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REVIEW

AI in healthcare: A narrative review [version 1; peer review: 1 not approved]

Antti Väänänen [iD]1, Keijo Haataja1, Katri Vehviläinen-Julkunen [iD]2, Pekka Toivanen1

1School of Computing, University of Eastern Finland, Kuopio, Pohjois-Savo, 70211, Finland
2Department of Nursing Science, University of Eastern Finland, Kuopio, Pohjois-Savo, 70211, Finland

Abstract

In this paper, we focus on providing a narrative review of healthcare services in which artificial intelligence (AI) based services are used as part of the operations and analyze key elements to create successful AI-based services for healthcare. The benefits of AI in healthcare are measured by how AI is improving the healthcare outcomes, help caregivers in work, and reducing healthcare costs. AI market in healthcare sector have also a high market potential with 28% global compound annual growth rate. This paper will collect outcomes from multiple perspectives of healthcare sector including financial, health improvement, and care outcome as well as provide proposals and key factors for successful implementation of AI methods in healthcare. It is shown in this paper that AI implementation in healthcare can provide cost reduction and same time provide better health outcome for all.

Keywords

Artificial Intelligence, Healthcare Analytics, Machine Vision, Machine Learning

Open Peer Review

Approval Status ❌ ✅

	1	2
version 2 (revision) 08 Oct 2021	❌ view	✅ view
version 1 06 Jan 2021	❌ view	

1. **Dipak Kalra** [iD], University of Gent, Gent, Belgium

2. **Marko Jäntti**, CEMIS (Center for Measurement and Information Systems), Kuopio, Finland

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This article is included in the Health Services gateway.

This article is included in the Artificial Intelligence and Machine Learning gateway.

Corresponding author: Antti Väänänen (antti.vaananen@uef.fi)

Author roles: Väänänen A: Conceptualization, Investigation, Resources, Visualization, Writing – Original Draft Preparation; **Haataja K**: Writing – Review & Editing; **Vehviläinen-Julkunen K**: Supervision, Writing – Review & Editing; **Toivanen P**: Project Administration, Supervision, Writing – Review & Editing

How to cite this article: Väänänen A, Haataja K, Vehviläinen-Julkunen K and Toivanen P. **AI in healthcare: A narrative review [version 1; peer review: 1 not approved]** F1000Research 2021, **10**:6 https://doi.org/10.12688/f1000research.26997.1

First published: 06 Jan 2021, **10**:6 https://doi.org/10.12688/f1000research.26997.1

Introduction

The healthcare industry is undergoing a revolution. The reasons for this revolution are the ever-increasing total spending on health care and the growing shortage of health care professionals. This drives to situation that healthcare industry wants to adopt new Information Technology based solutions and processes with advanced technology which could reduce costs and provide solutions for these emerging problems.

Before 2010, healthcare technology companies were focusing on the innovations provided by medical products providing historic and evidence-based care. Starting from 2010 development has focused on real-time medical platforms and outcome-based care. From 2020 technology is moving towards medical solutions delivering intelligent solutions for evidence- and outcome-based health where focusing is in collaborative and preventative care. These intelligent solutions can be achieved by using robotics, virtual and augmented reality and AI[1]. In a recent life science executives survey 69% of life science businesses are already piloting or adopted AI in their solutions and 22% are evaluating or planning to pilot AI solutions[2]. The annual savings potential by using AI in healthcare can be $150 billion by 2026 in US alone, and this should be also one of the factors to speed up the implementation of AI in healthcare sector[3]. Future studies will give answers if this savings will be achieved. There are multiple subdomains in healthcare domain where AI-based services are utilized.

AI applications in healthcare can be classified to the following domains: surgery, nursing assistant, medical consultation, administration and workflow, treatment design, cybersecurity, machine vision, automatic and preliminary diagnosis, health monitoring, medication management, and clinical trials. All these domains have applications utilizing AI in their operations. We have collected some of the AI-utilizing services in the healthcare sector and made a comparative analysis of the effectiveness and outcome when utilizing AI versus services which are not utilizing AI. As a result, in this paper we introduce AI-based services for healthcare sector that have a high impact in care outcome and propose collection of services which could provide best outcome in preventive healthcare and in clinical work.

Services utilizing AI in healthcare domain

In this section we review healthcare services which are utilizing AI. These services include healthcare services and supporting services which are shown in Figure 1. The reviewed services are collected from research papers and market analysis companies[3]. Services which are selected for analysis are providing instant care or providing direct support for care. These are robot-assisted surgery, clinical trial participation, virtual assistants for nursing and consultation, image diagnosis, dosage error reduction, medication management, preliminary diagnosis, and health monitoring. Some of the topics which have been recently studied in my research and which provide indirect services for healthcare processes but are not affecting directly to patient care, such as fraud detection, assistant for administration and workflow, cybersecurity, connected machines, and drug creation are excluded from this study. We also categorized healthcare services and applications based
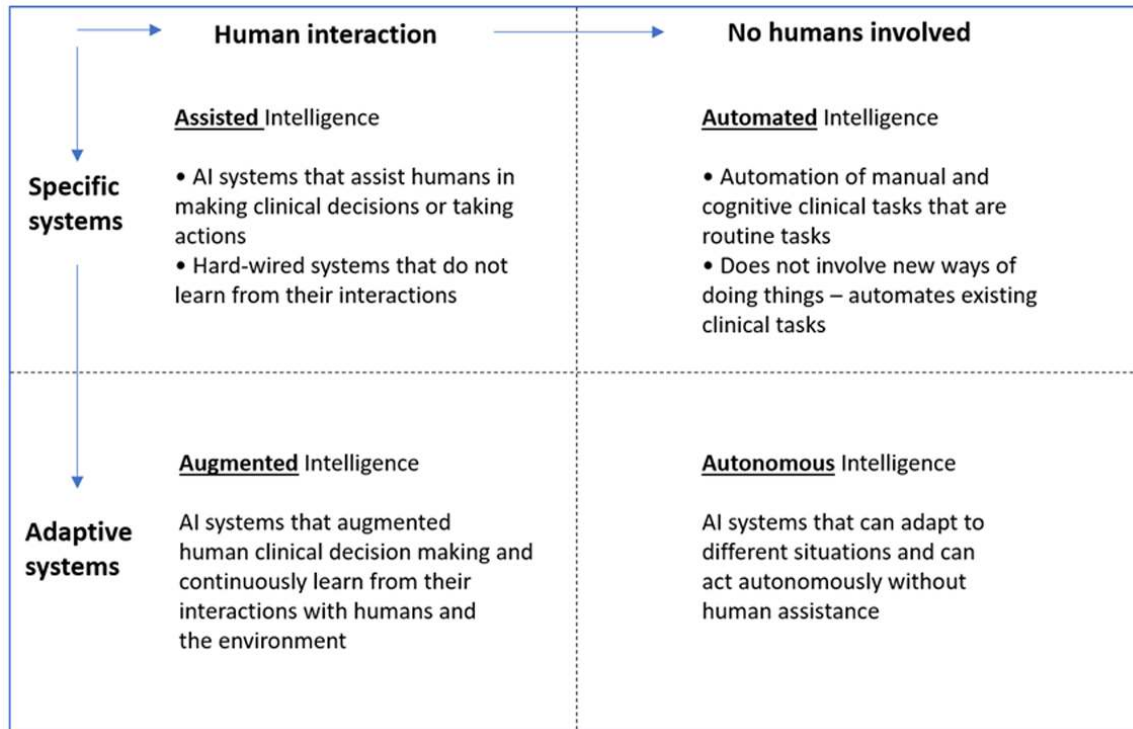
Figure 1. Categories of AI applications in Healthcare.

on degree of AI utilization and human involvement in clinical decision making[4].

Below we provide a short description of AI-methods which are commonly utilized in healthcare applications and services. Common applications for AI methods are shown in Figure 2.

Machine learning (ML) is a subfield of AI and presents AI solutions that are adaptive. The ML can be roughly categorized to three subareas. *Supervised learning* algorithms build a mathematical model of a set of data containing both the desired outputs and the inputs[5]. In *unsupervised learning* algorithms take a data set containing only inputs and find structure in the data, such as grouping or clustering of data points.

In unsupervised learning the algorithms learn from the test data that has not been classified, labeled or categorized[6]. *Reinforcement learning* algorithms do not assume knowledge of an exact mathematical model of discrete time stochastic control process. Reinforcement learning is used, for example, in situations where a self-driving car is operating in an environment where feedback about good or bad choices is not available in real time.

Natural language processing (NLP) is a subfield of AI that consist of tools and techniques to enable computers to read, understand, and derive meaning from human languages and enable natural interaction between computers and humans to make computer systems understand and manipulate natural

Figure 2. AI methods and applications.

languages to perform desired tasks. In healthcare, NLP is used, for example, to predict diseases based on patient's own speech and electronic health records[7].

Neural network (NN) consists of digitized inputs, such as an image or speech, which proceed through several hidden layers of connected artificial neurons, each layer responding to different feature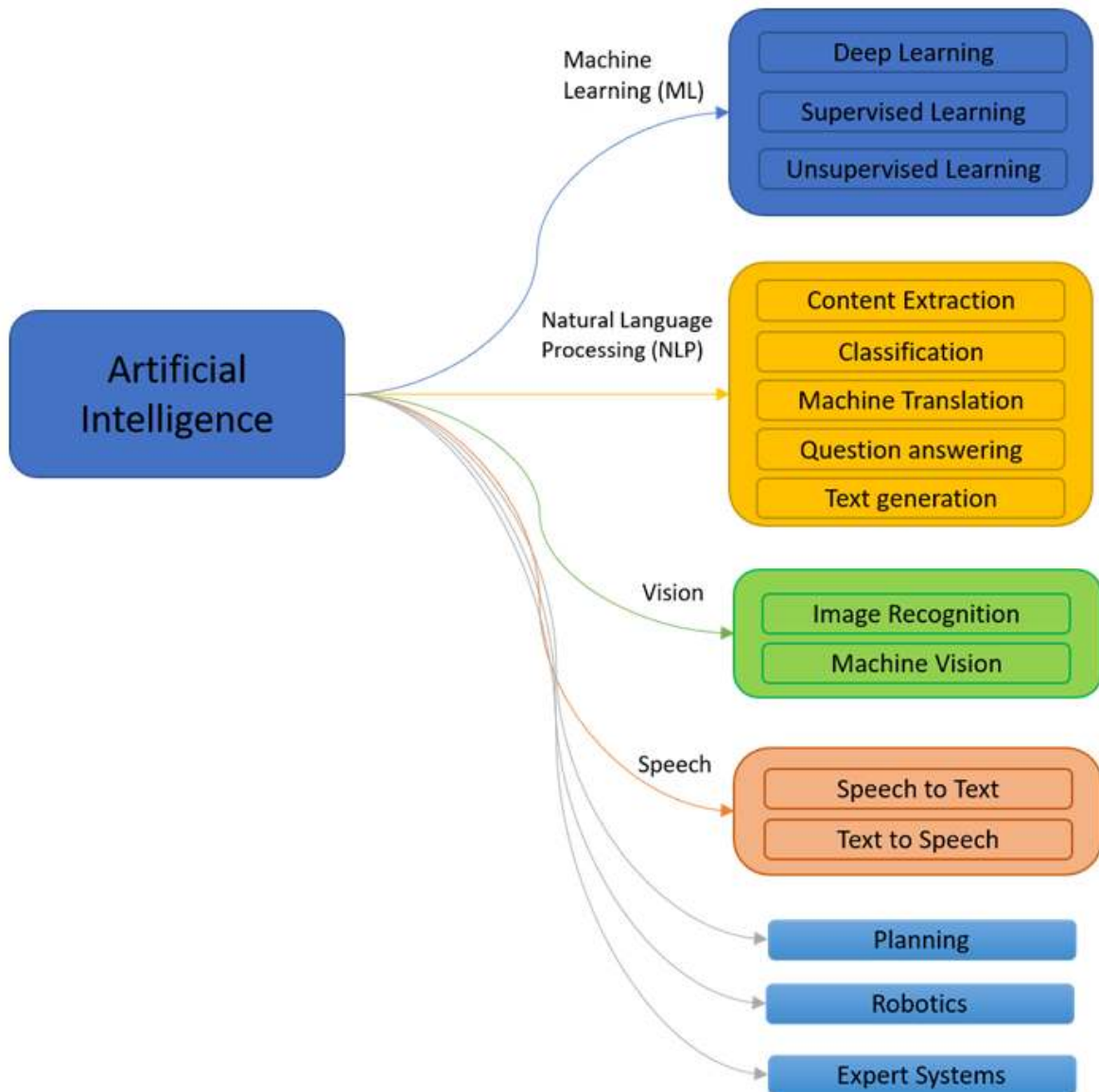s progressively detecting features and provide an output. Deep NNs (DNN) require special mention because as a subcategory of NN with its variations, such as recurrent, convolutional, transfer, generative adversarial, reinforcement, representation, and transfer, are used in various AI solutions in field medicine. Typical use case for DNN is when there is need for interpret data to certain patterns from different types of clinical images such as pathology, skin lesions, retinal, and endoscopy images and to find out patterns from datasets, such as medical scans, electrocardiograms, and vital signs.

Deep learning (DL) is a subfield of ML. DL is based on artificial NNs (ANNs), inspired by information processing and distributed communication nodes in biological systems, that use multiple layers to progressively extract higher level features from raw input. DL can be semi-supervised, supervised, or unsupervised. The term 'deep' refers to the number of layers (depth) through which the data is transformed. DL is a form of AI that enables computers to perform tasks based on existing data relationships.

Machine vision/computer vision (MV/CV) include the methods and the technology which is used to automatically extract information from an image. The extracted information can be a i.e. good-part / bad-part signal or a set of data such as the identity, orientation, and position of objects in an image. Extracted information can be later used for applications like automatic inspection, security monitoring, industry robots and process guidance, and vehicle guidance.

In the next sections we provide detailed information about topics in healthcare AI. Summary of these techniques are collected to Table 1 where we provide studied information about AI based services which are in use in healthcare business. Studied applications / services information is limited to Healthcare domain and include the following information: service / application type, category of AI service, application / service type, AI features which have been used in application / service, outcome as a result of AI utilization, and metrics which have been used to present the outcome.

Robotic-assisted surgical systems (RASS) and computer-assisted surgery (CAS)

The RASS have been used since year 1985[8] in multiple fields of surgery including cardiac surgery, thoracic surgery, gastrointestinal surgery, gynecology, orthopedic surgery, spine surgery, transplant surgery, urology, and general surgery[9–16]. RASS have been categorized to tree types based on the level of autonomous activity: supervisory controlled surgery, telesurgical, and shared control surgery.

In traditional surgery, surgeons can operate only on what their eyes can see and basically the only way to see inside a patient is to operate by open surgery. With RASS, surgeon can utilize cameras and tools which can be inserted through a small incision to perform procedures with exquisite precision. The minimally invasive approach is meant to provide faster patient recovery times and reduce postoperative complications. RASS can also lessen the physical burden of surgery staff. With RASS there is also possibility to collect all data and details such as video recording of the surgery, all movements and cutting and sewing actions of ongoing surgery, and use this collected data for further analysis and enhance and lean the surgery process. There are RASS manufacturers which are providing robotic surgery equipment worldwide. In this paper, we provide details about the one of the most used RASS at the time of writing this paper, DaVinci, developed by Intuitive Surgical Inc. DaVinci had 5406 installed bases in September 2019[17].

CAS is a second approach to assisted surgical systems. Where RASS is focusing the physical surgery robot, its controlling and applications, and robot assisted surgery technology, CAS technology use computer technology for surgical planning and enhances surgical guidance to surgeon. CAS involves techniques that can directly participate in surgery or can assist in the navigation or positioning of surgical instruments[18]. CAS contain a set of applications used at the surgical workplace preoperatively, intraoperatively, as well as improving surgical efficiency and efficacy postoperative surgery[19]. Main CAS features contain creation of virtual image from the patient, diagnostic, image analysis and processing, preoperative planning, surgical simulations, and surgical navigation. CAS have been major factor in the development of RASS.

When evaluating the clinical effectiveness of robotic surgery technology, a systematic review from 95 studies made in Canada in 2011 indicated that RASS in prostatectomy, hysterectomy, nephrectomy, and cardiac surgery compared to open or laparoscopic surgery there are many benefit in clinical outcomes which were: reduction of length of hospital stay, reduction of blood loss and transfusion rates, and reduction of complications[20]. There are some RASS operations in which operation times are reduced such as laparoscopic prostatectomy and, in some operations, increased such as open prostatectomy and open hysterectomy. In the same review, the economical evidence was also evaluated in prostatectomy, cardiac surgery, nephrectomy, and hysterectomy. Cost analysis showed that shortening the lengths of stay after robotic radical prostatectomy also produced reduction of hospitalization costs relative to laparoscopic surgery and open surgery. In other hand, acquiring and operational costs of surgical robots will lead to situation that approximately 75% of the surgeries in which robot assisted the surgery is more expensive. However, costs can be reduced by higher utilization rate of RASS.

A systematic review was made in 2017 to evaluate patient benefits, cost, and surgeon conditions when using RASS in gynecological oncology[21]. Using RASS as part of treatment in

Table 1. Features, outcome, and metrics of healthcare services utilizing AI.

Domain	Service / application	Service / Application type	Category	AI features	Data source(s)	Outcome vs. traditional method	Metrics / reference type	References
RASS	Robot assisted surgery	Robotic Prostatectomy, Hysterectomy, Nephrectomy, Cardiac, hepatectomy, Oncology	Assisted intelligence	MV, ML	Multiple studies	22% lower costs overall with RASS. Similar amount of complications	Costs, Amount of complications	21
VNA	Your.MD	Application / service providing personalized pre-primary care and home diagnosis for patients	Augmented Intelligence	ML	Not informed	85% diagnosis accuracy for 20 most common conditions. 92,60% accuracy for safe urgency advice	Diagnosis accuracy	22
VNA	ADA	Application / service providing personalized pre-primary care and home diagnosis for patients	Augmented Intelligence	ML, NLP	200 vignettes	Top-3 conditions suggestion 70,50% (GPs average 82.10%), 97% accuracy for safe urgency advice (GPs average 97%)	Conditions coverage, Conditions suggestion, safe urgency advice accuracy	23
VNA	Sensely	Digital nurse avatar	Augmented Intelligence	ML	72 chronic heart failure patients in clinical site	75% decrease in readmission rate 66% decrease in patient monitoring costs	Comparison of costs and readmission to traditional care process	24
MMER	MedAware	System for detecting medication errors and improving medical safety	Automated Intelligence	ML	Total 747985 patient visits in 2 medical centers with 1700 beds.	Flagging 75% of potential medication errors or issues	Identification of medication errors	25
MMER	Study	Mobile platform to increase stroke patients medication adherence on anticoagulation therapy	Automated Intelligence	MV	28 patients	100% adherence with AI, 50% adherence in control group	Level of medication adherence	26
MMER	Study	Software to visually identify patient, the drug and confirm ingestion of the drug	Automated Intelligence	MV, NN	75 patients	17.90% higher adherence in AI group comparing standard care	Level of medication adherence increase	27
CTP	Oncology clinical trial	IBM utilizing the Watson artificial intelligence platform enhancing the clinical trial participation rate	Automated Intelligence	ML, DL, NLP	N/A	80% increase in oncology clinical trial enrollment compared to earlier procedure	Level of medication adherence increase	28
CTP	Mendel.ai	Clinical trial participation pre-screening service for identifying patients which were potentially eligible for clinical trial	Augmented Intelligence	Optical Character Recognition (OCR), ML,	39442 patient records	1) 24% - 50% increase over standard practices 2) Screening time in Minutes compared to average 19 days for breast cancer and 263 days for lung cancer patients with standard screening practice	1) Identifying number of patients as potentially eligible for clinical trials 2) Time of screening the participants	29

Domain	Service / application	Service / Application type	Category	AI features	Data source(s)	Outcome vs. traditional method	Metrics / reference type	References
PDP	Medtronic Guardian Connect	Continuous glucose monitoring system	Augmented Intelligence	ML	118 participants	Glucose level prediction time increase. Alerting 98,50% accuracy in alerting of hypoglycemic events	Glucose level change indication time increase, Accuracy of glucose level alerts	30
PDP	Breast cancer prediction	Mammography results interpretation system	Automated intelligence	NLP	543 patients	99% accuracy compared to manual review by clinicians. Time and cost savings. 54 patient screening manually took approximately 50 – 70 hours.	Accuracy, time and cost saving	31
PDP	Tuberculosis diagnosis	Diagnosing tuberculosis with ensemble of AlexaNet and GoogLeNet CNNs	Automated intelligence	DCNN	1007 radiographs	96% accuracy compared to radiologists, Area Under Curve 0.99	Accuracy	32
PDP	Psychiatric diagnosis	Detection of the development of psychosis in susceptible individuals	Automated intelligence	NLP, ML	93 individuals	100% accurate detection compared to 79% accuracy in traditional diagnosis	Accuracy	33
MID	Medical Imaging with DL – systematic review	Meta-analysis and systematic review of DL diagnostic accuracies studies	N/A	ANN, CNN, DCNN	From 31587 studies 69 was selected	From 69 studies 79.10% sensitivity and 88.30% specificity. From 14 studies where validity between DL methods and healthcare professionals (HCP), pooled sensitivity 87% (86,70%) and specificity of 92,50% (90,50%).	Sensitivity and specificity	34
MID	Breast cancer prediction	Using three deep learning methods together to identify breast cancer from medical images	Automated intelligence	DL, MV	28953 women from UK and USA	In USA system produced 5,70% reduction of false positives and 9,40% reduction of false negatives. In UK 1.20% reduction of false positives and 9,40% reduction in false negatives. All compared to clinical readers	Decrement of false positives and false negatives	35
MID	OCT diagnosis	Recognizing 50 common eye problems	Automated intelligence	MV	14884 OCT images from 7621 patients	94.50% accuracy in identifying 50 common diseases eye problem. Similar accuracy than retinal specialists.	Level of identification accuracy increase	36

Domain	Service / application	Service / Application type	Category	AI features	Data source(s)	Outcome vs. traditional method	Metrics / reference type	References
MID	Image diagnosis for Oncology	Finding cancer from skin lesions	Automated intelligence	MV, ML, NN	130,000 images database of cancers	72% accuracy with AI compared to 66% accuracy with dermatologists	Accuracy of diagnosis	37
PHM	Heart failure monitoring	Providing heart diseases diagnosis based in anamnestic and instrumental data and previous clinical history	Augmented intelligence	NN	100 patients	86.10% diagnosis accuracy for test population	Accuracy of diagnosis	38
PHM	Health monitoring after surgery	Prediction of in-hospital mortality after repair of abdominal aortic aneurysm	Automated intelligence	ANN, ML	310 cases	87% sensitivity, 96.10% specificity and 95.40% accuracy	Prediction accuracy	39
PHM	Cancer patient monitoring	Monitoring and symptoms and providing instant care	Augmented intelligence	ML	Trial with 766 patients	Quality of life improvement for 31% of patients, 5,2 months longer life, reducing 4% in hospitalization and 7% in ER visits	Quality of life, survival time	40

cervical cancer, endometrial cancer, and ovarian cancer were studied by reviewing total of 76 references. Results were that safety in oncological surgery is similar compared with previous surgical methods, but RASS will also increase overall costs because of high RASS equipment application, acquisition, and maintenance costs.

In the research where cost and efficacy of robotic hepatectomy was studied there was indication that in RASS group operative time was 20% longer, length of stay was 35% shorter, perioperative costs were 10% higher, and postoperative costs 36% lower compared to group with normal open surgery. In the study, overall costs of RASS were 22% lower than in open surgery. Complications were similar between RASS and open surgery patient groups[41].

Virtual nurse assistants (VNAs) for healthcare
In modern digitalization, healthcare organizations and actors in healthcare processes have taken in use virtual assistants which have already been emerged to use in other business sectors. With virtual nurse assistants, hospitals can reduce sudden hospital visits and reduce the workload of healthcare professionals. These virtual assistant applications can listen, talk, and give advices/recommendations. Over the last two decades there have been studies of embodied conversational agents (ECAs) use in healthcare which have proven significant improvement in healthcare outcome when chatbots or conversational agents are in use. A majority of these ECAs have allowed user input which is used in common surveys such as multichoice or utterance. With latest advance in AI technologies, such as NLP, machine learning (ML), and neural networks (NN), have made possible to develop virtual assistants or virtual agents which are capable of utilizing conversational systems which can mimic human conversation[42,43].

One widely used platform meeting European Medical Device Directives is Your.MD. This virtual health assistant using AI and machine learning utilizes United Kingdom National Health Service (NHS) data for providing personalized pre-primary care. Pre-primary will act before patient makes decision to access primary care. With Your.MD patients can perform home diagnosis by using mobile app or website. With Your.MD benchmark tests in verified test cases from Harvard University and Royal College of General Practitioners have shown medical accuracy of 85% for 20 most common conditions[22].

In another study there was multiple symptom assessment apps studied, where the best results for condition coverage, accuracy of suggested conditions and urgency advice performance was measured with 200 vignettes representing real world scenarios and compared to five general practitioners (GPs). The best results were received by service ADA getting condition suggestion coverage of 99% and top-3 conditions suggestion 70.50% (GPs average 82.10%), 97% accuracy for safe urgency advice (GPs average, 97%)[23].

Another VNA platform is Sensely. Its digital nurse avatar use machine learning algorithms. It utilizes patient's medical history data, and it can monitor the condition of patient.

Additionally, the VNA can keep track of appointments, fill the gap between doctor visits and predict follow-up treatments. Platform was trialed in 2019 with 72 chronic heart failure patients in clinical site. Findings indicated that platform was able to decrease readmission rate by 75% and patient monitoring costs by 66% compared to traditional care process[24].

Medication management and medication error reduction (MMMER)
The effective MMMER services can provide remarkable healthcare cost expenditure reduction and can minimize unnecessary injuries and deaths. The estimated annual costs of drug-related mortality and morbidity resulting from nonoptimized medication therapy was $528 Billion in US. This is equivalent to 16% of total US health care expenditures in 2016[44]. Prescription drug errors cause substantial morbidity, mortality, and wasteful health care cost. In a National Audit Commission report there was evaluated that there are 7000 deaths annually in US due to medicine misuse and due to medication mistakes highlighting importance and urgency of preventive measures[45]. AI has multiple use cases in Medication management and dosage error reduction, such as improving medication safety, preventing drug overdoses, predict health risks and outcomes across large populations, reduce time and expenses, and monitor medication adherence.

Improving medical safety. MedAware created system for detecting medication errors. In this ML-based system researchers concluded that it was clinically useful in flagging 75% of potential medication errors or issues, with 18.80% classified as having medium clinical value, and 56.20% of the valid alerts as having high clinical[25].

Monitoring medication nonadherence. Medication nonadherence is significant issue in healthcare costs and healthcare outcome. Medication nonadherences contribute between $100 and $300 Billion dollars in US[46]. One study using AI platform on mobile devices in measuring and increasing stroke patients' medication adherence when ongoing anticoagulation therapy. Study indicated that in the intervention group medical adherence was 100% and in the control groups only 50%. The AI application was visually identifying the patient, the medication, and the confirmed ingestion. Adherence was later measured by plasma sampling and pill counts[26]. Another adherence monitoring AI platform utilizing neural network algorithm in machine vision was studied in clinical. Machine vision and neural network was used to identify visually patient, the drug, and confirm the ingestion of the drug. Study shows that adherence was 17.90% higher in AI group than standard-of-care modified directly observed therapy protocol[27].

Clinical trial participation (CTP)
As described by United States Food and Drug Administration (FDA) and U.S. National Library of Medicine, in a clinical trial, participants are receiving specific interventions based on the research plan or protocol which is created by the investigators or researchers. These interventions may be medical products, such as drugs or devices, procedures, or changes to participants' behavior, such as diet. Clinical trials have three models.

1. Comparing new medical approach to a standard model or approach that is already available. 2. comparison new approach to a placebo containing no active ingredients. 3 comparison to new approach where no intervention is done[47]. It is also notable that on average it takes 10 - 15 years and 1.5 - 2.0 Billion US dollars to develop and bring a new drug to the market. In drug development, approximately 50% of the time and investment is used for the clinical trial phases[48].

As a background to create more comprehensive clinical trials, for example, in one research done in Mayo Clinic participation for clinical trials of cancer patients was only 3-5% even though up to 20% were eligible[28]. AI can help in clinical trial design and it can be used in finding patterns of meaning automatically from large and unstructured datasets such as speech, text, or images. Natural language processing NLP understands and correlates content in spoken or written language, and in human-machine interfaces) allowing natural information exchange between humans and computers. These capabilities are used for correlating diverse and large datasets such as medical literature, electronic health records (EHRs), and databases for improving patient-trial match and recruitment or persons before starting actual trial. During actual clinical trial AI can be used monitor patients continuously and automatically. Moreover, AI utilization provide improved adherence, efficient endpoint assessment and increased control and yielding reliability. Based on this background information and need for enhancing the clinical trial participation rate there was a research conducted by IBM. In this research IBM utilized Watson artificial intelligence platform resulting 80% increase in oncology clinical trial enrollment. This increase was observed at Mayo Clinic. This new platform enabled high volume screening very efficiently[28].

Mendel.ai research network has created Clinical trial participation pre-screening service for identifying patients which were potentially eligible for clinical trial. In one research Mendel. ai was used to retroactively provide pre-screening two oncology studies, one for breast cancer and one for lung cancer. In trials where Mendel.ai was used it resulted in a 24 - 50% increase compared to standard practices to correctly identify the number of patients as potentially eligible for clinical trials. All patients who were correctly identified by standard practices were also identified by Mendel.ai. With standard pre-screening practice an average of 263 days for lung cancer and 19 days for breast cancer patients elapsed between actual patient eligibility and identification. Respectively, detection of potential eligibility with Mendel.ai took only minutes[29].

Preliminary diagnosis and prediction (PDP)

For decades diagnosis services have been using health history data and diagnosis data to provide more accurate diagnosis for the patient and more accurate health prognosis. With current advances in AI research we have found that AI have outperformed physicians in speed and accuracy of medical diagnosis in some fields of healthcare sectors as described in following example studies from various fields of healthcare.

Diabetes prediction

Diabetes prediction can be performed with four different application types: retinal screening, clinical decision support, predictive population risk and patient self-management tools. In retinal screening application perform detection of diabetic retinopathy, maculopathy, exudates, and other abnormalities from retinal scan. In clinical decision support application or service can contain detection and monitoring of diabetes and comorbidities such as nephropathy, neuropathy, and wounds. In predictive or population risk stratification identification focus is on identification of diabetes subpopulations at higher risk for complications, hospitalization, and readmissions. There are also self-management tools in patient use which can consist of artificial pancreas, AI-improved glucose sensors and dietary and activity tracking devices.

One of the diabetes tracking system is Medtronic's Guardian Connect. It was the first AI-powered and FDA approved continuous glucose monitoring (CGM) system. With predictive Machine Learning (ML) algorithm Guardian Connect can predict significant changes in blood glucose levels. Changes can be predicted up to 60 minutes before the change event. System consist also sensor, which is placed on the abdomen. This sensor monitors blood glucose levels in 5 minutes interval. System was able to give alert of about 98.50% of hypoglycemic events. By these alerts, patients could act proactively to normalize their blood sugar[30].

Cancer prediction

Houston Methodist researchers in the US have developed a NLP-based application that can interpret mammography results by using free text radiology and pathology reports from 543 patients and keywords. Application could perform with 99% accuracy compared to manual review by clinicians. Time saving is remarkable when comparing to manual review taken from 10% of these 543 patients for application accuracy validation. This manual validation for 54 patients took approximately 50 – 70 hours[31].

Tuberculosis diagnosis

For diagnosing tuberculosis tests were performed with two different DCNNs, AlexNet and GoogLeNet, which are learning positive and negative X-rays for tuberculosis. The accuracy of the models was tested in 150 cases. The most functional AI model was achieved by combination of AlexNet and GoogLeNet with 96% accuracy. There were differences between the two DCNN models in 13 cases of 150. The diagnostic accuracy of the radiologist in these cases was 100%. Previously machine learning was able to get only 80% results but using deep learning the accuracy has been increased. Artificial intelligence in diagnosing tuberculosis can play very important role in the fight against the tuberculosis in the near future[32].

Psychiatric diagnosis

Researchers at Columbia University's New York State Psychiatric Institute and the IBM Watson Research Center have developed an AI application using automated NLP with ML capable of 100% accurate detection of the development of psychosis in susceptible individuals. Traditional diagnosis reaches 79% accuracy. Research Utilizing artificial intelligence to diagnose this disease has proven to be beneficial. Like psychologists, the app analyzes speech patterns to differentiate patients who are susceptible to psychosis. IBM researchers realized that if the

mind of the interviewer (psychologist) began to wander for even a moment, they might have missed the signs that were essential to the development of psychosis, while the computer noticed them. An artificial intelligence diagnostic system eliminates human error and is therefore more accurate in diagnosis than experts[33].

Medical imaging and image diagnostics (MID)

Medical imaging data is one of the best sources of information about patients and at the same time the most complex. Traditionally interpreting medical imaging scans is a highly skilled, manual job requiring many years of training. In the field of medical imaging the AI technologies, such as DNN and DL, can produce remarkable improvement in healthcare outcome and have proven to provide enhancement in speed, accuracy, and cost reduction in interpretation of medical images. MID can be utilized in healthcare for multiple cases, such as for identifying cardiovascular abnormalities, detecting musculoskeletal injuries, identifying neurological diseases, identifying thoracic complications, and common cancers screening. In the business perspective AI have high potential in MID and it is estimated to rise from $21 billion in 2018 to a value of $265 billion by 2026[49].

Medical Imaging with Deep Learning

In one large meta-analysis and systematic review researchers compared diagnostic accuracy between DL methods (such as ANN, CNN and DCNN and healthcare professionals in medical imaging. From 31,587 identified studies on DL methods in medical imaging researchers included 69 studies. These studies provided enough data for calculation of accuracy with sensitivity with mean 79.10% and specificity with mean 88.30%. From these studies 14 used same sample for the out-of-sample validation between DL methods and healthcare professionals. With these 14 studies comparison results between DL methods and healthcare professionals was DL methods systematic review and meta-analysis of the complication rate and diagnostic accuracy compared to healthcare professionals 86.40% and DL models having pooled specificity of 92.50% compared to healthcare professionals 90.50%[34].

Image diagnosis for oncology

In oncology, lung cancer and breast cancer are the leading causes of cancer deaths in the world and therefore there is a need for early detection solutions of these cancer types[35]. Most common method in breast cancer screening is digital mammography. Reading mammography images is a difficult task for radiologist and can result in both false negatives and false positives. These inaccuracies can cause delays in cancer detection and starting the treatment which lead to higher workload for radiologists and unnecessary stress for patients.

McKinney *et al.* created an AI system with a set of three deep learning models. This new system was capable of surpass human experts in breast cancer prediction. Researchers evaluated the developed system with two large datasets from UK (n=25,856 women) and from USA (n=3097 women). In USA new service produced 5.70% reduction of false positives and 9.40% reduction in false negatives. In UK, new service produced 1.20% false positives reduction and 9.40% reduction in false negatives. All comparison was made between AI system and clinical readers[35].

In another research, a Stanford University research group taught the neural network with a database of 130,000 cancer images to automatically identify cancer and make diagnoses. The research team also tested the neural network with a database of 14,000 skin lesions. Neural network made valid diagnoses with 72% accuracy. The reference was dermatologists who were able to diagnose with a diagnosis accuracy of 66%. The test was extended to 25 doctors and there were 2000 skin lesion images, each with biopsies. The neural network was able to beat specialist doctors in all situations[37].

Optical coherence tomography (OCT) diagnosis

OCT is one of the most common imaging procedures and in US there was 5.4 Million OCT scans performed in 2014[36]. DeepMind's DL was being taught with 14,884 OCT scan images from 7621 patients to recognize 50 common eye problems including three of the biggest eye diseases (diabetic retinopathy, glaucoma, and age-related macular degeneration). The AI correctly identified types of eye disease from OCT scans 94.50% of the time and 36.

Researchers in China have developed a convolutional neural network-based AI platform that can identify, evaluate, and suggest treatment for congenital cataracts. Researchers tested the accuracy of CC-cruiser and the result was that the performance of the CC-Cruiser was comparable to that of an ophthalmologist: the CC-Cruiser was able to successfully diagnose all potential patients in 50 patients. Ophthalmologists were even slightly worse and made misdiagnoses in a few patients. The CC-Cruiser provided detailed care instructions to patients who needed surgical treatment and no misdiagnosis occurred[50].

Patient health monitoring (PHM)

Continuous PHM can reduce patient length of hospital stay and can increase recovery time and reduce mortality rate. In home use, PHM can provide information, instructions, and reminders for preventive care. In this paper, PHM consist of services and solutions using AI methods for continuous healthcare monitoring, healthcare assessment tools, and symptom checking solutions which can be used by patients and healthcare professionals periodically or continuously. HM services are utilized in hospitals or in home. When evaluating the user acceptance of HM services in our earlier research we found that AI-based health condition monitoring solutions were evaluated as the best of 15 as most considerable technologies for healthcare and the second-best service among 15 services what healthcare professionals are willing to use[51].

Heart failure monitoring

In Italy, researchers have developed a prototype of computer aided diagnosis, a computer-assisted diagnostic system for the diagnosis of heart disease, using artificial intelligence. The system is intended to assist general practitioners and nurses in clinical decision making that are not specialized in cardiology. The system receives anamnestic (pre-information) and

instrumental (instrument-related) data and makes a diagnosis and prognosis relative to the patient's current state of health. The system also considers the patient's previous clinical history when making diagnoses. In addition, the system builds a database of patients' data with heart failure by providing a valuable data repository for future utilization. The best results of all groups (mild, moderate, and severe) were obtained by using neural networks as the artificial intelligence method, which correctly classified the training population of 98/100 patients and the test group 31/36. The overall accuracy for the test population was 86.10%, which was the best of all technologies in the test[38].

Health monitoring after surgery
In one research, ANNs and ML algorithms was utilized to predict in-hospital mortality for patients undergoing repair of abdominal aortic aneurysm. Researchers used clinical variables such as patient history, medications, blood pressure, and length of stay as input to ANNs and ML algorithms. As a result, prediction system generated predictions of in-hospital mortality with sensitivity of 87%, specificity of 96.10%, and accuracy of 95.40%[39].

Health monitoring for oncology patients
Finnish company Kaiku health has developed a health intervention platform for symptom monitoring and management for improving cancer patient's quality of life and survival rate. In trial with 766 metastatic cancer patients made to evaluate effectiveness of symptom monitoring with Kaiku shows that digital symptom monitoring during chemotherapy provide patients 5.2 months longer overall lifetime, improve their quality of life within 31% of patients, and reduces hospitalization by 4% and ER visits by 7%[40].

Key elements for successful implementation of AI-based services in healthcare
Our research was using only a fraction of healthcare services and applications which has been studied globally. In our review we focused on research projects or healthcare services which are commonly in use by healthcare service providers and from these we also focused to services in areas which are focusing on actual care processes. From these areas we found that there are thousands of research articles from each area of healthcare where AI methods are used to provide enhancement to healthcare. We also selected the services which have been evaluated as most considerable AI services by healthcare professionals[51] and by general public[52] in earlier studies. Some areas from healthcare administration systems, for example, fraud identification, connected machines, information management, and data security were left out from this review.

Based on this review and our earlier studies we have noticed that there are multiple use cases where AI methods can be used to provide enhancement to healthcare processes. AI utilization can: 1) save time spent in healthcare work 2) give accurate diagnosis 3) make findings from medical images and medical reports 4) monitor health conditions and predict occurrence or progress of diseases 5) provide more quality to care 6) reduce complications in surgical operations 7) control medical

adherence and medication misuse and 8) provide help in clinical decision making. Identified benefits are collected in Figure 3.

When considering the success factors for implementation of AI methods to healthcare services we propose that successful implementation to actual healthcare use require at least:
a) A large clinically validated dataset to teach and validate AI methods.
b) Scientific research where new or existing AI methods are validated together with healthcare professionals and AI methods developers.
c) Clinically and scientifically proven enhancement in specific healthcare use case.
d) Medical device certification for target market area.
e) Clearly inform end users that AI does not make itself clinical decisions. It only give recommendations, provide help in clinical activities or support clinicians in decision making.

Conclusion and future work
As a conclusion of our systematic review we found out that AI can have remarkable possibilities in reducing healthcare costs, providing preventive healthcare, ease the work burden of healthcare professionals, and providing more accurate diagnosis faster and easier. The need for AI services arises in the facts that healthcare costs are continuously increasing. Additionally, age structure of population is changing, especially in developed countries, causing that there will be more chronic diseases within aged population needing expensive care. There will be also shortness of trained nurses and healthcare professionals. Moreover, access to modern and effective healthcare services are not available especially to poor and elderly people and for most of the population living in developing countries. When AI methods are used in healthcare research and IT processes in full scale, we can achieve remarkable savings in overall healthcare costs and same time improve health outcome and quality of life. The need for enhancement provided by AI methods can be seen in every studied healthcare service areas.

Moreover as conclusion we have identified and proven that there is very high potential for the state-of-the-art AI solutions in almost every healthcare sector to reduce costs, ease healthcare professionals workload, improve quality of life for patients, provide preventive health and improve overall health outcome. There are also AI based solutions which can be utilized for population in developing countries. These services include preliminary diagnosis, preventive health services, patient health monitoring services and virtual nurse assistants. In addition, it must also be emphasized that artificial intelligence solutions can produce $150 billion savings in global healthcare industry by 2026[3]. Based on these findings we can express that investing to AI in healthcare will pay for itself. We recommend all healthcare IT service development companies and research organizations to fully adopt scientifically validated AI methods in their research and development projects.
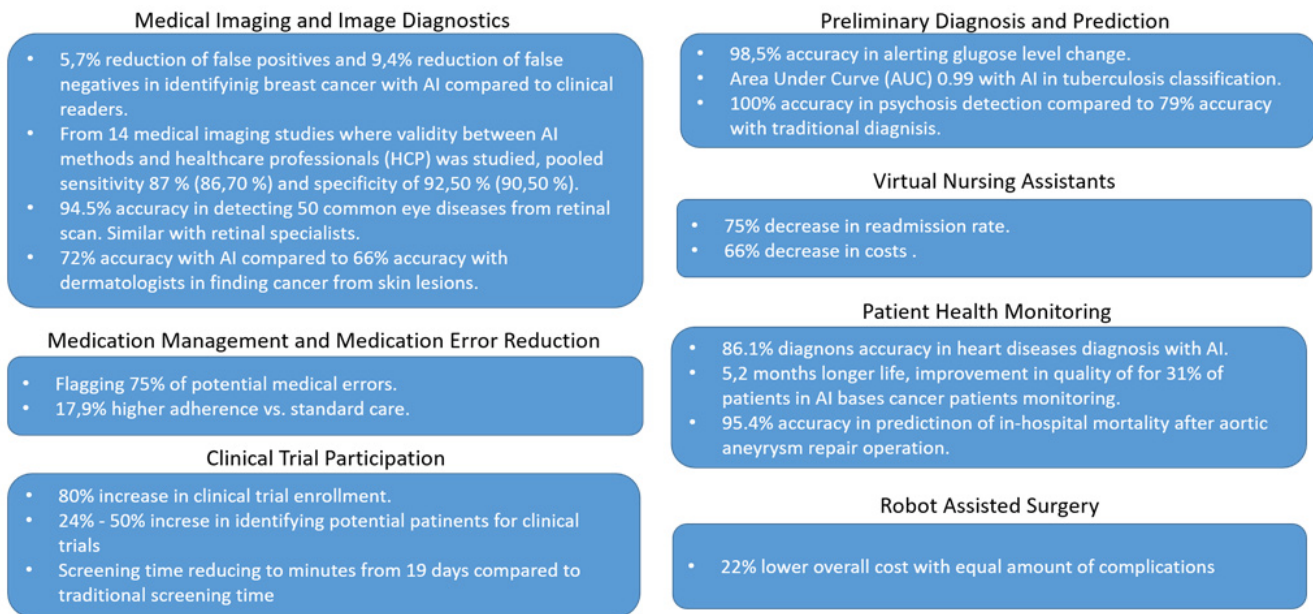
Medical Imaging and Image Diagnostics

- 5,7% reduction of false positives and 9,4% reduction of false negatives in identifyinig breast cancer with AI compared to clinical readers.
- From 14 medical imaging studies where validity between AI methods and healthcare professionals (HCP) was studied, pooled sensitivity 87 % (86,70 %) and specificity of 92,50 % (90,50 %).
- 94.5% accuracy in detecting 50 common eye diseases from retinal scan. Similar with retinal specialists.
- 72% accuracy with AI compared to 66% accuracy with dermatologists in finding cancer from skin lesions.

Medication Management and Medication Error Reduction

- Flagging 75% of potential medical errors.
- 17,9% higher adherence vs. standard care.

Clinical Trial Participation

- 80% increase in clinical trial enrollment.
- 24% - 50% increse in identifying potential patinents for clinical trials
- Screening time reducing to minutes from 19 days compared to traditional screening time

Preliminary Diagnosis and Prediction

- 98,5% accuracy in alerting glugose level change.
- Area Under Curve (AUC) 0.99 with AI in tuberculosis classification.
- 100% accuracy in psychosis detection compared to 79% accuracy with traditional diagnis.

Virtual Nursing Assistants

- 75% decrease in readmission rate.
- 66% decrease in costs .

Patient Health Monitoring

- 86.1% diagnons accuracy in heart diseases diagnosis with AI.
- 5,2 months longer life, improvement in quality of for 31% of patients in AI bases cancer patients monitoring.
- 95.4% accuracy in predictinon of in-hospital mortality after aortic aneyrysm repair operation.

Robot Assisted Surgery

- 22% lower overall cost with equal amount of complications

Figure 3. Benefits of AI methods in healthcare.

When developing and implementing new applications and services for industrial purposes and especially for healthcare industry safety and quality of service are also key elements for successful new service implementation. To maintain and enhance quality AI method developers need to fulfill standards, regulations and solve possible emerging legal constraints. During the research we found out that United States Food and Drug Administration have proposed a regulatory framework for AI and ML-based technologies that consist of new issues in utilizing AI in healthcare[53]. This new framework should be utilized when developing new AI based technologies to EU markets until EU Medical Device Regulation (MDR) will create own regulatory framework for AI and ML-based technologies.

Moreover, one recommended to healthcare AI service developers in AI methods implementation is to join into interest group and evaluation framework. There have been established the Focus Group on artificial intelligence for health which is a joint initiative of the World Health Organization and International Telecommunications Union that brings together

academia, industry, and governmental stakeholders to drive the application of AI in health by establishing an evaluation framework[54].

In our future work we design a model for novel state-of-the-art AI platform to be utilized by all healthcare service providers and healthcare IT services developers. Encouraged by the results of this research and as future work we continue the research and design of novel platform where AI methods and pre-trained AI methods can be utilized and adopted to healthcare IT services by an cloud-based, open access, easily integrated platform which use open access and even proprietary health data repositories, national health databases, hospital information systems and imaging databases as learning data and constantly evolving AI methods for providing fast, automated, and accurate diagnosis & prognosis.

Data availability
All data underlying the results are available as part of the article and no additional source data are required.

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Open Peer Review

Current Peer Review Status: ✕

Version 1

Reviewer Report 13 May 2021

https://doi.org/10.5256/f1000research.29820.r84684

✕ **Dipak Kalra** iD

The European Institute for Innovation through Health Data, University of Gent, Gent, Belgium

This is a valuable area of research, and appears to have been conducted well. However, the organisational structure of the paper has left me confused, and I think it needs some further work before it can be indexed.

The title describes the paper as a narrative review, but I suspect it has been extracted from a larger document. I note that on page 1 there is mention of "my research". The conclusion starts by referring to this as a systematic review. What I am missing in this paper is anything about the methodology.

The first part of the paper provides a nice description of the drivers for AI adoption, the contribution areas of AI and some of the major kinds of AI that can be useful in healthcare. However, it's missing an introduction to the paper as a paper. In other words, something at the very beginning leads to tell the reader that they are being presented with some kind of literature review (Narrative? Systematic?), how it has has been scoped and indeed why it has been written.

The table presenting the literature appears suddenly without any methodological section to indicate how these references have been identified (search criteria, filter criteria etc).

Then there is a section that seems like a nicely written results section which summarises the main findings from the literature presented in the table.

In other words, this is a rather nice literature review paper without its methodology! If this could be added then I think this would be a lovely paper to publish.

Without the methodology I don't feel that I have been able to carry out a proper review of the paper, although I did not find anything that I would like to be changed, just the methodology to be added. I would therefore be happy to review the paper again if the authors are in a position to add that methodology.

Is the topic of the review discussed comprehensively in the context of the current literature?
Partly

Are all factual statements correct and adequately supported by citations?
Yes

Is the review written in accessible language?
Yes

Are the conclusions drawn appropriate in the context of the current research literature?
Yes

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Health Informatics

I confirm that I have read this submission and believe that I have an appropriate level of expertise to state that I do not consider it to be of an acceptable scientific standard, for reasons outlined above.

> Author Response 02 Aug 2021
> **Antti Väänänen**, University of Eastern Finland, Kuopio, Finland
>
> Dear Professor Kalra.
>
> Thank you for your review and suggestions. I will add your proposed changes to my article this week and kindly ask you to do 2nd review to new version after i have uploaded it to F1000.
>
> Best regards,
> Antti Väänänen
>
> *Competing Interests:* No competing interests were disclosed.

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