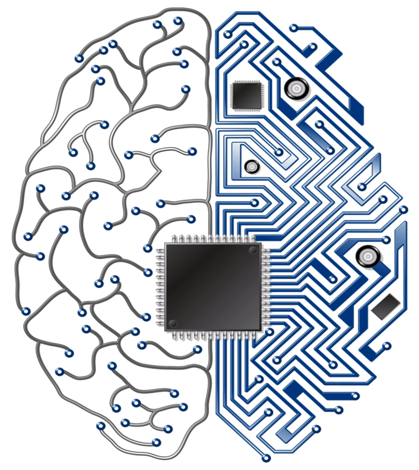

An introduction to machine learning in healthcare

Implications for clinicians

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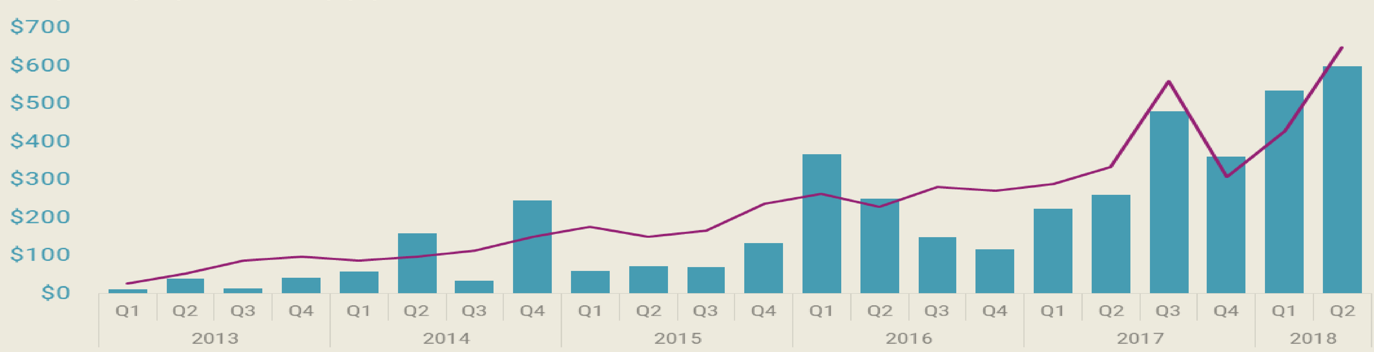
AI subdomain	tl;dr version	Findings	Implications
Image recognition	**Millions of patient scans can be analysed in seconds, and diagnoses made by non-specialists via mobile phones, with lower rates of error than humans are capable of.**	The increased use of digital imaging in clinical contexts has led to the generation of more data than can be viewed, analysed and classified by human beings [1]. Accurate, low-cost, automated image classification enables clinicians to manage, access and retrieve relevant information from medical image repositories [2;3]. Diagnosis of skin lesions [4] and retinal pathology [5] can be achieved with greater competence than human specialists.	Automated classification and diagnosis of conditions that are analysed visually, completed in milliseconds at much lower cost. This will free up time for clinicians to focus on patient interaction and care. The widespread availability of high resolution cameras via cheap mobile devices will introduce the ability of non-professionals to diagnose certain diseases earlier, and with more accuracy than clinical experts.
Video analysis	**Constant video surveillance of patients will alert providers of those at risk of falling, as well as make early diagnoses of movement-related disorders.**	Automated diagnosis of gait abnormalities or underlying pathology e.g. Parkinson's and osteoarthritis [6]. Real-time event detection in children with pathological gait [7]. Progress being made in developing "explainable AI", where algorithmic gait analysis can be linked back to unique patient variables [8]. Identification of individuals using using joint angle and time-distance data [6].	Constant video surveillance in clinical contexts will be used to track individual patients within health settings (i.e. who is where?), and alert care providers immediately at the occurrence of adverse incidents (e.g. falls). Patients at increased risk of falling can be identified early based on constant gait analysis, and changes in gait patterns - indicators of changes in pathology - can be highlighted to relevant staff.
Natural language processing	**Unstructured, freeform clinical notes will be converted into structured data that can be analysed, leading to increased accuracy in data capture and diagnoses.**	Clinical natural language processing that can generate structured, annotated text from unstructured clinical records for automated processing at scale [9;10]. Transcribe and summarise conversations between clinicians and patients that need only be approved by the care provider [11;12]. Challenges include varying linguistic structure and content across disciplines making it difficult to transfer NLP systems across specialties [13].	AI-based systems that generate semantic data from unstructured text will enable clinical research by identifying patterns and relationships across millions of patient records. Ambient audio recording and analysis of doctor-patient conversations will capture symptoms, medications, and other clinically relevant information into the EHR, lowering risk of data capturing errors and clinician burnout.
Robotics	**Robots will assist with physical tasks like patient transportation and possibly even take over manual therapy tasks from clinicians.**	Robotics has been used to demonstrate novel approaches to neurorehabilitation in the upper limb, and has potential for lower limb rehabilitation in the future [14;15]. Robot pets will provide companionship, reducing the effects of loneliness and psychophysiological stress in patients with depression and dementia [16;17]. Autonomous robots in clinical settings are rapidly becoming easier to use, lighter and more ergonomic, cheaper, and safer [18]. This will lead to the use of robots for patient transportation within facilities [19]. The development of dextrous, "soft" robot hands with embedded sensors for prosthetics that are capable of grasping a wide variety of objects [20;21].	The introduction of robots into health systems will provide support for service providers who are responsible for a variety of physical tasks like transporting and lifting patients. Therapists will likely see patients accompanied by robot companions that they have an emotional attachment to and will need to be sensitive to these relationships. Robotic hands with fine motor skills capable of sensing tissue damage will also be able to perform physiotherapy-specific tasks like mobilisation and soft tissue massage. There is no reason to think that two hands with ten fingers represents an optimal configuration for patient contact.
Expert systems	**Knowing things about conditions will become less important than knowing when to trust outputs from clinical decision support systems.**	Expert systems are being developed that will be capable of storing, accessing, and analysing all known conditions and pathologies related to human illness. These systems aim to provide clinical decision support in order to enhance decision-making [22]. Concerns about patient privacy in an age of increasingly connected health systems are an essential component of system design [23;24]. Bias that is inherent to the training data for machine learning is a concern but is a known problem and possibly easier to address than human bias [25;26].	Recall and reasoning cognitive functions are moving into software systems that increasingly outperform human beings when it comes to the prediction of patient outcomes. But clinicians will need to agree on a set of standards and vocabularies for these systems before they can capture and analyse relationships between billions of structured data points. If not, patient information will remain isolated and less useful for clinical decision support.
Prediction	**Clinicians should learn how to integrate the predictions of ML with human values in order to make better clinical decisions in partnership with AI-based systems.**	Machine learning can significantly improve the accuracy of cardiovascular risk prediction (increasing necessary treatment and reducing unnecessary treatment [27]. Real-time prediction of appropriate clinical interventions in the ICU (e.g. ventilation) using "noisy" (i.e. unstructured) data that significantly outperforms baseline models [28]. Algorithms are currently unable to provide contextually relevant judgements that take cultural, ethical and social factors into account [29;30].	We will see a shift in emphasis for clinicians, from diagnosis to judgment, in which value- and context-based decision-making exists alongside more accurate algorithmic prediction of clinical outcomes. Again, knowing things will become less important than knowing when and how to integrate human values and ethics into clinical judgement.

Download the poster and references at https://bit.ly/2JkjUnF

Background

Machine learning algorithms are enhancing clinical decision-making through the statistical analysis of very large data sets that are too complex for human beings to interpret on their own. Important applications of machine learning (ML) in healthcare include clinical decision support, diagnosis and prediction, patient monitoring and coaching, surgical assistance, patient care, and systems management. As the digital information we interact with in healthcare is increasingly filtered, shaped and analysed by algorithms we see that there are important implications for clinicians and the future of the profession. The aim of the study was to identify the ways in which ML algorithms are being used across the health sector that may impact physiotherapy practice.



Investment in clinical AI since 2013.

Methods

The researcher identified a range of AI research subdomains (column 1 above) and then conducted a literature review of related papers published in the clinical context between 2015-2019. The search was not limited to physiotherapy but included all health professions and also made use of a wide variety of keywords that are often conflated in the mainstream media: artificial intelligence/machine learning/deep learning/neural networks, computer vision/image recognition, video analysis, natural language processing, robotics, expert systems, and prediction.

An overview of such a broad area of research is necessarily limited and superficial. For each AI subdomain - even when limited to clinical practice - there were several thousand publications to consider. The researcher selected 10 articles for each subdomain based on the title, downloaded all of them, and then selected 3-5 articles based on the abstract. These became the foundation for the Findings section (column 3). Selection of articles was subjective, as was the analysis that led to the Implications (column 4), and no critical analysis of article methodology was conducted.

Conclusion

Machine learning algorithms are already "smarter" than human beings within certain narrow domains of clinical practice and will increasingly take over more of the cognitive and physical tasks that were previously the sole domain of human beings. Successful clinical practice in the 21st century will require an understanding of how to analyse and interpret the outputs of ML algorithms. Unless health professionals are actively engaged in a conversation around ML and artificial intelligence in clinical practice, we run the risk that our clinical decision-making will be subject to machine intelligence, rather than being informed by it. The challenge we face is to bring together computers and humans in ways that enhance human well-being, augment human ability and expand human capacity.