'raj (2018) reviewed the use of BDA in supply chain management in healthcare. Saheb and Izadi (2019) reviewed the use of big data sourced from Internet-of-Things devices in the healthcare industry. Such review studies are not designed to provide a comprehensive review of the literature on BDA in healthcare.

The second approach to reviewing this body of literature has focused on summarising broad topics related to the use of BDA in healthcare. For instance, studies often attempt to summarise the sources of big data (Galetsi and Katsaliaki 2019; Kaur, Sharma, and Mittal 2018), the technologies used in the analysis of big data (Bahri et al. 2018; Harerimana et al. 2018), the benefits offered by BDA (Galetsi, Katsaliaki, and Kumar 2020; Kamble et al. 2019), and the challenges involved in harnessing those benefits in healthcare (Amalina et al. 2019; Mehta and Pandit 2018). We appreciate the valuable knowledge about the use of BDA in healthcare offered by these studies. However, none of these studies have evaluated the quality of the documents in the sample under review. Consequently, the findings of these studies are subject to a critical limitation of their sample design. Therefore, the unavailability of a comprehensive summary of key takeaways from quality articles is a major research gap in the literature on the use of BDA in healthcare. Furthermore, there is a paucity of research aimed at identifying the contexts within healthcare where BDA is commonly applied.

The present study aims to address the research gaps in the literature on the use of BDA in healthcare by conducting a systematic literature review (SLR) (Dhir et al. 2020; Tandon et al. 2020; Talwar et al. 2020). SLRs have been recognised for their ability to summarise valuable knowledge about a topic of importance (Dhir et al. 2020; Talwar et al. 2020) and to guide future research on the topic (Dhir et al. 2020; Talwar et al. 2020). This SLR aims to address four research questions (**RQs**) as follows: **RQ1**. What is the current status of research on the application of BDA in healthcare? **RQ2**. In which contexts within healthcare are the applications of BDA being studied? **RQ3**. What are the key takeaways from prior research on BDA in healthcare? **RQ4**. What future agendas may advance research on BDA in healthcare?

The present SLR adopted a protocol for planning, performing, and presenting a review, as followed in prior studies (Behera, Bala, and Dhir 2019; Tandon et al. 2020). The current status of research on any topic under investigation can be represented in terms of key information, such as the annual distribution of publications, average citation count, top contributors, and methodologies adopted in the reviewed studies (Behera, Bala, and Dhir 2019; Tandon et al. 2020). Therefore, the current SLR answered **RQ1** by reporting a sample profile of the reviewed studies. A total of 39 out of 41 studies reviewed herein were published between 2015 and 2019, indicating that the research topic is relevant to the recent literature on BDA and healthcare. **RQ2** is answered by analysing the contexts of the reviewed studies. The synthesis of the findings of prior studies addresses **RQ3**. Furthermore, a comprehensive framework for the use of BDA in healthcare is developed based on the findings of the present study. Actionable future research agendas, the object of **RQ4**, emerged from the insights offered by the comprehensive framework. Two major contributions of the current study are as follows: (a) synthesis of the literature on BDA in healthcare, and (b) guidance for future researchers interested in the topic by providing them with a framework on the application of BDA in healthcare.

The rest of the paper is organised as follows. The next section presents a brief overview of the characteristics of big data, particularly in the context of healthcare. The third section outlines the methodology followed in this SLR. This is followed by a section on this study's findings. The fifth section discusses the outcomes and implications of this study. The sixth section is dedicated to acknowledging the limitations of the present study, suggesting future scopes of research, and presenting the concluding remarks of this SLR.

2. Background

2.1. Characteristics of big data

The concept of BDA overarches several data-intensive approaches to the analysis and synthesis of large-scale data (Galetsi, Katsaliaki, and Kumar 2020; Mergel, Rethemeyer, and Isett 2016). Such large-scale data derived from information exchange among different systems is often termed 'big data' (Bahri et al. 2018; Khanra, Dhir, and Mäntymäki 2020). Although it is referred to as 'big' data, its importance is associated with its ability to capture small details about the subject being studied (George, Haas, and Pentland 2014; McAfee et al. 2012). Kitchin (2014) summarised the characteristics of big data with seven 'V's as follows:

A) Volume (size). A large amount of data is a primary characteristic of big data.

B) Variety (complexity). Big data includes structured, semi-structured, and unstructured data in different formats, such as text, image, audio, video, and sensor data, among others.

c) Velocity (speed). Big data handles high rates of data inflow and processes the data in real-time.

d) Veracity (quality). Big data accumulates detailed data that is exhaustive in scope.

e) Value (knowledge). Big data offers in-depth information about a topic of discussion.

f) Variability (flexibility). Big data provides support for the constantly changing nature of data by offering extensionality (the addition of new data fields) and scalability (expansion in size).

g) Valence (connectedness). Big data connects common fields to conjoin different data sets.

2.2. Big data in healthcare

Applications of BDA in healthcare are gradually increasing with the growing volume of big data in this context (Galetsi and Katsaliaki 2019; Kamble et al. 2019). Among the possible sources of big data in healthcare are heterogeneous and multi-spectral observations, such as patient demographics (Malik, Abdallah, and Ala'raj 2018), treatment history (Ozminkowski et al. 2015), and diagnostic reports (Amirian et al. 2017). Mehta and Pandit (2018) suggest that such data may be structured (e.g., genotype, phenotype, or genomics data) or unstructured (e.g., clinical notes, prescriptions, or medical imaging). Implementing data in healthcare often requires the generation and collection of real-time data (Tang et al. 2019) of high quality (Wang, Kung, and Byrd 2018). Decision-makers in healthcare organisations are able to take meaningful action based on valuable insights derived from big data (Prasser et al. 2019; Wang, Kung, and Byrd 2018). Healthcare organisations deploy technologies to cope with the changing nature of big data (Harerimana et al. 2018; Zhang et al. 2015). Moreover, big data in healthcare can be employed to connect different fields to comprehensively study a disease (Zhang, Simon, and Yu 2017). In sum, all of the characteristics of big data mentioned above are observable in the context of healthcare.

2.3. Opportunities for BDA in healthcare

The applications of descriptive, predictive, and prescriptive analytical techniques when using big data offer opportunities to enhance the quality of various aspects of healthcare (Kaur, Sharma, and Mittal 2018). The literature proposed different opportunities offered by BDA in healthcare sector, such as the following:

a) Medical diagnosis

A data-driven diagnosis may detect diseases at an early stage and reduce complications during the treatment (Gu et al. 2017; Raghupathi and Raghupathi 2014).

b) Community healthcare

Authorities may take preventive steps against the predicted risks of chronic disease among a population (Lin et al. 2017) and contagious disease outbreaks (Antoine-Moussiaux et al. 2019).

c) Hospital monitoring

Real-time monitoring of hospitals can help government authorities ensure optimal service quality (Archenaa and Anita 2015).

d) Patient care

Customised patient care facilitated by BDA has the potential to provide rapid relief (Salomi and Balamurugan 2016) and reduce readmission rates in hospitals (Gowsalya, Krushitha, and Valliyammai 2014).

2.4. Challenges of BDA in healthcare

The application of BDA to healthcare may face various challenges (Aiello et al. 2019; Amalina et al. 2019). Common challenges in this area include the following:

a) Initial investment

The deployment of the requisites to leverage the benefits of big data incurs huge initial costs for organisations providing healthcare (Szlezak et al. 2014; Wu et al. 2016).

b) Quality of data

The lack of trained personnel and resistance to change in organisational routines may affect the quality of big data accumulated by the organisation (Wang, Kung, and Byrd 2018; Zhang et al. 2015).

c) Quality of insights

The poor quality of heterogeneous biomedical data has the potential drawback of yielding inadequate insights and misleading suggestions (McNutt, Moore, and Quon 2016; Sáez and García-Gómez 2018).

d) Privacy and security

Scholars warn about the privacy and security concerns of patients regarding exposure to unauthorised data access during intersystem exchanges (Mohammed, Far, and Naugler 2014; Weng and Kahn 2016).

3. Methodology

The protocol for the current SLR, as presented in Figure 1, is comprised of three sequential processes: planning the review, performing the review, and presenting the review (Behera, Bala, and Dhir 2019; Tandon et al. 2020). The present SLR includes preset inclusion and exclusion criteria (see Figure 1), as recommended by prior literature (Behera, Bala, and Dhir 2019; Tandon et al. 2020).

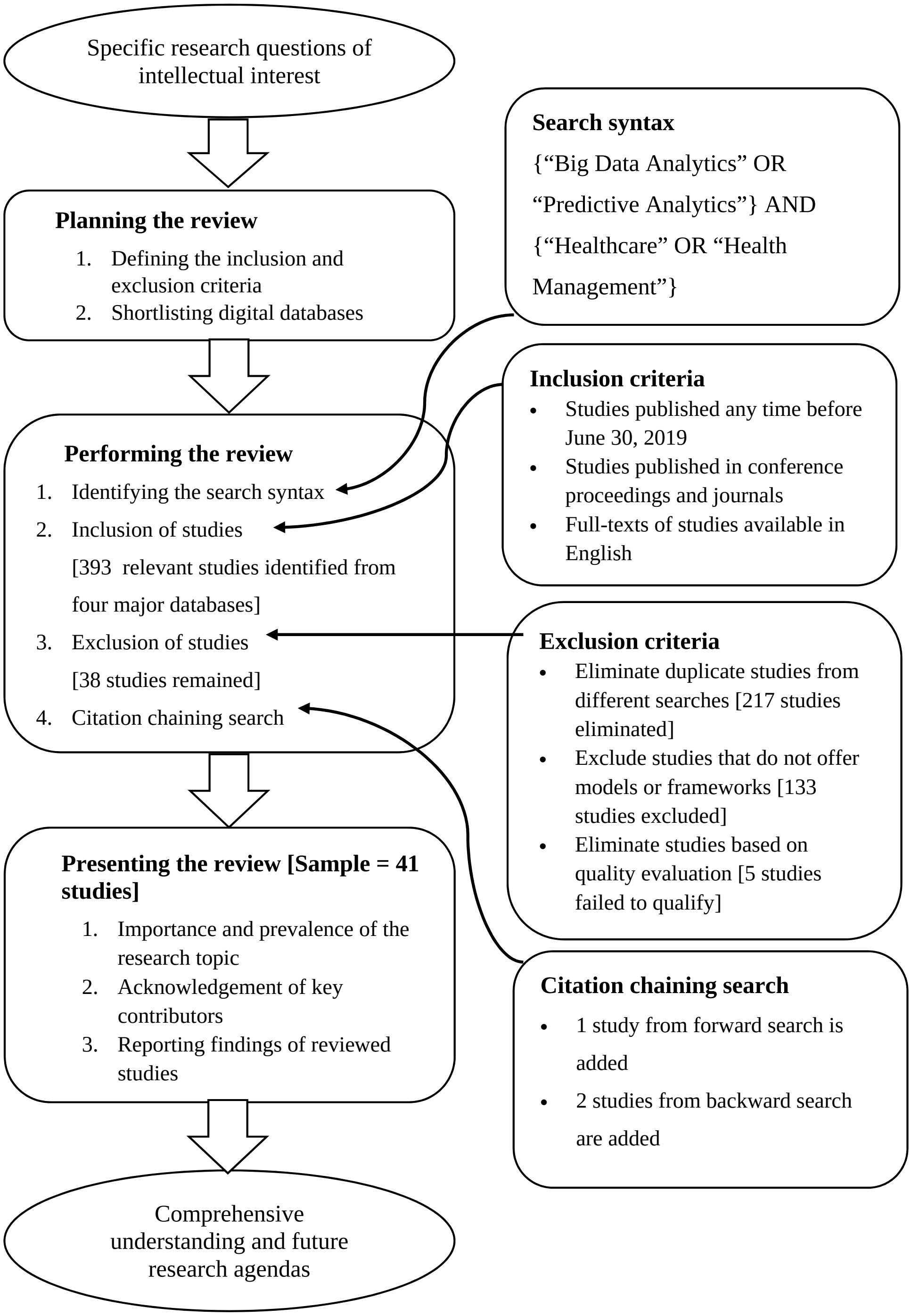

Figure 1. Protocol for systematic literature review.

3.1. Planning the review

First, appropriate keywords were identified to search for relevant studies in the databases. This SLR focused on four databases: Scopus, Web of Science, PsycINFO, and PubMed. These databases are reportedly the most important sources for studies related to medical health informatics (Behera, Bala, and Dhir 2019; Tandon et al. 2020). Full texts of the studies that appeared relevant were screened for eligibility. Next, studies meeting the eligibility criteria (namely, the inclusion and exclusion criteria) were assessed for quality and robustness. Finally, backward citation searches, followed by forward citation searches, were conducted prior to finalising the sample of the selected studies for the current SLR.

3.2. Performing the review

To determine the appropriate keywords, a search was performed on Google Scholar with the phrase 'big data analytics in healthcare.' The most commonly related terms were identified from the first 100 search results (Khanra, Dhir, and Mäntymäki 2020). We identified from the co-occurrence of keywords that the term 'predictive analytics' was frequently used to refer to 'big data analytics,' following an approach adapted by Khanra, Dhir, and Mäntymäki (2020). Raghupathi and Raghupathi (2014) highlighted applications of big data analytics in healthcare, including analysis of patient profiles with predictive modelling to identify suitable treatments, prediction of outcomes of different treatments, and percipience of the most clinically and cost-effective treatments for the patient. Similarly, we identified that the term 'health management' frequently represents different components of 'healthcare' in the extant literature. Among the major components of health management are the clinical diagnosis, clinical research, prediction of disease transmission, preventive healthcare, health insurance, and healthcare service delivery (Kamble et al. 2019). Therefore, four search syntaxes (see Table 1) were used to represent the phrase 'big data analytics in healthcare.'

Table 1. Database search summary.

Database	Search syntax	Total hits	Abstracts read*	Full text downloaded*
PsycINFO	'Big Data Analytics', 'Healthcare'	16	16	3
	'Predictive Analytics', 'Healthcare'	9	9	0
	'Big Data Analytics', 'Health Management'	20	20	2
	'Predictive Analytics', 'Health Management'	10	10	0
PubMed	'Big Data Analytics', 'Healthcare'	263	263	35
	'Predictive Analytics', 'Healthcare'	86	86	12
	'Big Data Analytics', 'Health Management'	15	15	3
	'Predictive Analytics', 'Health Management'	8	8	2
Scopus	'Big Data Analytics', 'Healthcare'	587	587	182
	'Predictive Analytics', 'Healthcare'	194	100	36
	'Big Data Analytics', 'Health Management'	17	17	4
	'Predictive Analytics', 'Health Management'	12	12	3
Web of Science	'Big Data Analytics', 'Healthcare'	228	228	76
	'Predictive Analytics', 'Healthcare'	140	100	17
	'Big Data Analytics', 'Health Management'	126	100	11
	'Predictive Analytics', 'Health Management'	87	50	7

Note: The search results included resources from different disciplines, such as information science, healthcare, and management, and were published through different outlets, such as academic journals, practitioners' journals, conference proceedings, and books. The search results were sorted based on 'relevance' prior to reading the abstracts.

*In many cases, a study appeared in multiple search results.

In July 2019, four databases were explored with predetermined combinations of keywords (see Table 1). Out of the 393 full texts identified in the databases, 217 were removed due to duplicity in the search results (see Figure 1). Consequently, 176 studies were downloaded for further screening. Of the screened studies, 133 were excluded from further analysis in accordance with the exclusion criteria (see Figure 1). A critical evaluation of these 43 studies was important to ensure transparent and unbiased outcomes from the current SLR (Behera, Bala, and Dhir 2019). Therefore, the quality score (QS) for each of the 43 selected articles was computed in Table 2; five studies failed to meet the threshold value (QS = 4.5). The forward and backward citation searches for the remaining 38 studies resulted in the identification of three new relevant articles that qualified to be included in the sample of the current study (see Table 2). Therefore, a final sample of 41 studies formed the basis of the SLR (see Exhibit A).

3.3. Presenting the review

The oldest study included in the sample was published in 2013; hence, the topic under discussion is, arguably, fairly new to the literature. Figure 2, which presents the annual distribution of studies, indicates that the topic has steadily gained in importance in recent years. Furthermore, an increase in the average citations received by studies in the sample demonstrates that the topic of the current SLR is quickly gaining prevalence in academia (see Figure 2).

Exhibit A presents summaries of 41 studies in our sample and reveals the following information about these studies:

a) Key contributors

A total of 152 researchers co-authored the studies under review. Among them, He Li and Jing Wu co-authored three studies each, while Yichuan Wang, Neeraj Kumar, Lee-Ann Kung, Joel Rodrigues, and Ling Liu co-authored two studies each. The first authors of the studies in our sample are affiliated with institutes from 19 countries. However, more than half of these studies come from three countries: the United States (8 studies), China (7 studies), and India (7 studies).

b) Key outlets

Studies in the sample were published in 20 peer-reviewed journals and 17 conference proceedings (see Exhibit A). Among the 13 publishers that contributed to the sample of the current study, the leading sources are *IEEE Access* (3 studies), *Big Data* (2 studies), and *Information and Management* (2 studies). IEEE (17 studies) is the most prominent publication house, followed by Elsevier (8 studies), and ACM (3 studies).

c) Common methodologies

In terms of methodology, conceptual (17 studies) and mathematical (17 studies) approaches were found to be prevalent in the selected studies, followed by case studies (6 studies), descriptive statistics (6 studies), econometric models (2 studies), and qualitative analysis (1 study).

Table 2. Computation of quality scores (QS).

Author(s)	2013	2014	2015	2016	2017	2018	2019^	Citations	H-index	QE1[a]	QE2[b]	QE3[c]	QE4[d]	QE5[e]	QS
Agnihothri, Banerjee & Thalacker (2015)	0	0	1	0	0	1	0	2	42	2	1.5	1.5	1	1	7
Aiello et al. (2019)	–	–	–	–	–	–	–	1	35	0	1.5	1.5	1	0	4
Amirian et al. (2017)	0	0	0	0	3	3	1	7	40	2	2	1.5	1	1	7.5
Antoine-Moussiaux et al. (2019)	–	–	–	–	–	–	–	0	37	0	1.5	1.5	1	0	4
Austin and Kusumoto (2016)	0	0	0	5	6	11	5	27	26	0	2	1.5	1.5	1	6
Babar et al. (2016)	0	0	0	0	0	0	1	1	37	0	2	1.5	1	0	4.5
Babu, Vasavi, and Nagarjuna (2017)	–	–	–	–	–	–	–	5	23	0	1.5	1.5	1	0	4
Boudhir, Ben Ahmed, and Soumaya (2017)	0	0	0	0	0	0	0	0	1	0	1.5	1.5	1	1	5
Bravo et al. (2018)	0	0	0	0	0	0	2	2	84	1.5	1.5	1.5	1.5	1	7
Chandola, Sukumar, and Schryver (2013)[#]	1	7	14	9	12	17	3	63	77	2	1.5	1.5	2	1	8
Chehade and Liu (2019)	0	0	0	0	0	0	0	0	49	2	1.5	2	1	1	7.5
Chen et al. (2017)	0	0	0	1	16	77	50	146	57	2	1.5	1.5	2	1	8
Cheng, Kuo, and Zhou (2018)	0	0	0	0	0	0	1	1	45	2	1.5	2	1	1	7.5
Christensen, Petersen, Pontoppidan & Cremonini (2018)	0	0	0	0	0	0	0	0	15	2	1.5	2	1	1	7.5
De Silva et al. (2015)	0	0	0	0	3	2	2	8	12	2	1.5	1.5	1	1	7
Forestiero and Papuzzo (2018)	0	0	0	0	0	0	0	0	18	2	0	1.5	1	1	5.5
George, Chacko, and Kurien (2019)	0	0	0	0	0	0	0	0	18	0	2	1.5	1	0	4.5
Gopal et al. (2019)	0	0	0	0	0	0	3	3	48	0	1.5	1.5	1.5	0	4.5

(*Continued*)

Table 2. (Continued).

Author(s)	2013	2014	2015	2016	2017	2018	2019	^Citations	H-index	QE1[a]	QE2[b]	QE3[c]	QE4[d]	QE5[e]	QS
Gowsalya, Krushitha & Valliyammai (2014)	0	0	0	0	0	2	0	2	8	2	0	1.5	1	0	4.5
Hadi et al. (2019)	0	0	0	0	0	0	11	11	57	2	1.5	2	1.5	1	8
Jin, Wu, Nishimura & Ogihara (2016)	0	0	0	0	0	9	0	7	9	0	1.5	1.5	1	1	5
Jindal et al. (2018)	0	0	0	0	0	2	6	8	56	2	1.5	2	2	1	8.5
Koliogeorgi et al. (2017)	0	0	0	0	0	0	1	1	15	0	1.5	1.5	1	1	5
Kuo et al. (2015)	0	0	0	5	2	2	0	9	8	0	1.5	1.5	1	1	5
Li et al. (2015)	0	0	0	2	1	0	0	3	18	2	1.5	1.5	1	1	7
Lin et al. (2017)	0	0	0	0	5	16	10	31	79	2	1.5	2	2	1	8.5
Ma et al. (2018)	0	0	0	0	0	2	2	4	25	0	2	1.5	1	0	4.5
Manogaran et al. (2018)	0	0	0	0	1	44	36	81	68	2	2	2	2	1	9
Moreira et al. (2018)	0	0	0	0	0	3	2	5	30	2	0	2	1	1	6
Moutselos et al. (2018)	–	–	–	–	–	–	–	0	13	0	1.5	1.5	1	0	4
Moutselos et al. (2018)	0	0	0	0	0	0	0	0	33	0	1.5	1.5	1	1	5
Narayanan and Greco (2016)	0	0	0	2	1	0	0	3	23	2	1.5	1.5	1.5	1	7.5
Navaz et al. (2018)	0	0	0	0	0	0	1	1	45	2	2	2	1	1	8
Ozminkowski et al. (2015)	0	0	0	1	2	1	2	6	23	2	1.5	1.5	1	0	6
Patil and Seshadri (2014)#	0	0	8	15	27	33	22	105	26	0	1.5	1.5	2	1	6
Praveena and Rao (2018)*	0	0	0	0	0	0	0	0	6	1.5	1.5	1.5	1	0	5.5

(*Continued*)

Table 2. (Continued).

Author(s)	2013	2014	2015	2016	2017	2018	2019^	Citations	H-index	QE1[a]	QE2[b]	QE3[c]	QE4[d]	QE5[e]	QS
Sabharwal, Gupta, and Thirunavukkarasu (2016)	0	0	0	0	0	0	1	1	12	0	1.5	1.5	1	1	5
Shao et al. (2016)	0	0	0	0	2	5	0	7	57	2	1.5	1.5	1.5	1	7.5
Tseng, Chou, Yang & Tseng (2017)	0	0	0	0	0	3	1	4	9	2	1.5	1.5	1	1	7
Vargheese (2014)	–	–	–	–	–	–	–	9	–	0	1.5	1.5	1	0	4
Wang, Kung, and Byrd (2018)	0	0	0	0	41	125	69	245	66	1.5	2	2	2	1	8.5
Wang et al. (2018)	0	0	0	0	2	38	20	60	56	1.5	1.5	2	2	1	8
Wu et al. (2016)	0	0	0	0	10	12	3	25	56	2	1.5	2	1.5	1	8
Wu et al. (2017)	0	0	0	0	1	4	6	11	35	2	2	2	1	1	8
Yasin and Rao (2018)	0	0	0	0	0	0	0	0	3	2	1.5	1.5	1	0	6
Zaragoza, Kim, and Chung (2017)	0	0	0	0	0	0	0	0	8	2	1.5	1.5	1	0	6
Total citations in a year	1	7	23	40	135	412	261								
Average citations in a year	0.02	0.17	0.56	0.98	3.29	10.05	6.37								

Note: Quality evaluation criteria are adopted from Behera, Bala, and Dhir (2019) and Tandon et al. (2020). The studies that received QS < 4.5 (threshold value) are highlighted in grey.
^ As of 31 July 2019; * studies included from forward citation searches; # studies included from backward citation searches.
[a]QE 1: Evidence of data analysed in the study – 'quantitative (+2),' 'qualitative (+1.5),' and 'no evidence (+0).'
[b]QE 2: Investigation of pros and cons of the topic under discussion – 'yes (+2),' 'partially (+1.5),' and 'no (+0)'; the score for partial investigation is assigned when discussion lacks depth.
[c]QE 3: Justification of the study outcome in accordance with the methodology used in the study – 'yes (+2),' 'partially (+1.5),' and 'no (+0)'; the score for partial justification is assigned when limited techniques are explained or detailed explanation of a technique used is unavailable.
[d]QE 4: Recognisability of the article and reliability of the source – (+2) when the sum of citations and H Index exceeds 100; (+1.5) when the sum of citations and H index is between 50 and 99; (+1.0) when the sum of citations and H index is between 1 and 49; (+0) when the sum of citations and H index is 0.
[e]QE 5: Comparability of the method(s) used with robust methods – 'yes (+1)' and 'no (+0).'

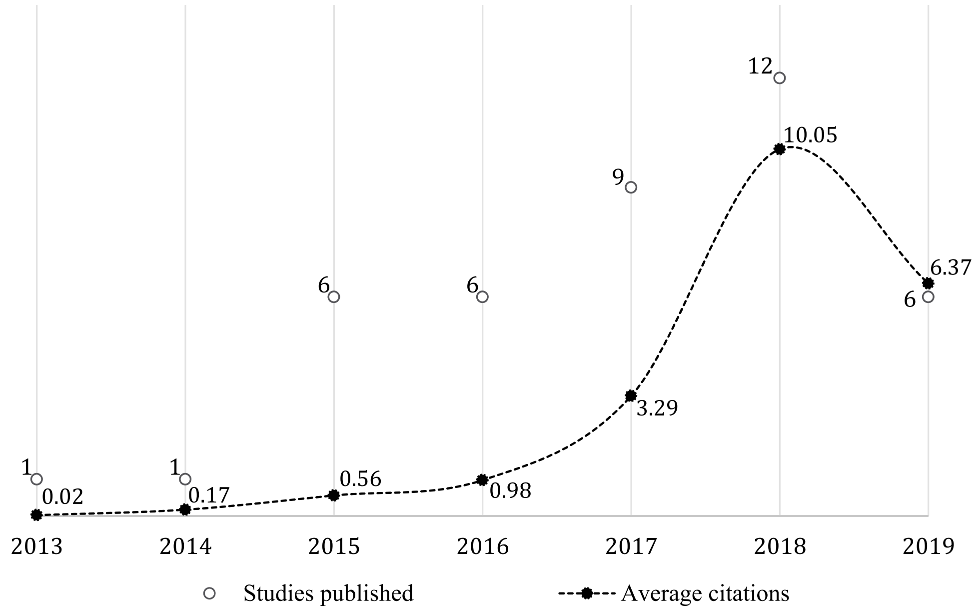

Figure 2. Year-wise distribution of studies. Note: Studies published – the number of studies in our sample published in a year.Average citations – an average of the number of times a study in our sample is cited in a year.Data till 30 June 2019, are reported as the number of studies published in 2019.

4. Findings

4.1. Applications of BDA in healthcare

The selected studies were reviewed following a meta-ethnography-based approach (Noblit and Hare 1988), which indicated that the contexts of these studies can be synthesised into five broad themes (see Table 3), as discussed below:

Health awareness. This theme involves different facets of general awareness of the holistic health and well-being of patients. For instance, prior studies on health awareness discussed health insurance (Chandola, Sukumar, and Schryver 2013), living environment (Jin et al., 2016), and sports behaviour (Tseng et al. 2017), among other topics. Chandola, Sukumar, and Schryver (2013) suggested that insurance claims data reveal important insights about the prevalence of fraudulent activities in healthcare. Jin et al. (2016) proposed that cyber technologies can provide a safe and secure living environment for the elderly. Tseng et al. (2017) identified that personalised healthcare apps might analyse users' sports patterns and trends of heart rate change during exercise.

Healthcare ecosystem. This theme captures the dynamic relationships among stakeholders in the healthcare ecosystem in managing hardware resources (Koliogeorgi et al. 2017), device networks (Jindal et al. 2018), data warehousing (Sabharwal, Gupta, and Thirunavukkarasu 2016), and other facilities required for reaping the benefits of BDA (Wang, Kung, and Byrd 2018). Koliogeorgi et al. (2017) suggested that parallel execution of accelerated kernels delivers remarkable speed and scalability. Jindal et al. (2018) proposed

Table 3. Contexts of reviewed studies.

Theme	Details
Health awareness	Chronic care (Lin et al. 2017); health insurance (Chandola, Sukumar, and Schryver 2013; Ozminkowski et al. 2015); hearing aids (Christensen et al. 2018); living environment (Jin et al., 2016); sports behaviour (Tseng et al. 2017); wearable devices (Li et al. 2015; Wu et al. 2016; Wu et al. 2017)
Healthcare ecosystem	Holistic healthcare (Forestiero and Papuzzo 2018; Gopal et al. 2019; Jindal et al. 2018; Koliogeorgi et al. 2017; Kuo et al. 2015; Ma et al. 2018; Moutselos et al. 2018; Sabharwal, Gupta, and Thirunavukkarasu 2016; Wang, Kung, and Byrd 2018; Praveena and Rao 2018)
Hospital management	Hospital administration (Babar et al. 2016; Chen et al. 2017); medication assignment (Boudhir, Ben Ahmed, and Soumaya 2017); outpatient management (Hadi et al. 2019); patient experience (Narayanan and Greco 2016); pre-admission testing (Agnihothri et al., 2015); private hospitals (Yasin and Rao 2018)
Specific medical condition	Alzheimer's disease (Chehade and Liu 2019); cancer (Boudhir, Ben Ahmed, and Soumaya 2017); cardiology (Austin and Kusumoto 2016); diabetes (De Silva et al. 2015; Gowsalya, Krushitha, and Valliyammai 2014; George, Chacko, and Kurien 2019); gestational diabetes (Moreira et al. 2018); nosocomial diseases (Cheng, Kuo, and Zhou 2018)
Technology aspects	Disease surveillance (Amirian et al. 2017); e-Health networks (Shao et al. 2016); monitoring and alerting system (Manogaran et al. 2018); m-Health services (Bravo et al. 2018; Navaz et al. 2018; Li et al. 2015; Wu et al. 2016, Wu et al. 2017); privacy and security issues (Patil and Seshadri 2014)

the possibility of classifying big data generated from device networks in healthcare. Sabharwal, Gupta, and Thirunavukkarasu (2016) highlighted that BDA might revolutionise many aspects of healthcare, such as patient profiling, genomic analysis, and monitoring. However, the capabilities required for implementing big data analytics impact transformation practices in healthcare (Wang, Kung, and Byrd 2018).

Hospital management. This theme involves the practices of hospital management, such as medication assignment (Boudhir, Ben Ahmed, and Soumaya 2017), outpatient management (Hadi et al., 2019), and pre-admission testing (Agnihothri et al., 2015). Boudhir, Ben Ahmed, and Soumaya (2017) proposed a big data architecture for decision making in medications assignment. Hadi et al. (2019) identified that cellular network optimisation for outpatients might predict serious medical conditions. Agnihothri et al. (2015) suggested that process innovation and efficient scheduling are keys to addressing bottlenecks in healthcare service delivery.

Specific medical conditions. This theme includes studies that discuss specific medical conditions, such as Alzheimer's disease (Chehade and Liu 2019), cancer (Boudhir, Ben Ahmed, and Soumaya 2017), and diabetes (De Silva et al. 2015). Chehade and Liu (2019) developed a structural degradation modelling framework for sparse data sets and reported that the framework works in the case of Alzheimer's Disease. Boudhir, Ben Ahmed, and Soumaya (2017) proposed a system architecture that facilitates medication assignment to cancer patients. De Silva et al. (2015) suggested that BDA has the potential to identify disease patterns among diabetes patients.

Technology aspects. This theme captures the application of technology to meet the responsibilities of healthcare through e-Health (Shao et al. 2016) and m-Health (Bravo et al. 2018) services. This theme also encompasses related issues, such as disease surveillance (Amirian et al. 2017) and alert systems (Manogaran et al. 2018). Shao et al. (2016) developed an algorithm based on a reduced variable neighbourhood search to improve the functioning of e-Health networks. Bravo et al. (2018) reported that m-Health services could be employed in conducting real-time assessment of patients. Amirian et al. (2017) identified that BDA could be used to extract insights from demographic data. Manogaran et al. (2018) concluded that a suitable architecture is required to address the complexity and security issues that arise with the sensor data.

4.2. Value delivered by BDA in healthcare

The aptness of BDA to add significant value to healthcare became evident after an analysis of the findings of the studies under review. This analysis reveals that the value delivered by BDA in healthcare can be classified into six themes (see Table 4) as follows:

Table 4. Summary of findings of reviewed studies.

Theme	Details
Conceptual evolution	Platform-as-a-service (Boudhir, Ben Ahmed, and Soumaya 2017); healthcare-as-a-service (Jindal et al. 2018); crowdsourced e-Health networks (Shao et al. 2016); care coordination programme (Kuo et al. 2015); efficient scheduling (Agnihothri et al., 2015); enhancement of service quality (Yasin and Rao 2018); strategic cloud design (Moutselos, Kyriazis, and Maglogiannis 2018); distributed network (Forestiero and Papuzzo 2018); layers of the healthcare system (Ma et al. 2018); theoretical framework (George, Chacko, and Kurien 2019; Tseng et al. 2017)
Data governance	Access rights management (Zaragoza, Kim, and Chung 2017); data from social media and clinical servers (Forestiero and Papuzzo 2018); data from mobile devices (Navaz et al. 2018); architecture for sensor data (Manogaran et al. 2018); structured data (Babar et al. 2016); application of Hadoop (Praveena and Rao 2018); efficiency-privacy paradox and benefit-cost trade-off (Wu et al. 2016); security and privacy of patient data (Patil and Seshadri 2014); trade-offs between healthcare efficiency and privacy risk (Li et al. 2015)
Decision support	Advanced decision support (Lin et al. 2017); decision-making models (Agnihothri et al., 2015; Boudhir, Ben Ahmed, and Soumaya 2017; Moreira et al. 2018); decision-support systems (Wang, Kung, and Byrd 2018); evidence-based decision (Moutselos et al. 2018); faster decision-making (Navaz et al. 2018); network analysis (Chandola, Sukumar, and Schryver 2013); integrating techniques (Cheng, Kuo, and Zhou 2018); insights from sociodemographic data (Amirian et al. 2017; Narayanan and Greco 2016); insurance claims (Chandola, Sukumar, and Schryver 2013); fraud identification (Chandola, Sukumar, and Schryver 2013); structural degradation modelling (Chehade and Liu 2019); macro-level phenomena (Cheng, Kuo, and Zhou 2018); public-health policy (Christensen et al. 2018); social welfare policies (Wu et al. 2016)
Disease prediction	Serious medical conditions (Chen et al. 2017; Hadi et al. 2019; Yasin and Rao 2018); gestational diabetes mellitus (Moreira et al. 2018); diabetes (George, Chacko, and Kurien 2019; Gowsalya, Krushitha, and Valliyammai 2014); disease patterns (De Silva et al. 2015); efficient risk profiling (Lin et al. 2017); diagnostic frameworks (Babar et al. 2016); prediction models (Manogaran et al. 2018); prioritising individuals (Ozminkowski et al. 2015; Sabharwal, Gupta, and Thirunavukkarasu 2016); personalised healthcare apps (Tseng et al. 2017); patient monitoring (Christensen et al. 2018; Sabharwal, Gupta, and Thirunavukkarasu 2016); disease-based monitoring systems (Bravo et al. 2018); real-time assessment in m-Health (Bravo et al. 2018); secure living environment for elderly (Jin et al., 2016)
Strategy formulation	BDA-based capabilities (Austin and Kusumoto 2016); investment in BDA (Sabharwal, Gupta, and Thirunavukkarasu 2016); efficient resource allocation (Gowsalya, Krushitha, and Valliyammai 2014); knowledge management (Christensen et al. 2018); firm strategy (Li et al. 2015); new business ideas (Wang, Kung, and Byrd 2018); process innovation (Agnihothri et al., 2015); cost-efficient service plans (Lin et al. 2017); business benefits for healthcare organisations (Wang, Kung, and Byrd 2018); market conditions (Wu et al. 2017); industry rivalry (Wu et al. 2016)

(*Continued*)

Table 4. (Continued).

Theme	Details
Technology development	Embedded intelligent technologies (Gopal et al. 2019); capability enhancement (Wang, Kung, and Byrd 2018); cloud-based infrastructure (Jindal et al. 2018); hardware and software stacks (Koliogeorgi et al. 2017); intelligent healthcare systems (Ma et al. 2018); radial basis function network (Moreira et al. 2018); wearable devices (Wu et al. 2017); parallel execution of accelerated kernels (Koliogeorgi et al. 2017); technology requirements (Jin et al., 2016); algorithms (Chen et al. 2017; Forestiero and Papuzzo 2018; Shao et al. 2016); architecture (Amirian et al. 2017; Boudhir, Ben Ahmed, and Soumaya 2017); schemes (Jindal et al. 2018)

Conceptual evolution

This theme encapsulates the contributions of BDA in introducing new concepts in healthcare, for instance, platform-as-a-service (Boudhir, Ben Ahmed, and Soumaya 2017), healthcare-as-a-service (Jindal et al. 2018), and crowdsourced e-Health networks (Shao et al. 2016). Boudhir, Ben Ahmed, and Soumaya (2017) identified the potential of big data in conjunction with cloud computing to provide the platform-as-a-service model. Jindal et al. (2018) conceptualised the healthcare-as-a-service model using BDA in cloud computing. Shao et al. (2016) developed an algorithm to solve the data-congestion problem in crowdsourced e-Health networks.

Data governance

This theme captures the legal and ethical concerns regarding the usage and security of data in healthcare, for example, access rights management (Zaragoza, Kim, and Chung 2017), the security of patient data (Patil and Seshadri 2014), and trade-offs between healthcare efficiency and privacy risk (Li et al. 2015). Zaragoza, Kim, and Chung (2017) proposed improving healthcare data storage through encryption and access rights management. Patil and Seshadri (2014) attributed paramount importance to the security and privacy of patient data as BDA transforms healthcare. Li et al. (2015) concluded that the trade-offs between healthcare efficiency and privacy risk need to be balanced.

Decision support

This theme acknowledges how BDA has improved decision-making processes in healthcare organisations with evidence-based decisions (Moutselos, Kyriazis, and Maglogiannis 2018) and faster decision making (Navaz et al. 2018); it also shows how improved design produced better public health policy at the national level (Christensen et al. 2018). Moutselos et al. (2018) suggested that system trust could be preserved by a cloud design wherein tools are decoupled from data stores and interfaces. Navaz et al. (2018) proposed that efficient analytics could optimise the handling, processing, and analysis of health data from mobile devices. Christensen et al. (2019) identified that the duration of device use influences the physical activity level of patients.

Disease prediction

This theme captures the ways of predicting serious medical conditions in patients by using the efficient application of BDA, for example, in the prediction of diseases (Moreira et al. 2018), the identification of disease patterns (De Silva et al. 2015), and disease-based monitoring systems (Bravo et al. 2018). Moreira et al. (2018) identified that an artificial neural network-based approach is an excellent predictor for gestational diabetes mellitus.

De Silva et al. (2015) suggested that BDA can effectively identify disease patterns in patients. Bravo et al. (2018) reported that m-Health services could be used to facilitate continuous monitoring of patients.

Strategy formulation

This theme discusses how BDA can aid healthcare organisations to formulate sustainable business strategies, for example, capability development (Austin and Kusumoto 2016), resource allocation (Gowsalya, Krushitha, and Valliyammai 2014), and profit enhancement for healthcare organisations (Wang, Kung, and Byrd 2018). Austin and Kusumoto (2016) confirmed that the application of BDA has the potential to improve healthcare services. Gowsalya et al. (2014) highlighted how data-driven decision making facilitates efficient resource allocation in healthcare. Wang, Kung, and Byrd (2018) suggested that BDA could deliver business benefits to healthcare organisations that follow strategic approaches.

Technology development

This theme involves advancement in technology to discover novel benefits of BDA in healthcare, for example, in embedded intelligent technologies (Gopal et al. 2019), cloud-based infrastructure (Jindal et al. 2018), and parallel execution of accelerated kernels (Koliogeorgi et al. 2017). Gopal et al. (2019) suggested that applications of embedded intelligent technologies will be crucial for healthcare organisations. Jindal et al. (2018) proposed that a fuzzy rule-based classifier can efficiently classify the big data generated from using cloud computing. Koliogeorgi et al. (2017) identified that parallel execution of accelerated kernels might deliver remarkable speed and scalability.

4.3. A comprehensive framework for the use of BDA in healthcare

Insights from the current SLR helped us develop a comprehensive framework comprising six important components of BDA in healthcare (see Figure 3). The six components that exhibit a degree of interconnectedness were reported as follows:

Medical records

Medical records act as building blocks of historical data in healthcare, particularly for sourcing patient data. These are commonly obtained from diagnostic reports (Amirian et al. 2017; De Silva et al. 2015), hospital registers (Austin and Kusumoto 2016; Babar et al. 2016), and patients' history (Ozminkowski et al. 2015; Zaragoza, Kim, and Chung 2017). Medical records are often available in electronic formats, such as electronic medical records containing a patient's treatment history from past visits to a doctor. The electronic health record may comprise of comprehensive information about a patient, such as the patient's records from multiple doctors, medical history, and medications, among other information, for a longer-term.

Sensor data

Increased adoption of newer technologies make real-time data from sensors in electronic devices available to healthcare functions. These data are often accumulated from health devices (Gopal et al. 2019; Ma et al. 2018), Internet of Things (IoT) devices (Bravo et al. 2018; George, Chacko, and Kurien 2019), and smartphone applications (Navaz et al. 2018;

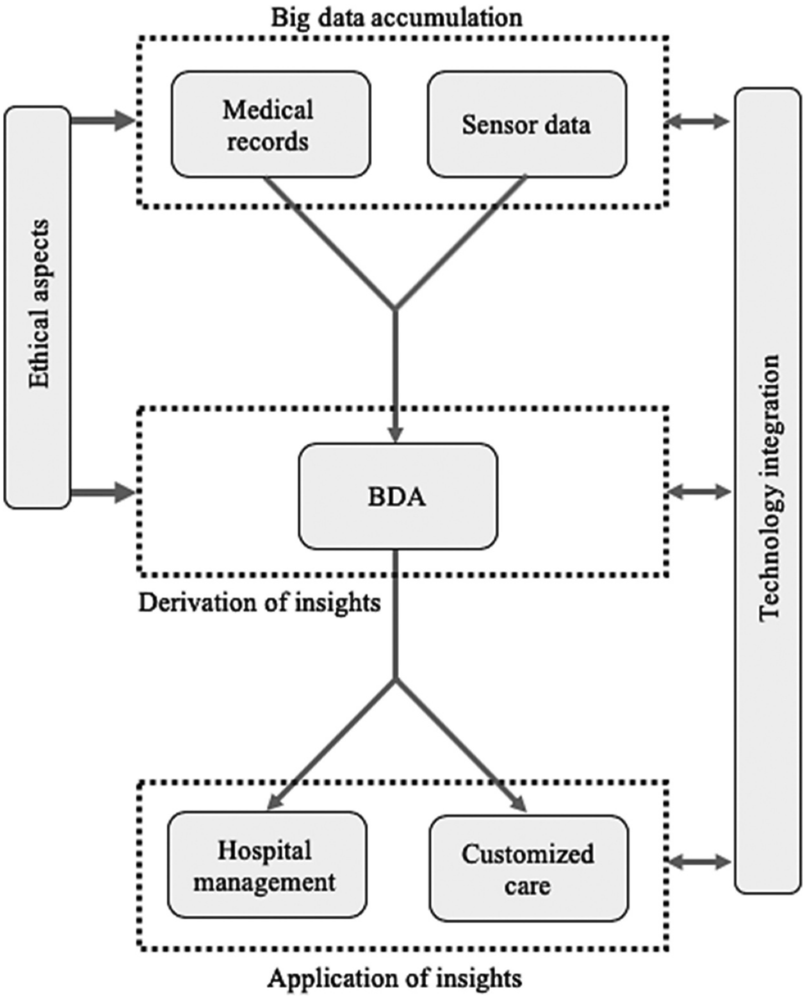

Figure 3. A comprehensive framework for applications of BDA in healthcare.

Wu et al. 2017). In general, body temperature sensors, blood oxygen sensors, and electrocardiogram sensors, among other sensors are attached to a patient's body to monitor health parameters continuously.

Ethical aspects

Big data in healthcare must be accumulated with permission from appropriate stakeholders. Among the issues raised by the use of BDA in healthcare are data privacy (Chen et al. 2017; Hadi et al. 2019), security concerns (Koliogeorgi et al. 2017; Patil and Seshadri 2014), and surveillance (Cheng, Kuo, and Zhou 2018; Sabharwal, Gupta, and Thirunavukkarasu 2016). Therefore, it is critical for authorities accumulating big data to ensure that legal and ethical guidelines preserve data integrity. For instance, collection, storage, and sharing of personally identifiable information in medical records need to comply with the Health Insurance Portability and Accountability Act in the United States.

Technology integration

Integrated technologies in healthcare play a holistic role in the accumulation of big data and delivering the benefits of BDA to appropriate beneficiaries. The literature on BDA in healthcare attributes great importance to the use of peripheral support technologies, such as big data platforms (Gowsalya, Krushitha, and Valliyammai 2014; Manogaran et al. 2018), cloud storage (Chehade and Liu 2019; Kuo et al. 2015), and smartphone-based interfaces (Li et al. 2015; Wu et al. 2016). Therefore, healthcare administrators often view the integration of state-of-the-art technologies as a critical part of organisational value chains.

Hospital management

Applications of BDA have the potential to derive reliable insights for specific beneficiaries in healthcare, including hospital administrators, doctors, and nurses. BDA can serve to help hospital administrators in resource allocation (Agnihothri et al., 2015; Jindal et al. 2018), doctors in patient profiling (Narayanan and Greco 2016; Lin et al. 2017), and nurses in providing disease-specific patient facilitation (Boudhir, Ben Ahmed, and Soumaya 2017; Moreira et al. 2018). For instance, hospital management may dynamically allocate resources for treating the Covid-19 patients by using BDA-based insights from data on confirmed cases, population density, demographics, and migration flow.

Customised care

Patients are often key beneficiaries of insights derived from BDA. BDA can aid in providing personalised care to patients by controlling medications (Christensen et al. 2018; Wang, Kung, and Byrd 2018), predicting diseases (Tseng et al. 2017; Wang, Kung, and Byrd 2018), and supervising patients (Jin et al., 2016; Shao et al. 2016). The rapid spread of Covid-19 has threatened to overwhelm health systems across the world, forcing hospitals to defer scheduled surgeries and treatments for an unknown period. A BDA-enabled smartphone application may conduct a personalised risk assessment of patients awaiting surgeries, provide suggestions to address minor health complications, and prioritise patients based on the urgency in the requirement of medical attention from doctors.

The framework posits that the primary sources of big data in the context of healthcare are medical records and sensor data. Big data are accumulated from healthcare sources through the use of integrated technologies. BDA extracts pertinent insights from the accumulated data. The accumulation and utilisation of healthcare data to derive such insights are subject to certain ethical considerations. The derived insights are useful to hospital management and are used in delivering customised care to patients. Integrated technologies in healthcare play critical roles in converting insights from BDA into actions (see Figure 3).

4.4. Future research agendas

The prior literature on BDA in healthcare examined herein acknowledged three main limitations that pertain to study assumptions, data collection, and methodological constraints (see Table 5). Furthermore, the studies reported five categories of future research scopes, namely, conceptual advancement, methodological rigour, study extension, technological advancement, and research design (see Table 5). The five categories of future

Table 5. Summary of study limitations and future scopes.

Themes		Details
Limitations acknowledged by prior research	Study assumptions	About consumer behaviour and firm strategy (Li et al. 2015); about model parameters (Lin et al. 2017; Wu et al. 2016; Wu et al. 2017); generalisation (Agnihothri et al., 2015)
	Data collection	Access to data (Narayanan and Greco 2016); data from singular source (Lin et al. 2017); data sources (Wang, Kung, and Byrd 2018); limited data (Gopal et al. 2019); quality of data (Sabharwal, Gupta, and Thirunavukkarasu 2016); small size (Christensen et al. 2018); convenience sampling (Narayanan and Greco 2016)
	Methodological constraints	Available methods (Wang, Kung, and Byrd 2018); errors and variations in results (Sabharwal, Gupta, and Thirunavukkarasu 2016); execution time (Navaz et al. 2018); simulation-based results (Shao et al. 2016)
Future scopes recommended by prior research	Conceptual advancement	Accounting for human aspect (Wang, Kung, and Byrd 2018); model complexity (Tseng et al. 2017; Wang, Kung, and Byrd 2018); model efficiency (Lin et al. 2017); model extension (Agnihothri et al., 2015; Kuo et al. 2015; Shao et al. 2016); model optimisation (Chehade and Liu 2019; Shao et al. 2016); multi-view learning (Chandola, Sukumar, and Schryver 2013); multitasking learning (Lin et al. 2017)
	Methodological rigour	Advanced statistical methods (Narayanan and Greco 2016); grasping unstandardised data (Sabharwal, Gupta, and Thirunavukkarasu 2016); data quality (Narayanan and Greco 2016); incompatible data formats (Sabharwal, Gupta, and Thirunavukkarasu 2016); simulations (Wu et al. 2016); scrutinising fragmented data (Sabharwal, Gupta, and Thirunavukkarasu 2016); controlled studies (Narayanan and Greco 2016)
	Study extension	Depth and range (Hadi et al. 2019); scale (Christensen et al. 2018; Hadi et al. 2019; Jin et al., 2016); scopes (Gowsalya, Krushitha, and Valliyammai 2014; Kuo et al. 2015; Tseng et al. 2017); scopes in other industries (Wang, Kung, and Byrd 2018); replication in different countries (Zaragoza, Kim, and Chung 2017); research on specific pathologies (Boudhir, Ben Ahmed, and Soumaya 2017)
	Technological advancement	Affective computing (Ma et al. 2018); algorithm development (Jin et al., 2016); application of newer technologies (Bravo et al. 2018; George, Chacko, and Kurien 2019; Gopal et al. 2019); cognitive computing (Ma et al. 2018); deep learning (Ma et al. 2018); open data exchange (Austin and Kusumoto 2016); optimisation of batteries (Navaz et al. 2018)
	Research design	Security issues (Jindal et al. 2018); criteria to choose a hospital (Yasin and Rao 2018); integrate data from social media (Amirian et al. 2017); market entry strategy (Wu et al. 2017); measurement of programme success (Ozminkowski et al. 2015); monitoring care programmes (Ozminkowski et al. 2015); resource management (Jindal et al. 2018)

research scopes are evident in the four sets of future research agendas emerging from the comprehensive framework, as subsequently discussed.

Problems in health data accumulation

Prior research observed several issues related to big data accumulated in healthcare, such as data quality (Sabharwal, Gupta, and Thirunavukkarasu 2016) and data quantity (Gopal et al. 2019). However, there is a lack of research into the types of problems that may occur during data accumulation processes in healthcare and how these may arise from a variety of sources, such as diagnostic reports, hospital registers, and patient history. Future research should look into addressing this research gap and find solutions to the identified problems. This set of future research agendas reinforces future research scope of improving methodological rigour (see Table 5).

Concerns regarding data governance

Scholars can explore opportunities to better govern the data harvested from sensors, such as health devices, IoT devices, and smartphone applications. Research on cyber laws and policies for the use of health data is not adequate at the moment. Moreover, ensuring the privacy of patient data and securing sensitive information against unauthorised access deserves more attention from researchers. Thus, this set of future research agendas relates to two future research scopes, namely, conceptual advancement and research design (see Table 5).

Role of new technologies

This set of future research agendas connects to the future research scope of incorporating technological advancements in healthcare (see Table 5). Advances in new peripheral technologies may increase the quality of the insights derived by BDA in healthcare. Therefore, future researchers might do well to explore the potential benefits that state-of-the-art technologies, such as augmented reality, machine learning, and quantum computing, offer to healthcare delivery. Another promising avenue of research might be to explore possible ways to integrate emerging technologies, such as digital twins, 5 G communications, and the physical internet, in healthcare delivery.

Investigating the success of BDA

BDA reportedly helps hospital management improve their efficiency in delivering healthcare services and in providing customised care to patients. Future research is invited to empirically study the role of BDA in improving service quality in hospitals. It is hoped that scholars will also explore further means of providing more sophisticated personal assistance to individuals, especially senior citizens and patients suffering from chronic diseases. Overall, this set of future research agendas reiterates the future research scope of extending the present study (see Table 5).

5. Discussion and implications

RQ1 aimed to synthesise the current research profile of BDA in healthcare. In answering this question, Figure 2 presents an increasing trend in the number in publications, exhibiting a growing prevalence of the research topic in academia. Furthermore, prominent contributors who are advancing the literature are duly acknowledged. **RQ2** enquired about where in the healthcare domain BDA can be applied. This question has been answered by analysing the contexts of the reviewed studies (see Table 3). **RQ3** attempted to analyse the key takeaways from the reviewed studies. A summary of the findings of the studies under review provides the answers to this question (see Table 4). Also, based on the insights of the selected studies, a comprehensive framework was developed that summarises the use of BDA in healthcare (see Figure 3). **RQ4** aimed to identify future agendas to advance BDA research in healthcare. Future research is invited to address the limitations acknowledged herein and follow future research scopes recommended in the prior literature on BDA in healthcare (see Table 5). Moreover, four sets of future research agendas emerged from the comprehensive framework developed in this study.

5.1. Theoretical implications

Research on the application of BDA in healthcare is gaining popularity, particularly within the domains of information systems and medical studies. As one of the earliest comprehensive reviews on the topic, the present study offers three major implications to theory, as subsequently discussed. First, this study presents a current research profile on the applications of BDA in healthcare. This research profile includes information about the key contributors, prominent publication outlets, and common methodologies prevalent in the reviewed studies. Second, the current study has identified the themes of healthcare contexts in which BDA is applied and where BDA can deliver value. Our review of prior literature indicated that the contexts can be synthesised into five broad themes addressing health awareness, healthcare ecosystems, hospital management, specific medical conditions, and technology aspects. A thematic identification organised prior literature and aimed to catalyse future research in various related domains of study. Third, the present study proposed a comprehensive framework that captures the interplay among the process of health data accumulation, derivation of the insights from the data, and application of these insights to healthcare. The comprehensive framework also offers future research agendas for advancing the application of BDA in healthcare.

5.2. Practical implications

This study identified that aptness of BDA to add significant value to healthcare can be classified into six themes, namely, conceptual evolution, data governance, decision support, disease prediction, strategy formulation, and technology development. It is expected that the findings of this study will be useful to healthcare practitioners, policymakers, and service developers, as subsequently discussed.

First, healthcare practitioners, particularly hospital administrators, should take note of the innovative ways presented herein to improve efficiency in healthcare service delivery using BDA. These innovative approaches include, for example, the supervision of patients with specific medical conditions, medication assignment, and pre-admission testing.

Second, policymakers will find inputs from the current study's findings for formulating healthcare policies, optimising public funds usage, and developing legal frameworks.

Suitable public policies may deliver efficient decision-support systems, infrastructure development, and technological advancement in healthcare.

Third, service developers may do well to follow our study findings when exploring opportunities to develop new services for the healthcare sector using state-of-the-art technologies. For instance, the application of augmented reality, quantum computing, and digital twins have the potential to maximise the value added by BDA to healthcare in the future.

Fourth, at present, we are facing a tough challenge from the Covid-19 outbreak. BDA can help medical professionals, scientists, epidemiologists, public health officials, and policymakers fight this pandemic. For example, scientists and policymakers can use BDA to comprehend and trace the impact of the Covid-19 pandemic. BDA not only helps in locating the fast spread of the Covid-19, but it can also aid various efforts undertaken to control and prevent its spread.

6. Conclusion and future scopes

The current study intended to address four research questions related to the application of BDA in healthcare. These questions have been answered following a standard protocol for reviewing resources from key databases. The prior literature on the application of BDA in healthcare has focused on five main themes, namely health awareness, stakeholders of the healthcare ecosystem, hospital management practices, specific medical conditions, and healthcare service delivery through technology use. The study has identified the gaps in the existing literature and provided an actionable research agenda for future research on the utilisation of big data in the healthcare sector. However, despite the significant contributions of this current study, it suffers from three main limitations: first, book chapters, magazine articles, and thesis studies have been excluded from the scope of this study; second, journal articles and conference studies not available in English were not considered; third, studies not available in the four databases were not reviewed unless they appeared in the forward and backward searches. Future research is invited to overcome these limitations. Also, we recommend that scholars study the application of BDA in services provided by, for example, banking and financial institutions, media and broadcast channels, and the travel and hospitality industry by adopting the protocol followed in the current study. Similarly, the application of new technologies, such as blockchain, cloud computing, and machine learning, in healthcare provides promising avenues of exploration. We conclude this SLR with a call for theory development regarding the specific applications of BDA and the general integration of technology in the healthcare sector.

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Exhibit A:. Studies reviewed in this SLR.

Author(s)	Affiliation	Journal/Conference	Publisher	Author Keywords	Method	Key Constructs
Agnihothri, Banerjee & Thalacker (2015)	United States	Annual Hawaii International Conference on System Sciences	IEEE	Business analytics; Healthcare; Pre-admission test; Preoperative assessment clinic; Process improvement; Quality management	Case study, descriptive statistics	Patient, wait time, registration, schedule, checks, discharge
Amirian et al. (2017)	United Kingdom	*Pervasive and Mobile Computing*	Elsevier	Big data analytics; Global health; Internet of Things; Machine-generated data; Machine learning; Point of care	Descriptive statistics	Data from point of care, batch layer, speed layer, service layer, MS Azure
Austin and Kusumoto (2016)	United States	*Journal of Interventional Cardiac Electrophysiology*	Springer	Analytics; Big data; Cardiology; Data management; Electrophysiology	Conceptual	Health records, insurance transactions, biometric data, application data, data warehouse, big data cluster, quality reporting, physician dashboard, logistics, registration
Babar et al. (2016)	Pakistan	IEEE International Conference on Computer and Communications	IEEE	Big data; Data analytics; Data mining; Decision support; Healthcare; Machine learning	Conceptual	Data clusters, data similarity, AI techniques, live patient data, propose medicine, predict disease severity
Boudhir, Ben Ahmed, and Soumaya (2017)	Morocco	Mediterranean Symposium on Smart City Applications	ACM	Analytics; Big data; Hadoop; Healthcare	Conceptual	Medical images, digital patients' folders, biology report, medical report, treatment assignment
Bravo et al. (2018)	Spain	*Sensors*	MDPI	Big data analytics; Frameworks; Human–computer interaction; M-health	Conceptual	Mobile device layers, biometric device layers, server layers, patient, doctor, food, disease, monitoring, devices

(*Continued*)

Exhibit A:. (Continued).

Author(s)	Affiliation	Journal/Conference	Publisher	Author Keywords	Method	Key Constructs
Chandola, Sukumar, and Schryver (2013)	United States	International Conference on Knowledge Discovery and Data Mining	ACM	Fraud detection; Healthcare analytics	Case study, mathematical	Drugs, providers, diagnoses, beneficiaries, speciality, procedures
Chehade and Liu (2019)	United States	*IEEE Transactions on Automation Science and Engineering*	IEEE	Collaborative model; Condition monitoring; Dissimilarity; Healthcare; Predictive analytics; Prognostics; Recommender system	Case study, mathematical	Recommenders, observations, tuning function, degradation
Chen et al. (2017)	China	*IEEE Access*	IEEE	Big data analytics; Healthcare; Machine learning	Mathematical	Accuracy, precision, learning rate, risk prediction
Cheng, Kuo, and Zhou (2018)	China	*Journal of Medical Systems*	Springer	Disease outbreak; Healthcare-associated infections; Person-to-person contact analytics; Traceability; Tracking	Mathematical	Detection probability, tracing probability, prediction probability, transition probability, observation probability
Christensen, Petersen, Pontoppidan & Cremonini (2018)	Denmark	International Conference on Signal Image Technology and Internet Based Systems	IEEE	Big data analytics; Evidence-based public health policies; Hearing aids; Mixed models; Multilevel clustered-data	Case study, econometric	Hearing aid usage, sound pressure level, signal-to-noise ratio
De Silva et al. (2015)	Australia	*Australasian Journal of Information Systems*	ACS	Big data analytics; Business analytics; Clinical decision support; Health informatics; Information fusion; Translational research	Conceptual, descriptive statistics	Blood pressure, fasting blood, medical condition, exercise routines, ECG, personal information

(*Continued*)

Exhibit A:. (Continued).

Author(s)	Affiliation	Journal/Conference	Publisher	Author Keywords	Method	Key Constructs
Forestiero and Papuzzo (2018)	Italy	International Conference on Web Intelligence	IEEE	Big data analytics; Distributed algorithm; Healthcare; self-organisation	Mathematical	Server, virtual link, virtual key, neighbours
George, Chacko, and Kurien (2019)	India	International Conference on Distributed Computing and Networking	ACM	Big data analytics; Diabetes mellitus; Electronic health record (EHR); Genomics; Interoperability	Conceptual	Personalised medicine, remote monitoring intelligent systems, genomic analytics, platform for hospitals
Gopal et al. (2019)	Germany	Clinical Chemistry and Laboratory Medicine	de Gruyter	Advanced analytics; Artificial intelligence; Big data platform; Digital transformation; healthcare; Internet of Things (IoT); Machine learning	Conceptual	Patient outcomes, operational efficiency, data-driven clinical innovations, patient experience, intelligent technologies, health data platforms
Gowsalya, Krushitha & Valliyammai (2014)	India	International Conference on Advanced Computing	IEEE	Big data; Diabetes; Healthcare; Predictive analytics	Conceptual, descriptive statistics	Patient, speciality provider, server, client, MapReduce
Hadi et al. (2019)	United Kingdom	*IEEE Access*	IEEE	Big data analytics; Cellular network design (including other technical specifications); Patient-centric network optimisation; Resource allocation; Resource management	Mathematical	Conventional network, patient-centric network, outpatient
Jin, Wu, Nishimura & Ogihara (2016)	Japan	International Conference on Advanced Cloud and Big Data	IEEE	Holistic support; Living assist; Personal data analytics; Smart home; Ubiquitous living environment	Conceptual	Accident prevention, wandering decision support, healthcare control support, daily living support

(*Continued*)

Exhibit A:. (Continued).

Author(s)	Affiliation	Journal/Conference	Publisher	Author Keywords	Method	Key Constructs
Jindal et al. (2018)	India	*IEEE Journal of Biomedical and Health Informatics*	IEEE	Big data analytics; Cloud computing environment; Fuzzy rule-based classifier; Healthcare applications	Mathematical	Device network, vehicular ad hoc network, body sensor network, transmission layer, computation layer
Koliogeorgi et al. (2017)	Greece	IEEE Computer Society Annual Symposium on VLSI	IEEE	Accelerated analytics; Cloud infrastructure; Resource monitoring	Conceptual	Hardware resource, software resource, conventional analytic, accelerated analytic
Kuo et al. (2015)	Canada	IEEE International Conference on Smart Cities	IEEE	Big data; Big data analytics; Data mining; Data privacy; Healthcare	Conceptual	Clinical data warehouse, test database, user interface
Li et al. (2015)	China	Pacific Asia Conference on Information Systems	AIS	Big data analytics; Efficiency; Healthcare; Privacy; Two-dimensional product differentiation; Wearable devices	Mathematical	BDA adoption, firm profit, efficiency–privacy trade-offs
Lin et al. (2017)	United States	*MIS Quarterly: Management Information Systems*	MIS Research Centre	Bayesian data analysis; Design science; Electronic health records; Health IT; Healthcare predictive analytics; Multitask learning	Mathematical	Patient information, diagnosis, treatment, labs, and exams
Ma et al. (2018)	China	International Wireless Communications and Mobile Computing Conference	IEEE	Data analytics; Healthcare systems; Mobile computing	Conceptual	Research data, medical data, clinical data, individual activity and emotion data, data manager layer, data collection layer

(*Continued*)

Exhibit A:. (Continued).

Author(s)	Affiliation	Journal/Conference	Publisher	Author Keywords	Method	Key Constructs
Manogaran, Varatharajan, Lopez, Kumar, Sundarasekar & Thota (2018)	India	*Future Generation Computer Systems*	Elsevier	Big data analytics; Cloud computing and health care; Internet of Things; Wireless sensor networks	Mathematical	Transportation system, smart hospital, medical diagnosis system, weather agency, fog computing, cloud computing
Moreira et al. (2018)	Portugal	*Journal of Computational Science*	Elsevier	Artificial neural networks; Big data analytics; Computational intelligence; Data mining; Decision making; Gestational diabetes; Pregnancy	Mathematical	Age, plasma glucose, blood pressure, serum insulin, body mass index, number of pregnancies
Moutselos et al. (2018)	Greece	IEEE International Conference on Big Data	IEEE	Big data healthcare architecture; Health analytics; k-anonymity; Public health policies; Trustworthiness	Conceptual	Health analytic tools, user interfaces, data stores
Narayanan and Greco (2016)	New Zealand	*Big Data*	Mary Ann Libert	Big data analytics; Data acquisition and cleaning; Data mining	Econometric	Interaction with general practitioner, practice access, practice-patient interaction,
Navaz et al. (2018)	United Arab Emirates	*Computer Methods and Programs in Biomedicine*	Elsevier	Analytics customisation; M-health; Mobile big data; Mobile offloading; Processing; Resources optimisation	Mathematical	Resource optimisation, analytics, customisation, offloading optimisation, data collection, preprocessing, analytics, visualisation

(*Continued*)

Exhibit A:. (Continued).

Author(s)	Affiliation	Journal/Conference	Publisher	Author Keywords	Method	Key Constructs
Ozminkowski et al. (2015)	United States	*Big Data*	Mary Ann Libert	Big data analytics; Case management; Data acquisition and cleaning; Medicare; predictive analytics	Descriptive statistics	Administrative data, claims data, pharmacy data, survey data, programme data, programme management
Patil and Seshadri (2014)	United States	IEEE International Congress on Big Data	IEEE	Big data security; Healthcare; Privacy; Security analytics	Conceptual	Clinical, social, physical, genomic, environmental, psychology
Praveena and Rao (2018)	India	*International Journal of Engineering and Technology*	Science Publishing Corporation	Big data; Big data analytics; Health analytics; Tools	Qualitative	Data sources, application area, analytical capability, tools
Sabharwal, Gupta, and Thirunavukkarasu (2016)	India	IEEE International Conference on Computing, Communication and Automation	IEEE	Analytics; Applications; Architectural framework; Big data; Challenges	Conceptual	Big data sources, big data transformations, big data platforms, big data analytics applications, queries, reports, data mining, middleware, data warehouse
Shao et al. (2016)	China	*IEEE Access*	IEEE	Congestion control; Crowdsourced e-health networks; Data analytics; Optimisation	Mathematical	Scene parameters, node parameters, packet parameters
Tseng, Chou, Yang & Tseng (2017)	Taiwan	International Conference on Technologies and Applications of Artificial Intelligence	IEEE	Activity analysis; Big data Analytics; Heart rate analysis; Personalised health services; Sports behaviour analysis	Mathematical	User information, exercise records, heart rate, GPS logs, data processing, feature extraction, pattern mining, sports behaviour analysis, heart rate trend

(Continued)

Exhibit A:. (Continued).

Author(s)	Affiliation	Journal/Conference	Publisher	Author Keywords	Method	Key Constructs
Wang, Kung, and Byrd (2018)	United States	*Technological Forecasting and Social Change*	Elsevier	Big data analytics; Big data analytics architecture; Big data analytics capabilities; Business value of information technology (IT); Healthcare	Case study	Data source, data aggregation layer, analytics layer, information exploration layer, data governance layer
Wang et al. (2018)	United Kingdom	*Information and Management*	Elsevier	Big data analytics; Business value of IT; Content analysis; Healthcare; IT-enabled transformation; Practice-based view	Case study	Resources, capabilities, evolutionary level practices, revolutionary level practices, IT infrastructure benefits, strategic benefits, operational benefits, managerial benefits, organisational benefits, business value
Wu et al. (2016)	China	*Information and Management*	Elsevier	Big data analytics; Consumer density; Healthcare; Two-dimensional product differentiation model; Wearable devices	Mathematical	BDA adoption, firm profit, efficiency–privacy trade-offs
Wu et al. (2017)	China	*Electronic Commerce Research and Applications*	Elsevier	Big data and analytics; Efficiency; Healthcare; Privacy; Two-dimensional product differentiation; Wearable devices	Mathematical	BDA adoption, firm profit, efficiency–privacy trade-offs

(*Continued*)

Exhibit A:. (Continued).

Author(s)	Affiliation	Journal/Conference	Publisher	Author Keywords	Method	Key Constructs
Yasin and Rao (2018)	India	*ARPN Journal of Engineering and Applied Sciences*	ARPN	Big data; Data analytics; Data science; Healthcare; Predictive analytics	Conceptual, mathematical	Health data, price data, patient, hospital, welfare organisation, researchers
Zaragoza, Kim, and Chung (2017)	South Korea	*International Journal of Control and Automation*	Science and Engineering Research Support Society	Big data; Big data analytics; U-healthcare	Conceptual, descriptive statistics	Information extraction, feature selection, predictive modelling, information encryption and storage, access rights management, information decryption