

Editorial

Towards responsible use of artificial intelligence in daily practice: what do physiotherapists need to know, consider and do?

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Consider the clinical reasoning process of the physiotherapist: the physiotherapist analyses the information (data) available from different sources (the client's narrative/perspective, context, medical history/examination), formulates hypotheses (rationalisation) on the basis of prior knowledge (natural algorithms), identifies the most likely underlying explanation (diagnosis/classification) on the basis of elimination (feature selection), and decides what course of treatment fits this specific case (prognosis, shared decision, action).¹ This results in clinical experience and is adapted into skill/knowledge (learning).² The above basic description of a natural clinical reasoning workflow shows many similarities with the workflow of computer algorithms or artificial intelligence (AI);³ however, when venturing deeper into the essence of this 'seemingly identical twin' there are differences. To aid in its responsible use, it is critical for clients and modern physiotherapists to develop a deeper understanding of AI.^{4,5} This Editorial aims to: provide an overview of the relevant developments in AI for healthcare providers, focusing specifically on physiotherapists; and provide an introductory practical guide to responsible use of AI in clinical practice, with an emphasis on clinical reasoning (Figure 1).

What is artificial intelligence?

There are many definitions of AI; however, the European Government recently adopted legislation on AI and defined it as follows:

Software that is developed on the bases of data driven statistical techniques which is able, on the bases of predefined goals by humans, to generate output that can create content and provide predictions, recommendations or decisions that impact the environment in which it is applied.

In short, AI is a collection of algorithms that are able to mine, process and interpret large datasets in order to refine meaningful insights that can be used in daily life.^{3,6} AI statistics closely resemble common statistical techniques used in scientific research (eg, regression and cluster analysis). What makes AI different is its highly dynamic properties: as data are constantly iteratively added, AI can 'learn' from data in order to adopt its output. Another feature is the ability to use many sources and forms of data input, ranging from text/voice data to image recognition or – what is of special interest here – output from normal clinical reasoning processes (non-computerised cognitive rationalisations) and intervention outcomes.^{7,8}

Combined with the abundance of available data (eg, healthcare records) and its versatility, an AI-driven application can often be implemented easily in digital systems and almost immediately impact the environment in which it is used.

The most common form of AI is also known as 'machine learning' (ML); however, other forms of AI known as 'deep learning' are becoming more frequently used and will become more common in the future.^{6,8} Before going into detail on the technical aspects of ML, the use of AI or ML should be only considered in the context of a supportive role during shared decision-making between the professional and patient.

ML can be classified on the basis of the mode in which it evolves: supervised, unsupervised or reinforcement 'learning'.⁶ In supervised learning, data of each individual and its context are used to create a prediction or classification algorithm on the basis of the occurrence or absence of an event in historical data (eg, detecting comorbidity like chronic fatigue, predicting safe discharge from ICU or personalised exercise regimens). Unsupervised learning focuses on datasets that are unlabelled (no pre-set outcome or event has occurred) and aims to explore, unravel or confirm existing patterns within a dataset. Reinforcement learning is a subcategory of ML that focuses on optimising predictions/classification by maximising the likelihood of correct and/or incorrect outcomes. Although all forms of ML may be of use in relation to physiotherapy, supervised ML algorithms are most common due to the type of output that often resembles clinical reasoning processes (eg, decision trees or decision rules) and are often easy to understand/implement. A second important feature is that AI algorithms are first trained on a portion of a dataset (training set) and are subsequently cross-validated on an independent dataset, and their performance is documented in ways resembling standardised clinical tests commonly used in physiotherapy. The performance measures of an AI algorithm (sensitivity, specificity, area under the curve and other AI-specific measures of recall and bias) adhere to roughly the same principles as standardised clinical tests.^{3,6,7}

Although AI algorithms can process more data from more sources than humans, AI can only perform the task it is designed for. Therefore, an AI algorithm should be viewed in a similar way as a standardised clinical test. It aids in the clinical reasoning process but does not dictate it and does not take over at all. Even with advanced software for data-supported clinical decision-making, the duo of patient and physiotherapist should – based on their respective preferences, experiences and expertise – consider the validity of the advice generated by AI.



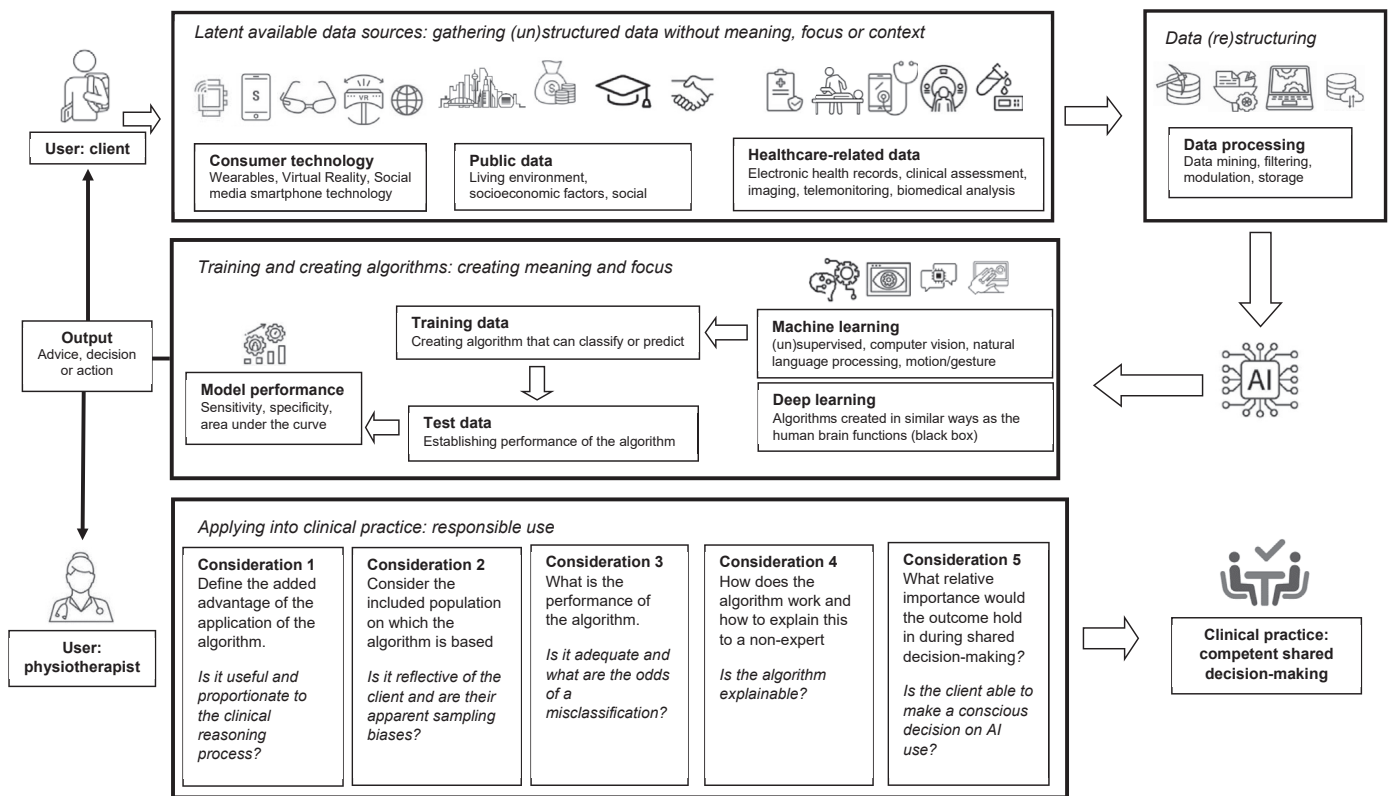


Figure 1. Data use in daily physical therapy practice.

Digital transitions in society and healthcare

The internet has been a driving force for technological innovation and societal transformation since 1969.⁹ Data are now being generated and stored within all aspects of daily life, originating from diverse sources like social media, wearables and machine data. Modern-day society is generating massive quantities of data that are fuelling multiple applications that are able to monitor, predict and – to a certain level – influence human behaviour.¹⁰ The digitisation of society has progressed considerably and will probably continue to do so in an exponential way, in which the digital representation of an individual (in all its facets) resembles the majority of actions of an individual in real life at an increasing rate.⁹ Over time, this results in vastly enlarging personal digital footprints that can be actively mined and used in all sorts of algorithms in cyberspace. These algorithms are deployed in many fields, including healthcare.⁹

Data technology like AI has penetrated society to such an extent that the abundance of information in combination with AI enables the creation of meaningful insights that may be used in the real world. The common internet and sources of data are highly unstructured and often insecure. AI is now deeply embedded in daily life to such an extent that individuals are only partly aware of the presence of an AI that is influencing them in daily life. This development has led to a complex debate on the essence of human identity and autonomy, as well as fundamental discussions on a human rights level.^{4,9} Health-related decision-making is a conscious and explicit individual process based on expertise, preferences and evidence, where AI should be supportive.^{3,5} Due to the often sensitive nature of health-related data, it is crucial that, in order to use data and AI responsibly, there should also be a regulated data infrastructure that allows timely availability for the individual and adheres to privacy legislation. This concept of a findable, accessible, interoperable, reusable (FAIR) infrastructure is also known as ‘the internet of FAIR data and Services (IOFAIRDS)’.¹¹ Although the developments in this area are vital for the coming transformation in healthcare, implementation is limited. Due to privacy and the extensive need for securing these vast amounts of data, most relevant sources of data in healthcare are inaccessible and can often not be used for the same

patient as well as for others. Within IOFAIRDS it is possible to exchange insights in data (without migrating data) and ensure privacy through federated learning principles and multiparty computation. In essence this means that algorithms are sent to multiple databases, a concept that is named ‘Personal Health Train’ (see the link below for a brief introduction), and insights into that data are created without data being transported from their original location and the need to inspect the databases of interest. This is potentially the most impactful development, already seen as a real game changer, which will change healthcare and healthcare-related research and probably all other sectors outside the healthcare sector.

Artificial intelligence in healthcare and physiotherapy

Although the implementation of AI in the domain of physiotherapy has been relatively limited,⁷ some examples of its use have been published and shown to aid in home-based rehabilitation and exercise coaching^{12,13} or clinical biomechanics.¹⁴ In medicine, AI has made a notable impact ranging across automated tumour detection in radiology/oncology,¹⁵ intensive care triage¹⁶ and predictive modelling in pediatrics.⁵ As demonstrated in many instances and all the more by the recent COVID-19 pandemic, the required care will become more complex through increasing presence of comorbid conditions, aging¹⁷ and an ongoing exponential influx of technology in formal and informal care settings.¹⁸ To provide this ever-increasing complex care requires innovations that: reduce the burden of registration; increase efficiency; permit multi-disciplinary informal and formal caregivers collaboration; and aid in providing the best health and healthcare with that individual.¹⁸ All of this is needed in order to fully profit from these developments now and in the future for the improvement of health.^{4,6} Despite the omnipresence of AI technology and the high likelihood of the usage of AI algorithms for new purposes in the near future, limited education seems to be being provided on the topic of AI in healthcare.^{5,19} In many curricula for allied health professions or medicine, the topic of AI and how to use this technology responsibly embedded in daily practice – especially in its essential combination with natural intelligence – is omitted.^{5,19}

Box 1. Considerations for physiotherapists when applying artificial intelligence (AI) algorithms.

- **Consider the purpose of the algorithm and the added advantage for clinical reasoning for that individual client.** In the instance of AI algorithms that are embedded in other software, consider the meaning of the suggestions of the AI in the context of that patient prior to action.
- **Consider the origin of the data or population on which the algorithm is trained.** Consider whether this reflects the characteristics of the current patient but also the context in which the AI is applied or the relevant physical and social context of the patient. No international recommendations on minimum sample size are available; however, the required sample size increases when the time to event becomes larger or as the number of determinants increases.
- **Consider the performance of an AI model.** An AUC < 0.70 is considered unfit for usage and an AUC \geq 0.85 is required for application in clinical reasoning.
- **The algorithm and the manner in which it is constructed should be explainable to the physiotherapist or client.**
- **Shared decision-making is key when considering the application of AI or when interpreting the result of embedded AI.** Patients, as professionals, should be aware of the benefits and risks (similar to the application of medical devices and in essence similar to the use of natural intelligence in clinical reasoning), as people themselves – as well as AI discovered, developed and deployed by people – are all vulnerable to human error.

AI = artificial intelligence, AUC = area under the curve

Considerations for responsible use of AI in physiotherapy

The main concerns of developing and using AI algorithms is the occurrence of unconscious bias in data resulting in wrong predictions/classifications and therefore actions, especially when AI is used autonomously, with a lack of transparency and not iteratively embedded and thereby checked by natural reasoning by humans.^{9,10} This use of AI is unwanted and should be carefully regulated or even prohibited, as incidents have occurred in which autonomous AI has caused injustice, racism and injury or worse. All AI algorithms should be scrutinised and the considerations shown in Box 1 may aid when applied within clinical reasoning.

A practical illustration of the considerations for responsible use of AI

The following case presents itself in private practice: the client is a 12-year-old boy recovering from complex surgery as a result of car trauma, living in a low socioeconomic environment. Mobility has recovered during rehabilitation and the remainder of the rehabilitation will be provided in a private practice in the vicinity of the client's home. The physiotherapist has concluded that there are still significant residual issues in functional ability; however, it is unclear whether the residual issues may be considered a normal consequence or a sign of degradation, as well as what the underlying factors may be. The ACT4FATIGUE algorithm (Box 2) is an algorithm that can be used in detecting these potential underlying factors as well as accounting for environmental factors, and provide early warning for functional and participatory decline and also remote monitoring. It has been tested on a general population of chronic diseases (Box 2) and uses commonly used electronic questionnaires and commercial wearables (eg, Fitbit). The metrics show that the algorithm is able to detect 86 of 100 cases (and thus has adequate precision). When considering aspects of sensitivity and specificity, the ability of the ACT4FATIGUE algorithm to accurately classify those at risk is high (sensitivity), whilst the ability to correctly exclude a child as being not at risk is low (specificity), indicating that the risk of false classification is higher when the algorithm indicates 'not at risk'. Therefore,

Box 2. A practical example.

ACT4FATIGUE clinical prediction tool

Application target: Early detection of youth diagnosed with chronic diseases at risk of developing functional and participatory decline.

Background: The reasons for functional and participatory decline can vary greatly between children, especially when challenged by chronic diseases. As such, growth, development and social inclusion can be severely affected whilst growing up. Fatigue, pain and physical activity as well as physical and social environmental factors can all be of importance; however, assessing the importance in each specific case is challenging clinically.

Population: 300 children aged 5 to 24 years diagnosed with: musculoskeletal disorders (39%), pulmonary or cardiovascular diseases (12%), mental health issues (22%), post-surgical or post-trauma (8%), diseases of connective tissue or skin (11%), cerebral or brain trauma (8%).

Data and algorithm: Data are based on commonly used clinical questionnaires, Fitbit monitoring and data extractions from electronic health records. Classification algorithms are expressed in classification decision trees and optimised by random forest models.

Performance metrics: Area under the curve = 0.86, sensitivity = 87%, specificity = 31%.

Application output: Clinical decision tree.

AI = artificial intelligence

additional scrutiny is required for patients classified as not at risk and further assessment may be required when using this algorithm. The output is a decision tree that is explainable and can be used in a consultation; however, it may be complex for the client to understand. In conclusion it may be beneficial to use the ACT4FATIGUE application and discuss the outcome of the algorithm. In conjunction with the client and his parents, it is decided to apply the ACT4FATIGUE algorithm and consult the rehabilitation centre at regular intervals if additional specialised care is required. However, as the included post-surgical population is limited and the number of individuals with low socioeconomic status is small, which may be a source of bias, the physiotherapist decides to evaluate the client's progress to decide whether additional monitoring is still warranted by the algorithm.

Conclusion

Data technology, with special emphasis on AI, has changed the way we view society fundamentally as well as the views on health and healthcare. As such, AI is now providing new innovative ways to aid both patients and professionals in providing more efficient, accessible and personalised care. However, healthcare professionals should learn to adopt these AI driven technologies responsibly in respect to clinical reasoning but also in address the possibilities and threats of AI into the standard curricula of future healthcare professionals.

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