Use Of Artificial Intelligence in Physiotherapy and Rehabilitation

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Introduction

Artificial intelligence (AI) is revolutionising biomedical research and treatment. Machine learning (ML) and advanced algorithms are being used to analyse large amounts of health and medical data more efficiently. In particular, for headache disorders such as migraine, AI has promising potential in various applications such as understanding disease mechanisms (Park et al., 2020) and predicting treatment response (Thakur et al., 2020; Tso et al., 2021). The next generation of AI applications in headache research and treatment can contribute to clinical practice by providing patient-specific treatments (Davenport & Kalakota, 2019; Bajwa et al., 2021), thereby improving patient and public health outcomes and reducing clinician workload (Messina & Filippi, 2020).

In another definition, artificial intelligence (AI) is a research field focused on creating systems that emulate human intelligence (Rowe, Nicholls & Shaw, 2021). AI involves mathematical methods that can enhance the healthcare system by supporting evaluation, decision-making, and patient participation (Ravali et al., 2022). It can automate healthcare decisions and provide predictions based on patient data (Barradell, 2017; Ramanandi, 2021). However, challenges such as ethics, privacy, and security are critical considerations in the application of AI in healthcare (Özdemir & Bilgin, 2021). In specialized fields like pediatric physiotherapy, AI offers benefits such as time efficiency, increased patient motivation, and suitability for infectious scenarios (Söderlund, 2019). Artificial intelligence is primarily recognized for its use of machine learning and deep learning methods.

Machine Learning:

Machine learning can be defined as the ability of computer systems to apply knowledge gained from previous experiences or data to similar situations in the future.

This learning technique may include the assistance of a trainer with examples. The learning algorithm consists of data sources, input information and results. In machine learning, systems generalise by inferring from previous experience. Accordingly, machine learning systems use datasets consisting of training data; these datasets include the codes of observational samples and various formats that enable their interpretation (Akgöbek & Çakır, 2009). Machine learning algorithms are categorized into four main types based on their objectives: supervised learning, unsupervised learning, clustering

(classification), and regression learning (Anderson, 2019).

Deep Learning:

Deep learning employs computational models with multiple processing layers to analyze data at different levels of abstraction (Krizhevsky et al., 2012; Szegedy et al., 2015). These methods have greatly advanced technologies in areas like speech and visual recognition, object detection, drug discovery, and genomics (Helmstaedter et al., 2013). By applying the back-propagation algorithm, deep learning uncovers complex patterns in extensive datasets, enabling each layer to derive representations from the preceding one. While deep convolutional networks have driven significant progress in processing images, videos, audio, and speech, recurrent networks effectively handle sequential data, including language and audio inputs (Lecun et al., 2015). Deep learning techniques are being utilized in research to develop robotic limbs equipped with sensors. For example, artificial neural networks, sensors, and deep learning techniques are crucial in the development of prosthetic hands, often known as 'wearable hand technology.' These prosthetic hands employ convolutional neural networks to grasp objects (Degol et al., 2016; Tang et al., 2016). Deep learning has numerous applications in healthcare, and the integration of these technologies offers a promising opportunity, especially in rehabilitation services.

Connecting physiotherapy and rehabilitation with artificial intelligence: At the crossroads of physical therapy and artificial intelligence (AI), AI's data analysis capabilities and machine learning algorithms offer specialized insights into physical functionality and disease conditions. Physical therapy is based on developing treatment strategies for the individual needs of patients in their recovery process. AI helps to create treatment plans specific to each patient by taking these individual differences into account. For example, AI algorithms fed with data from EHRs and wearable sensors create personalised treatment plans by analysing movement and biometric data (Korteling et al., 2021; Lanotte et al., 2023).

The integration of AI into physical therapy enables continuous monitoring and enhancement of the recovery process following illness or injury. Wearable sensors track movement patterns and physical activities in a patient's daily life, while AI systems analyse this data and provide objective data to update treatment plans. For example, sensor-based AI applications monitor the development of a patient's movement skills through functional assessments such as gait analysis in neurological diseases, and determine the most appropriate treatment to improve treatment efficacy (Albert et al., 2014; Lanotte et al., 2023).

AI algorithms also contribute significantly to diagnostic processes in physiotherapy. Image analysis systems assist in identifying musculoskeletal disorders, while motion tracking systems and video-based AI solutions are crucial for evaluating neurological conditions (Ehteshami Bejnordi et al., 2017; Lonini et al., 2018). These AI-supported applications, when blended with big data, enable the development of individualised treatment approaches and provide data-driven support for clinical decisions (Lanotte et al., 2023).

The use of AI in Physiotherapy Assessment:

The application of artificial intelligence in physiotherapy assessment can be categorized under the following subheadings:.

Gaitkeeper: GaitKeeper is an AI-powered mobile application designed to assess health status by evaluating walking speed. Walking speed is closely associated with important health indicators such as fall risk, frailty, cognitive decline, and cardiovascular health, particularly in older adults (Fritz & Lusardi, 2009; Rockwood & Mitnitski, 2007). The app standardizes these assessments by using an augmented reality virtual gait lab for quick analysis. It provides highly accurate results, outperforming traditional systems

like Vicon and GAITRite, with a Spearman correlation coefficient of 0.947. In addition, it ensures user privacy through secure data processing and encryption features. The app's portable design allows for use not only in clinical settings but also in home care and remote monitoring, promoting proactive health management.

Using AI in the Perinatal Period:

AI technologies are applied across a range of fields, including disease screening and management, remote monitoring, fetal health assessment, and genetic screening in women's health and obstetrics during the perinatal period (Tejera et al., 2011; Moreira et al., 2016). For example, artificial intelligence networks are used to identify pregnancy-related complications early, such as hypertensive disorders and gestational diabetes. (Polak and Mendyk, 2004; Moreira et al., 2018). Artificial intelligence-supported monitoring technologies such as cardiotocography allow instant control of fetal health by analysing fetal heart movements (Warrick et al., 2010). Models developed to evaluate the toxic effects of medications used during pregnancy on the fetus have demonstrated high accuracy in determining the safety categories of these drugs. (Boland, 2017). These AI-supported solutions facilitate access to healthcare services by reducing hospital visits during pregnancy (Caballero-Ruiz et al., 2017).

In the framework of treatment, AI-enabled models enable early diagnosis and management of complications in high-risk pregnancies (Paydar et al., 2017).

For example, fuzzy logic-based algorithms have been created to assess the risk of HELLP syndrome during pregnancy, and these models have proven effective in achieving successful outcomes. (Moreira et al., 2018). Remote monitoring systems in pregnancy are applied in areas like managing gestational diabetes and monitoring fetal health, thus facilitating the early intervention of both maternal and fetal complications (Kazantev et al., 2012). The implementation of such artificial intelligence technologies is pivotal in reducing maternal and fetal mortality and morbidity rates (Davidson and Boland, 2021).

The Use of AI in Rehabilitation:

AI is increasingly being used in the field of physical rehabilitation, especially because of It can process large and complex data sets, make objective assessments and individualise treatment (Aung et al., 2021; Garcia-Vidal et al., 2019; Bajwa et al., 2021). Machine learning algorithms enable the development of personalised treatment plans by analysing patients' movement and health data, precisely monitor the healing process and offer remote monitoring. For example, data collected with technologies such as wearable devices or smartwatches enable more precise assessment of the level of participation and response to treatment (Lo et al., 2018; Sandal et al., 2021). Furthermore, AI-enabled mobile applications encourage users to access treatment more easily and adhere to personalised exercise programmes (Anan et al., 2021; Lo et al., 2018).

In robotic prostheses, AI analyses biological signals such as muscle signals (EMG) or brain waves (EEG), enabling the prostheses to move more in line with user intent (Kristoffersen et al., 2021; Tombini et al., 2012). Although these developments increase the functionality of prostheses, challenges such as continuous calibration, lack of portability, and user fatigue in long-term use are encountered (Kristoffersen et al., 2021; Song et al., 2005). Again, AI-supported game-based systems increase the participation of users by making rehabilitation processes fun and offer low-cost alternatives; however, these systems have factors that negatively affect the user experience such as visual clarity problems and lack of personalisation (Avola et al., 2019; Yeh et al., 2014).

The article emphasises that the clinical effects of AI in rehabilitation have not yet been fully evaluated, so more extensive research in real-world settings is needed (Sumner et al., 2023). These technologies have a high potential to support personalised and effective treatment approaches in the future.

Use in Pediatric Rehabilitation: Artificial intelligence (AI) technologies in pediatric physiotherapy offer innovative solutions to improve physiotherapy processes for children. Following the widespread use of artificial intelligence in other healthcare fields, its use in pediatric physiotherapy has also increased. In this field, AI-powered exoskeletons help children move their arms, legs and hands, while virtual reality-based video games support participation and motivation in therapy (Rowe et al., 2021). While EMG (electromyography) technology measures how efficiently muscles are working, brain-computer interfaces contribute to orthotic-prosthetic decision-making processes (Ravali et al., 2022). In addition, telerehabilitation applications provide remote therapy and maintain the continuity between the patient and the therapist in long-term and infectious diseases (Barradell, 2017).

While AI lightens the therapists' workload, it also enables reaching more patients during the treatment process and enhances patient compliance. It offers advantages such as time savings in intensive and long-term pediatric physiotherapy, boosting patient motivation, and providing opportunities for use in high-risk infection environments (Ramanandi, 2021). However, ethical, privacy, and security concerns also play a substantial role in the implementation of artificial intelligence technologies. Although these technologies come with drawbacks like high expenses and limited availability, issues related to ethics and data protection are also critical factors to address (Özdemir & Bilgin, 2021; Söderlund, 2019).

Consequently, the implementation of AI-driven applications in pediatric physiotherapy brings about a major transformation in the fields of assessment, intervention design, and patient monitoring. With the advantages provided by AI, personalized evaluation methods enable the creation of effective treatment plans, while the quality and availability of pediatric physiotherapy services are enhanced through continuous tracking of patient progress (Karabulut, 2024).

Telerehabilitation: Artificial intelligence technologies in telerehabilitation applications have the potential to manage the rehabilitation process of patients in a remote and individualised manner. Özden et al (2020) highlight the role of AI-based systems in telerehabilitation, particularly in the field of orthopaedic physiotherapy, to develop and manage automated exercise protocols based on patient data. These systems create specific exercise instructions based on patient data and make them accessible to patients through a secure platform (Skwortsow and Molin, 2015).

Artificial intelligence applications can automatically update treatment protocols by tracking patient adherence during the telerehabilitation process. These systems allow physiotherapists to remotely monitor patients' treatment compliance and, if needed, adjust the treatment plan based on adherence levels. Additionally, AI-based applications offer advantages such as cost reduction and time efficiency in the telerehabilitation process (Wells et al., 2018; Novak & Riener, 2015).

Artificial intelligence systems integrated with mobile devices can utilize sensors like accelerometers and gyroscopes to track patient movements and support them in executing exercises accurately. For instance, in an application created by Ongvisatepaiboon et al. (2015), artificial intelligence technology was used to estimate shoulder rotation angle using only an accelerometer sensor. Such systems increase the effectiveness of treatment by allowing patients to accurately perform rehabilitation exercises at home without physiotherapist intervention, and support ongoing communication between the patient and physiotherapist (Ongvisatepaiboon et al., 2015).

Use of Artificial Intelligence in Headache: Artificial intelligence (AI) applications in patients with headaches hold significant potential, especially in managing conditions like migraines. According to Petrušić et al. (2024), AI stands out as a technology that can revolutionise headache research and treatment, helping to better understand disease mechanisms and predict patient response. The analysis of health data using machine

learning (ML) and advanced algorithms offers opportunities to both improve patient care and enhance clinical applications (Park et al., 2020; Thakur et al., 2020; Tso et al., 2021).

The use of AI in headache management accelerates clinical decision making by rapidly analysing large data sets, allowing clinicians to focus on more complex cases. For example, Cohen (2023) noted that AI-based diagnostic models can make headache treatment more accessible by improving the diagnostic accuracy of non-headache specialists (Cohen, 2023; Katsuki et al., 2023).

Digital applications and virtual health assistants have an important place in headache management. In a study by Stone et al (2003), electronic diaries were found to increase patient compliance to 94%, compared with 11% for paper diaries (Stone et al, 2003). In addition, Roesch et al. (2020) algorithms based on the ICHD-3 criteria were found to be very successful in classifying migraine and tension-type headaches (Roesch et al., 2020).

Wearable devices and virtual reality (VR) technologies are also emerging as adjuncts to headache management. For example, Noseda et al. (2016) showed that lenses specifically designed to manage photophobia in migraineurs reduced pain and light sensitivity by filtering blue light (Noseda et al., 2016). VR devices allow patients to manage their stress levels by receiving biofeedback in the home environment, and such devices have been observed to reduce symptoms of depression (Cuneo et al., 2023). According to Petrušić et al. AI-assisted tools not only improve patients' quality of life in headache management, but also reduce physicians' workload and provide more personalised treatment options (Petrušić et al., 2024). It is emphasised that data protection and ethical issues should also be considered for the successful integration of these technologies (Tana et al., 2024; Martelletti et al., 2023).

Results

Health services are vital to national economies, as they are central to human life. Advances in technology and science are pushing the healthcare sector beyond expectations, much like in other fields such as industry, services, education, and manufacturing. In this regard, systems referred to as "artificial intelligence" provide intelligent solutions for healthcare. AI applications are utilized across all subsectors of healthcare (Akalın & Veranyurt, 2020) and are especially involved in processes such as diagnosis, treatment, and classification, with a strong presence in various rehabilitation areas (Russell & Norvig, 2010). Specifically, this technology can be applied in any area where human-computer interaction is possible (Nicolas & Gil, 2012).

It is crucial to make machine learning methods, patient data measurement, and clinical decision support systems practical and usable in routine clinical practice. AI-powered systems are designed to enhance the accuracy and efficiency of clinical assessments in areas like balance, gait, daily activities, and the functional capabilities of both upper and lower extremities. By analyzing patient data, these systems allow for real-time tracking of rehabilitation progress, provide predictive insights into clinical advancements, and enable continuous monitoring, all of which contribute to personalized care and timely intervention in the rehabilitation process. (Köse, 2018).

The use of artificial intelligence-based intelligent technologies in rehabilitation services offers many benefits when evaluated from a health care management perspective. For example, wearable technologies that can be adapted to an individual's level and abilities can help reduce production costs. In addition, it provides benefits such as flexible adjustment of parameters such as duration, intensity, difficulty and speed of treatment; obtaining objective data with reliable and valid user detection devices; providing immediate feedback; facilitating training with real-life simulations; reducing patient and therapist burnout (Tarakçı, 2021).

The application of artificial intelligence in physiotherapy and rehabilitation significantly contributes to the individualization of treatment processes and the objective monitoring

of patients. By analyzing patients' movement data, AI, along with advanced data analysis, machine learning, and deep learning algorithms, enables the development of personalized treatment plans.. Additionally, AI-driven solutions such as wearable devices and robotic technologies make rehabilitation processes more dynamic and improve patient adherence by monitoring their daily activities. In specific areas such as telerehabilitation, pediatric physiotherapy, and stroke rehabilitation, AI reduces therapists' workload and improves treatment effectiveness. AI-based systems offer more accessible and cost-effective treatments by providing remote monitoring, automated assessments, and instant feedback. However, ethical and privacy concerns are critical when incorporating these technologies into healthcare systems. In summary, although AI applications in physiotherapy present groundbreaking solutions that may enhance patients' quality of life, additional thorough research is essential to evaluate their clinical impact in the future.

References

Akgöbek, Ö., & Çakır, F. (2009). Veri Madenciliğinde Bir Uzman Sistem Tasarımı. *Akademik Bilişim'09 - XI. Akademik Bilişim Konferansı Bildirileri*, 809–813. http://ab.org.tr/ab09/kitap/akgobek_cakir_AB09.pdf

Akalın, B., & Veranyurt, Ü. (2020). Sağlıkta Dijitalleşme ve Yapay Zeka. *SDÜ Sağlık Yönetimi Dergisi*, 2(2), 128–137.

Albert, M. V., Deeny, S., McCarthy, C., Valentin, J., & Jayaraman, A. (2014). Monitoring daily function in persons with transfemoral amputations using a commercial activity monitor: A feasibility study. *PM R,* 6, 1120-1127.

Anderson, D. (2019). Artificial Intelligence and Applications in PM&R. *American Journal of Physical Medicine & Rehabilitation*, 98(11), e128–e129. https://doi.org/10.1097/PHM.0000000000001171

Anan, T., Kajiki, S., Oka, H., Fujii, T., Kawamata, K., Mori, K., et al. (2021). Effects of an artificial intelligence-assisted health program on workers with neck/shoulder pain/stiffness and low back pain: Randomized controlled trial. *JMIR Mhealth Uhealth*, 9(9), e27535.

Avola, D., Cinque, L., Foresti, G. L., & Marini, M. R. (2019). An interactive and low-cost full body rehabilitation framework based on 3D immersive serious games. *Journal of Biomedical Informatics,* 89, 81–100. https://doi.org/10.1016/j.jbi.2018.11.004

Bajwa, J., Munir, U., Nori, A., & Williams, B. (2021). Artificial intelligence in healthcare: Transforming the practice of medicine. *Future Healthc J*, 8, e188–e194. https://doi.org/10.7861/fhj.2021-0095

Barradell, S. (2017). Moving forth: Imagining physiotherapy education differently. *Physiother Theory Pract*, 33(6), 439–447.

Boland, M. R., Polubriagniof, F., & Tatonetti, N. P. (2017). Development of a machine learning algorithm to classify drugs of unknown fetal effect. *Scientific Reports*, 7, 12839. https://doi.org/10.1038/s41598-017-12943-x

Caballero-Ruiz, E., Garcia-Saez, G., Rigla, M., Villaplana, M., Pons, B., & Hernando, M. E. (2017). A web-based clinical decision support system for gestational diabetes: Automatic diet prescription and detection of insulin needs. *International Journal of Medical Informatics*, 102, 35–49. https://doi.org/10.1016/j.ijmedinf.2017.02.014

Cohen, F. (2023). The role of artificial intelligence in headache medicine: Potential and peril. *Headache*, 63, 694–696. https://doi.org/10.1111/head.14495

Cuneo, A., Yang, R., Zhou, H., Wang, K., Goh, S., Wang, Y., et al. (2023). The utility of a novel, combined biofeedback-virtual reality device as add-on treatment for

chronic migraine: A randomized pilot study. *Clinical Journal of Pain,* 39, 286–296. https://doi.org/10.1097/AJP.0000000000001114

Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. *Future Healthc J,* 6, 94–98. https://doi.org/10.7861/futurehosp.6-2-94

Davey N, Harte G, Boran A, Mc Elwaine P, Kennelly SP. GaitKeeper: An AI-Enabled Mobile Technology to Standardize and Measure Gait Speed. *Sensors.* 2024; 24(17):5550. https://doi.org/10.3390/s24175550

Davidson, L., Boland, M.R. (2021). Towards deep phenotyping pregnancy: a systematic review on artificial intelligence and machine learning methods to improve pregnancy outcomes. *Briefings in Bioinformatics,* 22(5), 1-29. https://doi.org/10.1093/bib/bbaa369

Degol, J., Akhtar, A., Manja, B., & Bretl, T. (2016). Automatic grasp selection using a camera in a hand prosthesis. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, *EMBS,* 431–434. https://doi.org/10.1109/EMBC.2016.7590732

Ehteshami Bejnordi, B., Veta, M., Johannes van Diest, P., van Ginneken, B., Karssemeijer, N., Litjens, G., et al. (2017). Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in women with breast cancer. *JAMA,* 318, 2199–2210.

Fritz, S., & Lusardi, M. (2009). Walking speed: The sixth vital sign. *Journal of Geriatric Physical Therapy*, 32, 2–5. https://doi.org/10.1519/JGPT.0b013e318195b7bc

Garcia-Vidal, C., Sanjuan, G., Puerta-Alcalde, P., Moreno-García, E., & Soriano, A. (2019). Artificial intelligence to support clinical decision-making processes. *eBioMedicine,* 46, 27–29.

Gözaçan Karabulut, D. (2024). Artificial intelligence for pediatric physiotherapy. *RMJ,* 1(3), 20–22.

Helmstaedter, M., Briggman, K. L., Turaga, S. C., Jain, V., Seung, H. S., & Denk, W. (2013). Connectomic reconstruction of the inner plexiform layer in the mouse retina. *Nature,* 500(7461), 168–174. https://doi.org/10.1038/nature12346

Katsuki, M., Shimazu, T., Kikui, S., Danno, D., Miyahara, J., Takeshima, R., et al. (2023). Developing an artificial intelligence-based headache diagnostic model and its utility for non-specialists' diagnostic accuracy. *Cephalalgia,* 43, 3331024231156925. https://doi.org/10.1177/03331024231156925

Kazantev, A., Ponomareva, J., Kazantev, P., Digilov, R., & Huang, P. (2012). Development of e-health network for in-home pregnancy surveillance based on artificial intelligence. In *IEEE-EMBS International Conference on Biomedical and Health Informatics*, Hong Kong and Shenzhen, China, 2–7 January 2012.

Korteling, J. E. H., van de Boer-Visschedijk, G. C., Blankendaal, R. A. M., Boonekamp, R. C., & Eikelboom, A. R. (2021). Human- versus artificial intelligence. *Frontiers in Artificial Intelligence*, 4, 622364. https://doi.org/10.3389/frai.2021.622364

Köse, B. (2018). Türkiye'de ve dünyada mesleki rehabilitasyon. *Turkiye Klinikleri J Psychol-Special Topics,* 3(1), 30–41.

Kristoffersen, M. B., Franzke, A. W., Bongers, R. M., Wand, M., Murgia, A., & van der Sluis, C. K. (2021). User training for machine learning-controlled upper limb prostheses: A serious game approach. *Journal of Neuroengineering and Rehabilitation,* 18(1), 32.

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. *PervasiveHealth: Pervasive Computing*

Technologies for Healthcare, 25, 1–9. https://doi.org/10.1145/3383972.3383975

Lanotte, F., Shin, S. Y., O'Brien, M. K., & Jayaraman, A. (2023). Validity and reliability of a commercial wearable sensor system for measuring spatiotemporal gait parameters in a post-stroke population: The effects of walking speed and asymmetry. *Physiological Measurement*, 44, 085005.

Lecun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444. https://doi.org/10.1038/nature14539

Lo, W. L. A., Lei, D., Li, L., Huang, D. F., & Tong, K. F. (2018). The perceived benefits of an artificial intelligence-embedded mobile app implementing evidence-based guidelines for the self-management of chronic neck and back pain: Observational study. *JMIR Mhealth Uhealth*, 6(11), e198.

Martelletti, P., Leonardi, M., Ashina, M., Burstein, R., Cho, S. J., Charway-Felli, A., et al. (2023). Rethinking headache as a global public health case model for reaching the SDG 3 HEALTH by 2030. *Journal of Headache and Pain*, 24, 140. https://doi.org/10.1186/s10194-023-01666-2

Messina, R., & Filippi, M. (2020). What we gain from machine learning studies in headache patients. *Frontiers in Neurology*, 11, 221. https://doi.org/10.3389/fneur.2020.00221

Moreira, M. W. L., Rodrigues, J. J. P. C., Albuquerque, V. H. C., & Neto, A. V. (2018). Evolutionary radial basis function network for gestational diabetes data analytics. *Journal of Computer Science*, 27, 410–417. https://doi.org/10.1016/j.jocs.2017.07.015

Moreira, M. W. L., Rodrigues, J. P. C., Al-Muhtadi, J., Korotaev, V. V., & Albuquerque, V. H. C. (2018). Neuro-fuzzy model for HELLP syndrome prediction in mobile cloud computing environments. *Concurrency and Computation: Practice and Experience*, 33(7), e4651. https://doi.org/10.1002/cpe.4651

Moreira, M. W. L., Rodrigues, J. J. P. C., Oliveira, A. M. B., Saleem, K., & Neto, A. V. (2016). An inference mechanism using Bayes-based classifiers in pregnancy care. In *2016 IEEE 18th International Conference on e-Health Networking, Applications and Services (Healthcom)*. https://doi.org/10.1109/HealthCom.2016.7749475

Nicolas, L. F., & Gil, J. G. (2012). Brain computer interfaces, a review. *Sensors*, 12(2), 1211–1279. https://doi.org/10.3390/s120201211

Noseda, R., Bernstein, C. A., Nir, R.-R., Lee, A. J., Fulton, A. B., Bertisch, S. M., ... & Borsook, D. (2016). Migraine photophobia originating in cone-driven retinal pathways. *Brain,* 139, 1971–1986. https://doi.org/10.1093/brain/aww119

Novak, D., & Riener, R. (2015). Control strategies and artificial intelligence in rehabilitation robotics. *AI Magazine*, 36(4), 23–33. https://doi.org/10.1609/aimag.v36i4.2605

Ongvisatepaiboon, K., Chan, J. H., & Vanijja, V. (2015). Smartphone-based tele-rehabilitation system for frozen shoulder using a machine learning approach. *IEEE*.

Özdemir, L., & Bilgin, A. (2021). The use of artificial intelligence in health and ethical issues. *Journal of Health Nursing Management*, 8(3), 439–445.

Özden, F., Arık, A. F., & Tuğay, N. (2020). Current telerehabilitation approaches in orthopedic physiotherapy. *Türkiye Klinikleri Journal of Health Sciences*, 5(2), 354–360. https://doi.org/10.5336/healthsci.2019-70990

Park, C.-W., Seo, S. W., Kang, N., Ko, B. S., Choi, B. W., Park, C. M., et al. (2020). Artificial intelligence in healthcare: Current applications and issues. *Journal of*

Korean Medical Science, 35, e379. https://doi.org/10.3346/jkms.2020.35.e379

Paydar, K., Niakan Kalhori, S. R., Akbarian, M., & Sheikhtaheri, A. (2017). A clinical decision support system for prediction of pregnancy outcome in pregnant women with systemic lupus erythematosus. *International Journal of Medical Informatics*, 97, 239–246. https://doi.org/10.1016/j.ijmedinf.2016.10.018

Petrušić, I., Ha, W. S., Labastida-Ramirez, A., et al. (2024). Influence of next-generation artificial intelligence on headache research, diagnosis, and treatment: The junior editorial board members' vision – part 1. *Journal of Headache and Pain*, 25, 151. https://doi.org/10.1186/s10194-024-01847-7

Ramanandi, V. H. (2021). Role and scope of artificial intelligence in physiotherapy: A scientific review of literature. *International Journal of Advanced Scientific Research*, 6(1), X11–14.

Ravali, R. S., Vijayakumar, T. M., Lakshmi, K. S., Mavaluru, D., Reddy, L. V., Retnadhas, M., & Thomas, T. (2022). A systematic review of artificial intelligence for pediatric physiotherapy practice: Past, present, and future. *Neuroscience Informatics*, 2(4), 100045.

Rockwood, K., & Mitnitski, A. (2007). Frailty in relation to the accumulation of deficits. *Journal of Gerontology: Series A Biological Sciences and Medical Sciences*, 62, 722–727.

Roesch, A., Dahlem, M. A., Neeb, L., & Kurth, T. (2020). Validation of an algorithm for automated classification of migraine and tension-type headache attacks in an electronic headache diary. *Journal of Headache and Pain*, 21, 1–10. https://doi.org/10.1186/s10194-020-01139-w

Russell, S., & Norvig, P. (2010). Artificial intelligence (A modern approach). In *2010 The 2nd International Conference on Computer and Automation Engineering, ICCAE 2010* (Vol. 4). https://doi.org/10.1109/ICCAE.2010.5451578

Sandal, L. F., Bach, K., Øverås, C. K., et al. (2021). Effectiveness of app-delivered, tailored self-management support for adults with lower back pain-related disability: A selfBACK randomized clinical trial. *JAMA Internal Medicine*, 181(10), 1288–1296. https://doi.org/10.1001/jamainternmed.2021.4097

Skwortsow, N., & Molin, H. P. (2015). Exercise protocol creation and management system. *Google Patents*. https://patents.google.com/patent/US20150278132A1/en

Söderlund, A. (2019). Artificial intelligence and physiotherapy – Editorial. *European Journal of Physiotherapy*, 21(1), 1–1.

Song, R. (2006). A robotic system using myoelectrical control at the elbow joint for the rehabilitation of persons after stroke. *People's Republic of China: Hong Kong Polytechnic University*.

Stone, A. A., Shiffman, S., Schwartz, J. E., Broderick, J. E., & Hufford, M. R. (2003). Patient compliance with paper and electronic diaries. *Controlled Clinical Trials*, 24, 182–199. https://doi.org/10.1016/s0197-2456(02)00320-3

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., & Rabinovich, A. (2015). Going deeper with convolutions. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 07–12 June, 1–9. https://doi.org/10.1109/CVPR.2015.7298594

Tang, S., Ghosh, R., Thakor, N. V., & Kukreja, S. L. (2016). Orientation estimation and grasp type detection of household objects for upper limb prostheses with dynamic vision sensor. *Proceedings of the 2016 IEEE Biomedical Circuits and Systems Conference, BioCAS 2016*, 1(c), 99–102. https://doi.org/10.1109/

BioCAS.2016.7833734

Tana, C., Raffaelli, B., Souza, M. N. P., de la Torre, E. R., Massi, D. G., & Kisani, N., et al. (2024). Health equity, care access and quality in headache – Part 1. *Journal of Headache and Pain*, 25, 12. https://doi.org/10.1186/s10194-024-01712-7

Tejera, E., Joseareias, M., Rodrigues, A., Ramõa, A., & Manuelnieto-Villar, J., et al. (2011). Artificial neural network for normal, hypertensive, and preeclamptic pregnancy classification using maternal heart rate variability indexes. *The Journal of Maternal-Fetal & Neonatal Medicine*, 24(9), 1147–1151. https://doi.org/10.3109/14767058.2010.545916

Thakur, A., Mishra, A. P., Panda, B., Rodríguez, D. C. S., Gaurav, I., & Majhi, B. (2020). Application of artificial intelligence in pharmaceutical and biomedical studies. *Current Pharmaceutical Design*, 26, 3569–3578. https://doi.org/10.2174/1381612826666200515131245

Tombini, M., Rigosa, J., Zappasodi, F., Porcaro, C., Citi, L., & Carpaneto, J., et al. (2012). Combined analysis of cortical (EEG) and nerve stump signals improves robotic hand control. *Neurorehabilitation and Neural Repair*, 26(3), 275–281.

Tso, A. R., Brudfors, M., Danno, D., Grangeon, L., Cheema, S., Matharu, M., & Nachev, P. (2021). Machine phenotyping of cluster headache and its response to verapamil. *Brain*, 144, 655–664. https://doi.org/10.1093/brain/awaa388

Tarakçı, D. (2021, June 3). SD PLATFORM - Dergi - Rehabilitasyonda yapay zekâ. *SD Platform*. https://www.sdplatform.com/Dergi/1420/Rehabilitasyondayapay-zek.aspx

Yeh, S. C., Huang, M. C., Wang, P. C., Fang, T. Y., Su, M. C., Tsai, P. Y., et al. (2014). Machine learning-based assessment tool for imbalance and vestibular dysfunction with virtual reality rehabilitation system. *Computers in Methods and Programs in Biomedicine*, 116(3), 311–318.

YYM Aung, D. C. S. Wong, & D. S. W. Ting. (2021). The promise of artificial intelligence: A review of the opportunities and challenges of artificial intelligence in healthcare. *British Medical Bulletin*, 139(1), 4–15. https://doi.org/10.1093/bmb/ldab016

Warrick, P. A., Hamilton, E. F., Precup, D., & Kearney, R. E. (2010). Classification of normal and hypoxic fetuses from systems modeling of intrapartum cardiotocography. *IEEE Transactions on Biomedical Engineering*, 57(4), 771–779. https://doi.org/10.1109/TBME.2009.2035818

Wells, R., Price, T. R., Spooner, T., Van Andel, D., Dittmer, T., Kotwick, J., et al. (2018). Predictive telerehabilitation technology and user interface. *Google Patents*.

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