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Artificial Intelligence in Brain Informatics

A systematic review of artificial intelligence for pediatric physiotherapy practice: Past, present, and future

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ABSTRACT

Background: Artificial intelligence (AI) is one of the active research fields to develop systems that mimic human intelligence and is helpful in many fields, particularly in medicine. ("Role of Artificial Intelligence Techniques ... - PubMed") Physiotherapy is mainly involving in curing bone-related pain and injuries. The recent emergence of artificially intelligent machines has seen human cognitive capacity enhanced by computational agents that can recognize previously hidden patterns within massive data sets. ("(PDF) Artificial intelligence in clinical practice ...") In this context, artificial intelligence in pediatric physiotherapy could be one of the most important modalities in delivering better medical and healthcare services to needy people. It is an attempt to identify the types, as well as to assess the effectiveness of interventions provided by artificial intelligence on pediatric physical therapy optimization-related outcomes.

Methods: Data acquisition was carried out by systematic searches from various academic and research databases i.e., google scholar, PubMed, and IEEE from March 2011 to March 2021. Besides, numerous trial registries and grey literature resources were also explored. A total of 187 titles/abstracts were screened, and forty-eight full-text articles were assessed for eligibility.

Conclusions: This research describes some of the possible influences of artificial intelligence technologies on pediatric physiotherapy practice, and the subsequent ways in which physiotherapy education will need to change to graduate professionals who are fit for practice in the 21st century health system for promoting safe and effective use of artificial intelligence and the delivery of Pediatric Physical Therapy care to people.

1. Introduction

Artificial intelligence (AI) is one of the fields of computer science with a mathematical process that has the potential to enhance the healthcare system via novel delivery strategies, informed decision making, and facilitation of patient engagement. It can be used to automate decision-making and make predictions based upon patient data. The characteristics of this technological advancement are already influencing every aspect of society and creating the conditions for the disruption to human socio-economic, educational, health, legal, and moral systems, and which may have a more significant impact on human progress [1].

Physiotherapists often work with other health professionals to satisfy individual's healthcare needs. Unfortunately, the demands for physiotherapists are increasing than ever before, but the supply is quite limited. Physiotherapy has several benefits which include avoiding surgery, improved mobility, development, management of the age-associated illness, as well as improved balance too [1]. With the rise in demand for physiotherapy, its demand reception is additionally increasing. But we cannot deny the very fact there are some advantages of physiotherapy reception. Better health outcomes are immensely observed when an individual is surrounded by people with whom they feel connected and reception, they feel highly positive. Also, it is well observed that reception healing is completed quicker.

Indeed, it is seen that the innovation in the field of medication has been well demonstrated advantageous. A fluctuated measure

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of utilizations is being created which are making the existence of specialists just as patients simpler. Advancements like augmented simulation, man-made consciousness, and AI are among the most mainstream ones in medical applications [2]. An exoskeleton is one of them which is utilized for arms, legs, and hands videogames that persuade patients to move and propels them to improve. With the help of applications like these, medical technology therapists are getting the tools they need to provide the type of care and support that patient in need require. ("Artificially Intelligent Physiotherapy: Medicine ...") It also immensely minimizes therapist workloads and allows them to treat more patients than hitherto [3]. As a result, the advancement of medical technology with the help of cutting-edge computational technology has inspired us to create a system that will change the lives of therapists as well as patients everywhere.

In any movement how efficiently, the muscle is working that can be seen immediately with the help of Electromyography (EMG). It does not require any wire connection. Some probes are good enough to provide real-time data for us with the help of this data, one can obsolete those exercises for which better alternatives are available [4]. A recent study indicating that this is the best exercise for the core and biceps. It will bring uniformity in the guidance of the personal trainer, athletic trainers as well as physiotherapist. The pre-post treatment analysis will give us the exact improvement in objective terms. Return to sports will be calibrated more precisely than before and it is preventing any avoidable delay for the athlete [5]. It shows what kind of treatment is working bro what extent for the patient. The future of healthcare in Saudi Arabia looks bright and quite promising. AI with Femtophotography is something that has good potential in medical imaging which will help on-field physiotherapists in identifying the potential causes of field injuries.

1.1. Materials and methods

This scientific communication was conducted by the recommendations of the "Cochrane Handbook for Systematic Reviews" of Interventions [6]. This systematic review fulfills the Preferred Reporting Items for Systematic Reviews and Meta-Analyses statement too [7].

2. Criteria for considering and search strategy

All the chosen research studies that met the Cochrane Effective Practice and Organization of Care Group [26] exclusion and inclusion criteria were included in this review. It includes randomized controlled trials (RCT), non-randomized controlled trials (NRCT), controlled before-and-after studies (CBA), and interrupted time series analyses (ITS). Other kinds of study designs were excluded as they cannot be used to establish causation between interventions and outcomes (see Fig. 1).

Different electronic bibliographical databases were searched from date of March 2011 to March 2021. The search strategy involved a various combination of medical subject headings (MeSH) and keywords, relating to 'Artificial intelligence', 'Pediatric Physical Therapy', 'Physiotherapy Education', and the outcomes of interest, as well as truncation adapted for the requirements of each database. The MEDLINE search strategy was adapted for other databases too [8]. The searches were primarily conducted in the English language, but citations identified in any language were considered. To identify further published, unpublished, and ongoing trials, clinical trial registries and grey literature resources in addition to the websites of non-profit organizations were also explored for relevant appropriate studies. Citation tracking using Web of Science Cited Reference Search for all included studies, if any, was also planned. Finally, references of included studies, if any, were to be hand-searched to identify further additional studies. ("A systematic review of pharmacists' interventions to ...")

2.1. Artificial intelligence

The first attempt of AI and its application in public health and medicine specialties were begun in the 1960s, with a major focus on diagnosis and treatment [9]. Ted Shortliff of Stanford University and his pioneering MYCIN project are the most well-known early work in the medical AI field. MYCIN is a rule-based expert system with "if-then" rules and certain values. It was recommended to choose antibiotics for various infectious diseases [10,11]. Although MYCIN has not been used clinically, it has been proven to be superior to human infectious disease experts. In 1982, Scholowitz published a textbook on medical artificial intelligence, which contained a collection of research articles on various topics in the field. For physical therapists who have received the functional diagnosis, biomechanics is one of the best assessment tools [12]. Advanced analysis of the range of motion is done with a goniometer, but as technology advances, you can do more than you think. Use this motion analyzer to record EMG activation and muscle relaxation.

It might be helpful to think about what we mean by intelligence and, by implication, what we do not mean to better grasp what artificial intelligence entails. Reasoning, organizing, problem solving, abstract thinking, comprehending complex concepts, and knowing from experience all fall under the umbrella of intelligence [13]. It also represents a strong and deeper knowledge of our surroundings. This concept of intelligence makes no mention of self-awareness, conscience, sentiment, or morals, nor does it imply that intelligent behavior is inherently human [14]. Furthermore, nothing in this concept of intelligence implies that non-human intellectual behavior can be modeled after human thought processes. "There are a lot of ways to be smart that aren't smart like us," [14]. Today, AI is a multidisciplinary domain of study that uses computational, statistical, logical, mechanical, and biological concepts and devices to try to explain, model, and reproduce knowledge and cognitive processes [15].

It is the research into the development and interpretation of computational agents that exhibit intelligent behavior. In the field of artificial intelligence, an autonomous agent is something that behaves in a way that is suitable for its situations and objectives. In other words, given its perceptual and computational limits, the agent can respond to evolving contexts and goals, benefit from the experience, and make reasonable decisions [16]. The first is the widespread availability of low-cost computing. The second factor is the availability of large data sets on which machine learning algorithms can be equipped [17]. The third step is to refine programming methods and create more complex algorithms. The convergence of these three characteristics has resulted in an improvement in AI-based algorithms' ability to conclude in unknown circumstances that, in many ways, outperform human performance [18].

Today, AI-based research has resulted in the use of expert systems to direct clinical decision-making, machine vision algorithms that outperform humans in the study of Computerized Tomography (CT) and Magnetic Resonance Imaging (MRI) scans, improved diagnostics and assessment of medical outcomes, and improved administration and preparation in health systems [19,20]. Furthermore, developments in AI science are being made in the fields of information processing and retention, problem-solving and logic, image recognition, preparation, and physical manipulation. It is worth remembering that these are, in general, central features of physiotherapy practice. As a result, it is fair to speculate that much of physiotherapy practice could become increasingly susceptible to automation by AI-based systems. The primary aim of this paper is

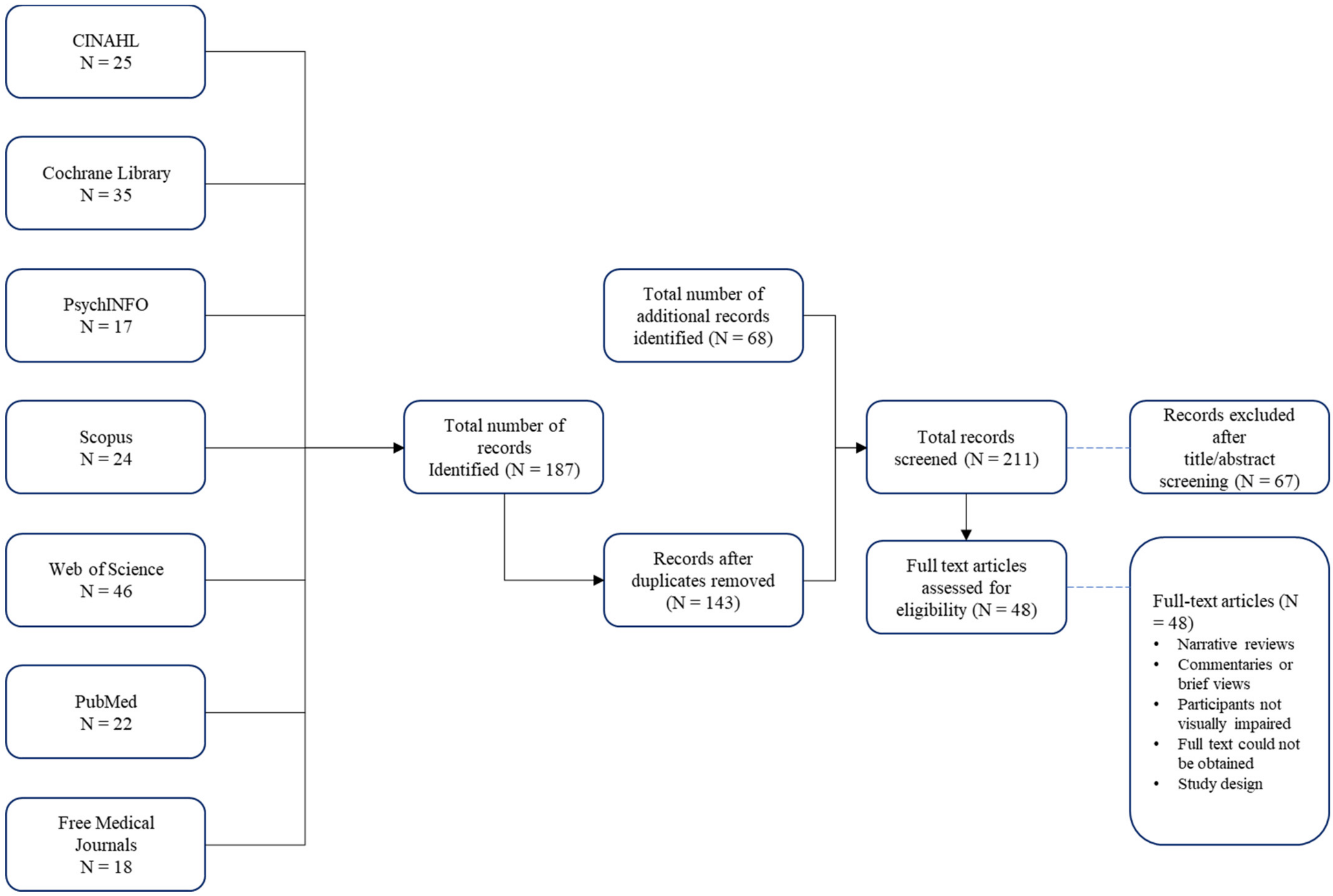

Fig. 1. Preferred reporting items for systematic reviews and meta-analyses flow diagram of screening process and reasons ("Conducting Research with Visually Impaired Older Adults").

to investigate the possible effect of AI-based technology in clinical practice, as well as the resulting changes that physiotherapy education might undergo to graduate practitioners who are ready to practice in the twenty-first century healthcare system [21].

3. Artificial intelligence in physiotherapy

Humans have long used education to respond to socio-economic commotion [22]; it is how we upgrade ourselves. However, as robots get smarter and the rate of progress quickens, the intrinsic worth of a technical degree declines [23]. As a result, in the recent decades having consistent access to technical education across our working lives will become exceedingly necessary. We can rethink physiotherapy edification as a time-limited degree program with which people graduate once in their lifetime and instead view it as a forum for enduring learning that offers learners customizable modules that they can practice whenever they need to [24]. This would be imperative as many learners return to higher education during their careers to remain ahead of technological advancement.

Furthermore, [25] focusing only on educating prospective healthcare practitioners will not suffice, since the speed of AI adoption in healthcare systems will rapidly outpace the retirement of practicing clinicians. In other words, [26] fresh physiotherapists will be incompetent to perform effectively as they are incapable to interact and work with AI-based programs. Neglecting professional learning may have become less serious in periods of incremental transition, but it would be troublesome in an age of profound restructuring that necessitates the retraining of thousands of clinicians. As a result, [27] we must develop better frameworks for continuing professional growth that help to provide existing practitioners with the expertise and skills that are extremely essential for professional practice in an intelligence era, yet to cultivate a flexible mentality that allows them to respond to a continually evolving workplace.

It is a matter of grave concern in physiotherapy education [28] shortly. It should not be contentious to say that the discipline is traditionally conservative, and that undergraduate education tends to prioritize experience and skills acquired over the agency required by students to negotiate unpredictable and evolving futures [29]. The new, more memorization-based program must be replaced by one that incorporates three fundamental literacies into the core physiotherapy curriculum i.e. (a) data literacy, (b) technical literacy, and (c) human literacy [30]. The clinicians require data literacy to read, analyze, understand, and use large datasets as they become single nodes (and perhaps not even the most significant nodes) within the knowledge networks [31,32]. As they are essential to interact more collaboratively with AI-based programs, they may need computational literacy to acquire the language of computer science and engineering as well as to interact with machines. Otherwise, the medics can merely be messengers and the technicians carrying out the commands specified by algorithms [33,34]. Finally, when robots take on computing and logic roles traditionally done by humans, physicians may need human literacy that is outside the reach of machine learning systems, assisting them in developing expertise of empathy, collaboration, and creativity [35,36].

With a pain prevalence of 30–50 percent in the United Kingdom, another application of controlled ML is the assignment of persons as pain phenotypes based on brain MRI [37]. The presence of pain without correlative tissue pathology, as well as the reliance on self-reporting for subgrouping, makes identifying the neuronal causes of pain a significant task. Outline the usage of ML to assign subjects of a predicted pain phenotype; summarize ML applications used in longstanding pain (not exclusively musculoskeletal). ("Artificial intelligence and machine learning ...") The study investigates experimental pain and low back pain (LBP) but does not conclude the efficacy of ML categories.

Based on brain MRI, ML approaches establish variable precision in distinguishing between people with discomfort and comfort. Biomarkers (for example, grey matter volume/density or functional connectivity between regions) may be used as a proxy for self-reporting [38]. The results of these findings are debatable given the heterogeneity of ache and the diverse interplay of various etiological, genetic, and environmental factors. Furthermore, perhaps practical MRI has a higher degree of precision, but it is often underutilized in terms of routine measurement of pain. Table 1 shows the ML's precision in identifying brain phenotype variations for different pain disorders (e.g., LBP, fibromyalgia) [39]. Nevertheless, the possible therapeutic application of ML-classified MRI for anatomical phenotyping of pain can emerge.

Wearable technology provides a rich source of epidemiological evidence through monitoring physical behavior; it is extremely useful in the management of chronic illness [40]. After being a predictor of good recovery, exercise adherence is often low. Data obtained by inertial sensors in wearable technology can be identified to determine if participants are correctly practicing and adhering to exercise protocols [41]. This was measured in an asymptomatic population (n=20) that followed a rotator-cuff exercise protocol while wearing an Apple iWatch. Various supervised learning approaches were used to classify exercise accuracy (in comparison to an existing dataset of "successful" performance), with excellent accuracy across all algorithms [42]. A neural network achieved 99.4 percent recognition accuracy, showing potential for the use of wearable devices and machine learning for exercise tracking. Due to the variable obstacles to adherence associated with exercise efficiency, it is possible that measuring performance by wearable devices alone would be inadequate to maximize adherence [43,44]. However, such data can be used to classify and alter patient behavior for therapeutic advantage.

Frontal plane knee biomechanics are linked to knee injury risk estimation. Researchers used inertial sensor data to identify single-leg squat results based on the degree of knee valgus (n=14, 140 images) and the opinions of three specialist raters on possible risk. They used supervised learning to divide the world into three categories ("poor," "moderate," and "good") [45]. The findings revealed that the accuracy was high during moderate categories but decreased by 30 percent when the difficulty of 3-class classification was introduced. Supervised learning regression has also been used to model internal knee abduction moment from video recordings of lower limb joint angles at gait. 3131 images were analyzed, and multiple ensemble (multi-layer) learning techniques performed well in estimating abduction moment [46]. Despite a lengthy training period, a neural network approach was determined to be the best predictor of knee power. These studies indicate that ML can analyze visual and inertial sensor data to predict injury risk trends associated with complex knee valgus. However, since accident risk is multifactorial, biomechanical.

Indeed, clinical decision support systems (CDSS) make diagnosis and care decisions. For LBP, systems such as the Start Back risk stratification tool, which defines prognostic markers to identify individuals into risk categories, have been created, as has a digital CDSS to stratify patients to self-management, GP participation, or self-referral to physiotherapy. An ontology and decision tree were created to identify subjects based on 43 decision factors, including general factors (e.g., occupation), 'psychosomatic' factors (e.g., stress, kinesiophobia), and severe pathology indications (i.e., red flags) [47]. Following that, supervised ML algorithms were used to identify individuals using the CDSS, with all individuals ranked higher than random allocation. This shows that the CDSS can be used effectively with ML to identify subjects, and further advancements may make the mixture more rigorous than human decision-making. In comparison, the human capacity to classify patients as a moderate, medium, or high risk using StartBack ranges between 72.1 and 78.1 percent sensitivity and 42.91–75 percent precision. Thus, in the future, ML can provide more precise service allocation while increasing the usability and speed of self-referral.

In the musculoskeletal area, there are few cases of unsupervised learning approaches being used. The Chronic Pain Challenge uses weighted values for health behaviors to estimate the likelihood of pain chronicity. It employs both controlled and unsupervised approaches, demonstrating precise pain (visual analog scale) and Oswestry Disability Index estimation based on related stress, diet, and physical activity ratings. Although this demonstrates the ability for machine learning (ML) to identify chronicity risk based on patient-reported results, the precision of unsupervised learning alone has not been identified. Digitization renders healthcare data available to algorithms, and the ML heavily relies on massive databases to precisely predict. Unsupervised learning is often used in data mining to allow new findings of risk or cause where doctors cannot perceive trends. Such methods have been used to classify signs of a chronic fatigue syndrome from a variety of data points. It is extremely pivotal to ensure data format, consistency, and protection to avoid bias from being introduced into algorithms and to preserve public interest in the use of health data [48].

Perhaps, health monitoring programs pose serious questions about data safety, but the patterns can be easily identified even with anonymized data. Therefore, physiotherapists should participate in digital innovation by being more computer-literate, and clinical development programs should provide data analysis fundamentals to train physicians for future practice. Physiotherapists should become interested in the standardization of diagnostic coding protocols to improve data accessibility and assist in the advancement of bespoke IT platforms, rather than the reactive, plugin modifications that are common in the healthcare domains [48]. This should expand interoperability within (and between) organizations, facilitating data exchange, which is quite critical in the unsupervised learning methods.

4. Conclusion

Indeed, artificial intelligence technologies are constantly pushing for improvements in the healthcare sector that would have far-reaching implications on how healthcare is delivered in the twenty-first century. These rapid transformative developments demand all healthcare professionals reassess their suitability in an intelligence era well-defined by smart computers, large data sets of immense sophistication, and radically different relationships with patients and algorithms. We should certainly take seriously the idea that yesterday's health careers will – and maybe should – be at least partially replaced by more suitable alternatives, such as AI-based schemes and less expensive alternatives. Perhaps, intelligent algorithms are now much smarter than humans in some specialties, and good clinical practice shortly would demand a higher understanding of how to view computer guidance, when to delegate authority to them, and when to disregard it. Based on our inclusion criterion, this systematic analysis found that no qualifying findings on pharmacist-provided interventions to promote medication optimization in patients with visual disability. Certainly, it demands

Table 1
AI techniques for musculoskeletal applications.

Country	Year	Classification question	Classification	Data source	Algorithm used	References
London, UK	2019	Can the risk of injury be classified based upon movement quality?	Structural MRI	CLBP	SVM	Aleksandar Vakanski
UK	2017	Is pathology present or not?	Fracture	X-ray	16-layer CNN	Ashinsky et al.
California	2014	Is pain neuro mapping phenotype identifiable with the clinical diagnosis?	Spondylolisthesis	MRI	CNN	Bagarinao et al.
China	2018	Can successfully exercise performance be identified?	Cartilage mapping	CPP	WND-CHRM	Burns et al.
USA	2014	Can the risk of injury be classified based upon movement quality?	Structural MRI	CLBP	SVM	Callan et al.
Sweden	2015	Can CLBP subgroups be stratified accurately?	Accurate exercise performance	FM	LR, MP, Bayes	Gin's Hidalgo
USA	2016	Can different gestures be described precisely?	Risk of injury	CLBP	SLR	Hideki Murakoshi
Manchester, UK	2017	Can the user's exercise pose be detected accurately?	Physiotherapy	Inertial Sensor	SVM, LR	Hisashi Hayashi
Australia	2017	Can patient's performance in prescribed	DTW	HER	CNN k-NN SVM	Jamaluddin et al.
London, UK	2018	rehabilitation exercises improved?	Human Movement	Camera	10F-CV	Jian Li
UK	2017	Is the ball entering the basket or not as a binary target variable?	Real time diagnosis	Motion Sensors	10F-CV LOSO-CV	Kianifar et al.
California	2017	Can the whole-body pose be estimated?	Confidence map	Video motion	DT BT	López-Solà et al.
China	2019	Is pathology present or not?	Fracture	COCO dataset	CUDA	Martínez
USA	2020	Is pain neuro mapping phenotype identifiable with the clinical diagnosis?	Spondylolisthesis	X-ray	16-layer CNN	Masato Nakai
Sweden	2018	Can successfully exercise performance be identified?	Cartilage mapping	MRI	CNN	Min Xian
USA	2016	Can the risk of injury be classified based upon movement quality?	Structural MRI	CPP	WND-CHRM	Nijewemed'Hollosy et al.
Manchester, UK	2014	Can CLBP subgroups be stratified accurately?	Accurate exercise performance	CLBP	SVM	Olczak et al.
Australia	2013	Can different gestures be described precisely?	Risk of injury	FM	LR, MP, Bayes	Richard Yang
California	2015	Can the user's exercise pose be detected accurately?	Physiotherapy	CLBP	SLR	Robinson et al.
China	2012	Can the user's exercise pose be detected accurately?	Physiotherapy	Inertial Sensor	SVM, LR	Sen Qiao
USA	2011	Can patient's performance in prescribed	DTW	HER	CNN k-NN SVM	Steven Chen
Sweden	2012	rehabilitation exercises improved?	Human Movement	Camera	10F-CV	Ung et al.
USA	2010	Is the ball entering the basket or not as a binary target variable?	Real time diagnosis	Motion Sensors	10F-CV LOSO-CV	Yalin Liao
Manchester, UK	2014	Can the whole-body pose be estimated?	Confidence map	Video motion	DT BT	Yilin Wang
Australia	2017	Can CLBP subgroups be stratified accurately?	Fracture	COCO dataset	CUDA	Yoshihiko Tsunoda

further research to investigate the types of treatments that could aid in the optimization of medications in these patients. It is also imperative to test and compare the efficacy of various approaches using rigorous research formats.

Declaration of competing interest

The authors declare that they have no conflict of interest.

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