Studia i Materiały Informatyki Stosowanej, Tom 16, Nr 2, 2024
str. 21-27

AI-SUPPORTED REASONING IN PHYSIOTHERAPY

Dariusz Mikołajewski[1], Emilia Mikołajewska[2]

[1] Kazimierz Wielki University, Faculty of Computer Science
Kopernika 1, 85-074 Bydgoszcz
e-mail: dariusz.mikolajewski@ukw.edu.pl
[2] Ludwik Rydygier Collegium Medicum in Bydgoszcz, Nicolaus Copernicus University in Toruń, Poland
Department of Physiotherapy, Faculty of Health Sciences
Jagiellońska 13-15, 85-087 Bydgoszcz

Abstract: *Systemy wspomagania wnioskowania klinicznego w fizjoterapii oparte na sztucznej inteligencji, a w szczególności na danych (uczenie maszynowe), mogą być przydatne w podejmowaniu i weryfikacji decyzji dotyczących diagnostyki funkcjonalnej oraz formułowania/utrzymywania/modyfikowania programu rehabilitacji. Celem niniejszego artykułu jest zbadanie, w jakim stopniu możliwości oferowane przez systemy oparte na sztucznej inteligencji w zakresie rozumowania klinicznego w fizjoterapii zostały wykorzystane i gdzie leży potencjał ich dalszego stymulowanego rozwoju.*

Słowa kluczowe: *Artificial intelligence; Machine learning; Clinical reasoning; Clinical Decision Support System; Interview; Musculoskeletal pain disorders; Physiotherapy; Usability, Recommender system; Self-management; mHealth.*

Wnioskowanie w fizjoterapii wspierane sztuczną inteligencją

Streszczenie: *Artificial intelligence (AI)-based clinical reasoning support systems in physiotherapy, and in particular data-driven (machine learning) systems, can be useful in making and reviewing decisions regarding functional diagnosis and formulating/maintaining/modifying a rehabilitation programme. The aim of this article is to explore the extent to which the opportunities offered by AI-based systems for clinical reasoning in physiotherapy have been exploited and where the potential for their further stimulated development lies.*

Słowa kluczowe: *Sztuczna inteligencja; Uczenie maszynowe; Wnioskowanie kliniczne; System wspomagania decyzji klinicznych; Wywiad; Zaburzenia bólowe układu mięśniowo-szkieletowego; Fizjoterapia; Użyteczność, System rekomendacji; Samokontrola; mZdrowie.*

1. Introduction

Artificial intelligence (AI)-based and especially data-driven (machine learning - ML)-based clinical reasoning support systems in physiotherapy can be useful in making and reviewing decisions regarding functional diagnosis and formulating/maintaining/modifying a rehabilitation programme.
The diversity of their tasks and the groups of patients undergoing physiotherapy must result in their advancement (including the groups of collected data and the algorithms searching, grouping and modeling them), but also perhaps the existence of separate solutions. for cardiac, neurological, orthopedic, and perhaps also pediatric, geriatric and sports physiotherapy. It also depends on the division of physiotherapists' specializations and their resulting competences.
This is detailed in the SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis (Table 1).
The aim of the article is to check to what extent the possibilities offered by AI-based systems for clinical reasoning in physiotherapy have been used and where the potential for their further stimulated development lies.

Table 1. SWOT analysis for AI-based clinical reasoning support systems in physiotherapy.

	Positive	Negative
Internal	STRENGHTS Faster and more accurate diagnosis More effective assessment and adjustment of the rehabilitation programme Possibly shorter hospitalisation	WEAKNESSES Significant cost of implementation The need for data collection Limited acceptance Lack of prepared staff
External	OPPORTUNITIES Target: preventive physiotherapy Better use of current capabilities for only the most severe cases Reducing queues Objectivising functional assessment	THREATS Lack of standards Cyber security Privacy

2. Results of the literature review

However, this group of solutions is developing too slowly.A review of six major bibliographic databases using specified keywords found only 5 articles concerning AI/ML-supported clinical reasoning in physiotherapy (1995-2024).
Granviken et al. presented an AI-based clinical decision support system (CDSS) to support physiotherapists and patients with treatment decisions for musculoskeletal pain disorders (MSK). It searches for a group of the most symptom-similar patients with a history of successful physiotherapy to make recommendations on the optimal physiotherapy programme for a given new patient, based on their symptoms. Using a group of previous similar patients with successful physiotherapy outcomes allows the physiotherapy programme to be concretised from general/universal recommendations to personalised therapy. It is crucial to develop inference mechanisms, model groups of patients with positive physiotherapy outcomes and to investigate the acceptance and use of the system by physiotherapists [1]. To date, both physiotherapists and patients have found the described system acceptable and useful, both as a preparatory, exploratory tool and to facilitate the physiotherapist-patient relationship. A limitation to date has been the use of the above system by physiotherapists primarily to support previous and current practice, rather than to improve patient involvement in decision-making and learning (learning from experience) from previous patients who have had therapeutic success with a similar injury/disease. This indicates that the described system did not significantly affect physiotherapists' clinical reasoning as well as the choice of physiotherapy programme based on information from the majority of similar successful patients. Analyses showed that this may have been due to perennially low (less than optimal) numbers of previous patients in the system or insufficient clinical implementation, limiting understanding and confidence in the CDSS [1].
In an AI/ML-supported physiotherapy clinical decision support system, patient history, patient-reported data and clinical outcomes are used to find similar patients with successful outcomes using case-based reasoning. A clinical dashboard is used to make shared decisions. Patient-reported data, a description of the rehabilitation programme and outcomes (including final patient outcomes) are retained for future troubleshooting. The patient is subject to relapse prevention at periodic follow-ups (Figure 1).

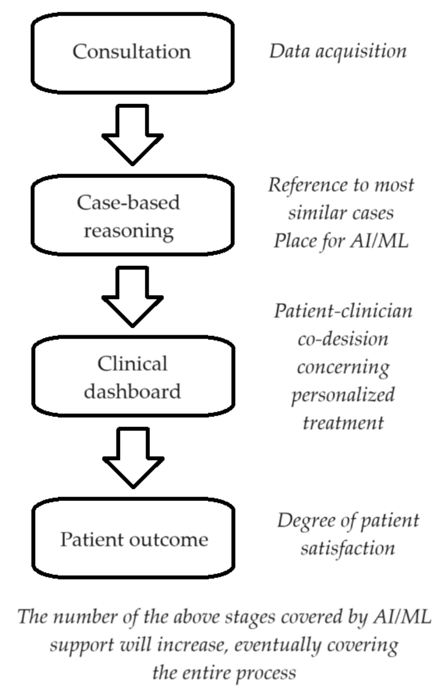

Figure 1. Information flow through an AI-supported clinical decision support system in physiotherapy [1].

OpenAI has released ChatGPT (Generative Pretrained Transformer) as a language model that analyses and generates human language, providing descriptions and recommendations, among other things. So far, they have had low, however, a study was performed to verify that ChatGPT 3.5 (free version) provides consistent and accurate clinical responses. The ability of this software to mimic human clinical reasoning in scenarios of varying complexity and the ability to produce differential diagnoses was tested. The study showed that the way the question was phrased significantly influenced the answers generated, so in order to achieve usability one needs to learn how to use AI, and it should be the other way around: it should be AI that learns from good medical professionals how to formulate a diagnosis and draw detailed conclusions from patient data. The consistency and accuracy of ChatGPT responses in clinical assessment was variable (from concise to complex), and important steps in the physiotherapy process were missed by ChatGPT in 30-40% of responses. ChatGPT in the clinical case analysis demonstrated the ability to develop evidence-based clinical reasoning, especially in simple clinical scenarios [2]. AI support may also apply to inference in telerahabilitation and prevention of recurrent injuries/disorders. An example of this is the self-treatment of low back pain (LBP) using the selfBACK app developed in collaboration with patients and clinicians. Furthermore, it is based on research on self-treatment of LBP. Patients who had sought LBP support of any duration in physiotherapy or general practice in the past 8 weeks were screened for eligibility using the PROMIS Physical Function-4a questionnaire and asked to use the selfBACK app for 6 weeks. The app provided respondents with weekly individual self-monitoring plans targeting physical activity, strength and flexibility exercises and education (supplementing knowledge of the condition and its treatment). Self-management plans were formulated using case-based reasoning (CBR) to capture and reuse information from previous cases with therapeutic success. Outcomes were collected throughout the intervention period, and the patient's subjective state before and after therapy (based on questionnaires) was also compared. The improvements observed were small and the pattern of time spent using the app varied significantly between the subjects, indicating the need to refine both the assessment and the app itself, and then conduct further studies using it [3]. Heart Monitor is an object-oriented, knowledge-based system designed to support clinical activities in cardiovascular (CV) rehabilitation. The original concept was developed in a study completed in 1992. This article describes a second-generation system that is currently being implemented in collaboration with a local cardiac rehabilitation programme. The UNIX PC-based system supports an extensive patient database organised by clinical area. In addition, a knowledge base is used to monitor the patient's condition. Automated rule-based inference is used to assess risk factors contraindicating exercise therapy and to monitor administrative and statutory requirements [4]. Computational linguistics allows you to understand the structure of language and various forms of expressing patients' perceptions. An example is the analysis of the discourse of people with chronic non-specific low back pain using sentiment analysis and network analysis. Correlations between patient profiles, pain intensity and disability status were examined and clusters were identified using unsupervised ML. For this purpose, data on participants' feelings after receiving the diagnosis were used. The majority (72%) of participants presented negative discourse, and the number of words and the largest strongly connected component were positively correlated with the level of education, but no statistically significant correlations were observed between pain intensity, disability level and network analysis, although two clusters were identified [5]. The optimization function of AI-based clinical reasoning is also interesting, as the concept of defensive medicine has emerged, defined as excessive caution in the treatment of patients, manifesting itself as excessive testing, unnecessary visits and additional therapeutic interventions. This may lead to the replacement of clinical reasoning with lists and guidelines that do not take into account patient complexity or an individual approach. This is due not only to high levels of uncertainty, but also to clinical experience with past cases, systemic pressures and patient expectations. Strategies to avoid the use of defensive medicine include the introduction of AI-based reasoning systems (second opinions) to partially remove the responsibility for uncertainty from diagnosticians/therapists. At the same time, this forces individualization of physiotherapy and cyclical assessment of its progress as part of the process of clinical reasoning in physiotherapy [6]. An important element of clinical reasoning in physiotherapy is determining which patients are suitable for blended care. The development of a checklist and/or decision support with a second opinion from the ML system would greatly assist physiotherapists in determining mixed treatment. Despite research, it is not fully known which patient characteristics predict a patient's suitability for mixed physiotherapy and which patient characteristics should be taken into account when determining the proportion (intensity, time) between therapeutic counseling and digital application. As many as eight areas can be taken into account: motivation, safety, equipment, digital skills, health knowledge, self-management, time and financial factors [7]. It is necessary to investigate the feasibility and predictive validity of such solutions as a guide for physiotherapists in their clinical practice when determining a personalized, blended physiotherapy treatment [7].

3. Discussion

Clinical inference in physiotherapy, supported by artificial intelligence (AI), is a fascinating field of research that combines advanced technology with medical practice. Using AI, physiotherapists can utilise huge patient datasets, predictive models and machine learning (ML) algorithms to aid in diagnosis, treatment planning and monitoring treatment progress. One of the key aspects of AI-supported clinical reasoning in physiotherapy is the analysis of patient data. This data can come from a variety of sources, such as electronic patient records (EHRs), health monitoring devices or even data from wearables. Machine learning algorithms are able to analyse this data and identify patterns and relationships that may be difficult for humans to detect. For example, they can help identify risk factors for injury, predict therapeutic outcomes or optimise a treatment plan [8-11]. In addition, AI can assist physiotherapists in clinical decision-making by generating therapeutic recommendations based on data analysis. These recommendations can be tailored to individual patients, taking into account their health status, preferences, and therapeutic goals. In this way, physiotherapists can make more informed and effective therapeutic decisions [12-15].
However, there are also challenges associated with introducing AI into physiotherapy practice. Care must be taken to ensure that patient data is properly secured, that predictive models are properly calibrated and validated, and that AI tools are easy to use and compatible with clinical practice. Clinical inference in physiotherapy, supported by artificial intelligence, has great potential to improve healthcare quality and therapeutic effectiveness. However, its successful implementation requires collaboration between scientists, engineers, physiotherapists and patients to ensure that AI tools are tailored to the specific needs and clinical context [16-19].
The development of cheap, reliable sensors and ML for motion capture and analysis facilitate the development of systems for automatic assessment of the patient's functional status and the progress of the rehabilitation process [20,21].

3.1. Limitations of current studies

Although AI-supported clinical reasoning in physiotherapy opens up many new possibilities, there are also important limitations that need to be considered:

– the effectiveness of AI/ML-based systems in physiotherapy is highly dependent on the availability and quality of data - incomplete, outdated or inadequately recorded data can lead to erroneous conclusions and therapeutic recommendations;
– even with sophisticated and validated ML algorithms, predictions may be subject to a degree of uncertainty, e.g. the model may misinterpret the data or fail to account for relevant factors, which may lead to incorrect diagnoses or treatment plans;
– interpretation of clinical data often requires additional subjective judgement on the part of the physiotherapist, which may be difficult for ML algorithms to capture and reproduce, hence the model may interpret the data in a way that is inconsistent with the physiotherapist's intentions or ignore important aspects of the clinical context.
– AI technologies continue to evolve and the predictive models and algorithms based on them need to be regularly updated and refined as new data and mechanisms are discovered - this is time-consuming and requires an ongoing commitment from specialists, as well as predicting the costs of keeping up to date;
– The introduction of AI into physiotherapy practice raises important ethical and legal issues (including those covered by the AI Act), such as patient data privacy, accountability for clinical decision-making and equality of access to healthcare, which need to be regulated accordingly [22-26].

Despite these limitations, AI/ML-supported clinical inference in physiotherapy has great potential to improve quality of care and therapeutic effectiveness within current and newly developed physiotherapy programmes. However, for this potential to be fully realised, it is necessary to understand and address these limitations when designing and implementing AI-based systems in physiotherapist clinical practice, including in line with evidence-based medicine (EBM) and evidence-based practice (EBP) paradigms [27-30].

3.2. Directions for further research

To date, several key directions for further research into AI-assisted clinical reasoning in physiotherapy have been identified. There is a belief that proper direction of research in this area areas may lead to faster development of this field:

– Research into more advanced predictive models may lead to a better understanding of the relationship between clinical data and physiotherapy outcomes, as modeling the complex interactions between various factors may enable more precise prediction of therapeutic outcomes and the identification of optimal treatment strategies for individual patients;
– Research on integrating data from various sources (medical records, medical imaging, health monitoring devices, genetic data and others) can provide more comprehensive information about a patient's health, which can help identify hidden patterns and relationships and personalize programs physiotherapy;
– The use of ML techniques to optimize physiotherapy interventions can help identify the most effective treatment strategies for specific cases or groups of cases. In this context, the ability to automatically or semi-automatically adapt physiotherapy programs based on clinical data and the patient's response to therapy may increase the effectiveness of physiotherapy and reduce the risk of complications/secondary changes/recurrences.
– The development of interactive decision support tools can make it easier for physiotherapists to analyze clinical data and generate therapeutic recommendations. AI-based second opinion systems can provide physiotherapists with relevant advice on a patient's health status and suggestions for best therapeutic practices;
– Increasing public awareness and trust in the use of AI in physiotherapy is extremely important, as it is necessary to better know, understand and take into account in clinical practice all issues related to data privacy, transparency of algorithm operation and responsibility for clinical decisions made with the use of AI [31-39].

Research in these directions may contribute to the further development of clinical reasoning in physiotherapy, supported by artificial intelligence, and improve the quality of health care for patients [40-43].

4. Conclusions

AI-based clinical reasoning support tools are gaining popularity in healthcare, but this is happening very slowly in physiotherapy. What is required is not only accelerated research, but also faster and more efficient implementation of systems and training of physiotherapists and building awareness among patients. The potential benefits of using AI-based vnixing systems are great in physiotherapy, but a balanced view of the strengths and limitations of this type of solution, careful vetting, treating them as second-opinion tools, and responsible and informed use in daily physiotherapy practice is required.

References

1. Granviken F., Meisingset I., Vasseljen O., Bach K., Bones A.F., Klevanger N.E., „Acceptance and use of a clinical decision support system in musculoskeletal pain disorders - the SupportPrim Project", BMC Med Inform Decis Mak. 2023, 23(1), 293. doi: 10.1186/s12911-023-02399-7.
2. Bilika P., Stefanouli V., Strimpakos N., Kapreli E.V., „Clinical reasoning using ChatGPT: Is it beyond credibility for physiotherapists use?", Physiother Theory Pract. 2023, 11, 1-20. doi: 10.1080/09593985.2023.2291656.
3. Sandal L.F., Øverås C.K., Nordstoga A.L., Wood K., Bach K., Hartvigsen J., Søgaard K., Mork P.J., „A digital decision support system (selfBACK) for improved self-management of low back pain: a pilot study with 6-week follow-up", Pilot Feasibility Stud. 2020, 6, 72. doi: 10.1186/s40814-020-00604-2.
4. Ryder R.M., Inamdar B., „An object-oriented, knowledge-based system for cardiovascular rehabilitation--phase II", Proc Annu Symp Comput Appl Med Care. 1995, 280-3.
5. Reis F.J.J., Bonfim I.D.S., Corrêa L.A., Nogueira L.C., Meziat-Filho N., Almeida R.S., „Uncovering emotional and network dynamics in the speech of patients with chronic low back pain", Musculoskelet Sci Pract. 2024, 70, 102925. doi: 10.1016/j.msksp.2024.102925.
6. Finucane L.M., Greenhalgh S.M., Mercer C., Selfe J., „Defensive medicine: A symptom of uncertainty?". Musculoskelet Sci Pract. 2022, 60, 102558. doi: 10.1016/j.msksp.2022.102558.
7. Kloek C.J.J., Janssen J., Veenhof C.. „Development of a checklist to assist physiotherapists in determination of patients' suitability for a blended treatment", Telemed J E Health. 2020, 26(8), 1051-1065. doi: 10.1089/tmj.2019.0143.
8. Mikołajewska E., Mikołajewski D., „Zastosowania automatyki i robotyki w wózkach dla niepełnosprawnych i egzoszkieletach medycznych", Pomiary Automatyka Robotyka 2011, 15(5), 58-63.
9. Lervik L.C.N, Vasseljen O,, Austad B., Bach K., Bones A.F., Granviken F., Hill J.C., Jørgensen P., Øien T., Veites P.M., Van der Windt D.A., Meisingset I., „SupportPrim-a computerized clinical decision support system for stratified care for patients with musculoskeletal pain complaints in general practice: study protocol for a randomized controlled trial", Trials. 2023, 24(1), 267. doi: 10.1186/s13063-023-07272-6.
10. Duch W., Nowak W., Meller J., Osiński G., Dobosz K., Mikołajewski D., Wójcik G.M., „Consciousness and attention

in autism spectrum disorders", Proceedings of Cracow Grid Workshop 2010, 202-211.
11. Foster N.E., Dunn K.M., Protheroe J., Hill J.C., Lewis M., Saunders B., Jowett S., Hennings S., Campbell P., Bromley K., Bartlam B., Babatunde O., Wathall S., Oppong R., Kigozi J., Chudyk A., „Stratified primary care for adults with musculoskeletal pain: the STarT MSK research programme including RCTs", Southampton (UK): National Institute for Health and Care Research; 2023.
12. Mikołajewska E., Mikołajewski D., „Roboty rehabilitacyjne", Rehabil. Prakt 2020, 4, 49-53.
13. Saunders B., Chudyk A., Protheroe J., Cooper V., Bartlam B., Birkinshaw H., Foster N.E., Hill J.C., „Risk-based stratified primary care for common musculoskeletal pain presentations: qualitative findings from the STarT MSK cluster randomised controlled trial", BMC Prim Care. 2022, 23(1), 326. doi: 10.1186/s12875-022-01924-3.
14. Al-Enezi L., May S., „Why do physiotherapists do what they do? A study of Kuwaiti physiotherapists", Physiother Res Int. 2017, 22(1), doi: 10.1002/pri.1640.
15. Prokopowicz P., Mikołajewski D., Mikołajewska, E., Kotlarz P., „Fuzzy system as an assessment tool for analysis of the health-related quality of life for the people after stroke". Artificial Intelligence and Soft Computing: 16th International Conference 2017.
16. Langridge N., Roberts L., Pope C., „The clinical reasoning processes of extended scope physiotherapists assessing patients with low back pain", Man Ther. 2015, 20(6), 745-50. doi: 10.1016/j.math.2015.01.005.
17. Mikołajewska E., Mikołajewski D., „Non-invasive EEG-based brain-computer interfaces in patients with disorders of consciousness", Military Medical Research 2014, 1, 1-6.
18. Riedel M., Kaefinger K., Stuehrenberg A., Ritter V., Amann N., Graf A., Recker F., Klein E., Kiechle M., Riedel F., Meyer B., „ChatGPT's performance in German OB/GYN exams - paving the way for AI-enhanced medical education and clinical practice", Front Med. 2023, 10, 1296615. doi: 10.3389/fmed.2023.1296615.
19. Su M.C., Lin L.E., Lin L.H., Chen Y.C., „Assessing question characteristic influences on ChatGPT's performance and response-explanation consistency: Insights from Taiwan's Nursing Licensing Exam", Int J Nurs Stud. 2024, 153, 104717. doi: 10.1016/j.ijnurstu.2024.104717.
20. Yu P., Fang C., Liu X., Fu W., Ling J., Yan Z., Jiang Y., Cao Z., Wu M., Chen Z., Zhu W., Zhang Y., Abudukeremu A., Wang Y., Liu X., Wang J., „Performance of ChatGPT on the Chinese Postgraduate Examination for Clinical Medicine: Survey Study", JMIR Med Educ. 2024, 10, e48514. doi: 10.2196/48514.
21. Tessler I., Wolfovitz A., Livneh N., Gecel N.A., Sorin V., Barash Y., Konen E., Klang E., „Advancing medical practice with artificial intelligence: ChatGPT in healthcare", Isr Med Assoc J. 2024, 26(2), 80-85.
22. Biswas S., Dobaria D., Cohen H.L.. „ChatGPT and the future of journal reviews: A feasibility study", Yale J Biol Med. 2023, 96(3), 415-420. doi: 10.59249/SKDH9286.
23. Mikołajewska E., Mikołajewski D., „Neurorehabilitacja XXI wieku. Techniki teleinformatyczne", Impuls, Kraków 2011.
24. Sandal L.F., Stochkendahl M.J., Svendsen M.J., Wood K., Øverås C.K., Nordstoga A.L., Villumsen M., Rasmussen C.D.N., Nicholl B., Cooper K., Kjaer P., Mair F.S., Sjøgaard G., Nilsen T.I.L., Hartvigsen J., Bach K., Mork P.J., Søgaard K., „An app-delivered self-management program for people with low back pain: protocol for the selfBACK randomized controlled trial", JMIR Res Protoc. 2019, 8(12), e14720. doi: 10.2196/14720.
25. Sandal L.F., Bach K., Øverås C.K., Svendsen M.J., Dalager T., Stejnicher Drongstrup Jensen J., Kongsvold A., Nordstoga A.L., Bardal E.M., Ashikhmin I., Wood K., Rasmussen C.D.N., Stochkendahl M.J., Nicholl B.I., Wiratunga N., Cooper K., Hartvigsen J., Kjær P., Sjøgaard G., Nilsen T.I.L., Mair F.S., Søgaard K., Mork P.J.. „Effectiveness of app-delivered, tailored self-management support for adults with lower back pain-related disability: A selfBACK randomized clinical trial". JAMA Intern Med. 2021, 181(10), 1288-1296. doi: 10.1001/jamainternmed.2021.4097.
26. Nordstoga A.L., Aasdahl L., Sandal L.F., Dalager T., Kongsvold A., Mork P.J., Nilsen T.I.L.. „The role of pain duration and pain intensity on the effectiveness of app-delivered self-management for low back pain (selfBACK): Secondary analysis of a randomized controlled trial". JMIR Mhealth Uhealth. 2023, 11, e40422. doi: 10.2196/40422.
27. Little P., Stuart B., Stokes M., Nicholls C., Roberts .L, Preece S., Cacciatore T., Brown S., Lewith G., Geraghty A., Yardley L., O'Reilly G., Chalk C., Sharp D., Smith P., „Alexander technique and Supervised Physiotherapy Exercises in back paiN (ASPEN): a four-group randomised feasibility trial", Southampton (UK): NIHR Journals Library; 2014
28. Velikova G., Absolom K., Hewison J., Holch P., Warrington L., Avery K., Richards H., Blazeby J., Dawkins B., Hulme C., Carter R., Glidewell L., Henry A., Franks K., Hall G., Davidson S., Henry K., Morris C., Conner M., McParland L., Walker K., Hudson E., Brown J., „Electronic self-reporting of adverse events for patients undergoing cancer treatment: the eRAPID research programme including two RCTs", Southampton (UK): NIHR Journals Library; 2022.
29. Rojek I., Jasiulewicz-Kaczmarek M., Piechowski M., Mikołajewski D., „An artificial intelligence approach for improving maintenance to supervise machine failures and support their repair" Applied Sciences 2023, 13 (8), 4971.
30. Hartmann R., Avermann F., Zalpour C., Griefahn A., „Impact of an AI app-based exercise program for people with low back pain compared to standard care: A longitudinal cohort-study", Health Sci Rep. 2023, 6(1), e1060. doi: 10.1002/hsr2.1060.
31. Zhang M., Zhu L., Lin S.Y., Herr K., Chi C.L., Demir I., Dunn Lopez K., Chi N.C., „Using artificial intelligence to improve pain assessment and pain management: a scoping review", J

Am Med Inform Assoc. 2023, 30(3), 570-587. doi: 10.1093/jamia/ocac231.
32. Rintala A., Rantalainen R., Kaksonen A., Luomajoki H., Kauranen K., „mHealth apps for low back pain self-management: scoping review", JMIR Mhealth Uhealth. 2022, 10(8), e39682. doi: 10.2196/39682.
33. Mikołajewska E., Mikołajewski D., „Informatyka afektywna w zastosowaniach cywilnych i wojskowych", Zeszyty Naukowe/Wyższa Szkoła Oficerska Wojsk Lądowych im. gen. T. Kościuszki 2013, 2(168), 171-184.
34. Alhussein G., Hadjileontiadis L., „Digital Health Technologies for Long-term Self-management of Osteoporosis: Systematic Review and Meta-analysis", JMIR Mhealth Uhealth. 2022, 10(4), e32557. doi: 10.2196/32557.
35. Hodges P.W., van den Hoorn W., „A vision for the future of wearable sensors in spine care and its challenges: narrative review", J Spine Surg. 2022, 8(1), 103-116. doi: 10.21037/jss-21-112.
36. Kopowski J., Rojek I., Mikołajewski D., Macko M., „3D printed hand exoskeleton - own concept", In: Trojanowska, J., Ciszak, O., Machado, J., Pavlenko, I. (eds) Advances in Manufacturing II. Manufacturing 2019. Lecture Notes in Mechanical Engineering. Springer, Cham. https://doi.org/10.1007/978-3-030-18715-6_25.
37. Zeng Q., Cimino J.J., „A knowledge-based, concept-oriented view generation system for clinical data", J Biomed Inform. 2001, 34(2), 112-28.
38. Broverman C.A., Clyman J.I., Schlesinger J.M., Want E., „Clinical decision support for physician order-entry: design challenges", Proc AMIA Annu Fall Symp. 1996, 572-6.
39. Johansson B.G., Wigertz O.B., „An object oriented approach to interpret medical knowledge based on the Arden syntax", Proc Annu Symp Comput Appl Med Care. 1992, 52-6.
40. Aggarwal V., „The application of the unified modeling language in object-oriented analysis of healthcare information systems" J Med Syst. 2002, 26(5), 383-97. doi: 10.1023/a:1016449031753.
41. Krol M., Reich D.L., „Object-oriented analysis and design of a health care management information system", J Med Syst. 1999, 23(2), 145-58. doi: 10.1023/a:1020545404268.
42. Piszcz A., „BCI w VR: imersja sposobem na sprawniejsze wykorzystywanie interfejsu mózg-komputer", Studia i Materiały Informatyki Stosowanej 2021, 13(1), 5-10.
43. Galas K., „Efektywność klasyfikacji mrugnięcia z wykorzystaniem wybranych sieci neuronowych", Studia i Materiały Informatyki Stosowanej 2021,13(1), 11-16.