Effectiveness of Intelligent Control Strategies in Robot-Assisted Rehabilitation—A Systematic Review

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***Abstract*— This review aims to provide a systematic analysis of the literature focused on the use of intelligent control systems in robotics for physical rehabilitation, identifying trends in recent research and comparing the effectiveness of intelligence used in control, with the aim of determining important factors in robot-assisted rehabilitation and how intelligent controller design can improve them. Seven electronic research databases were searched for articles published in the years 2015 – 2022 with articles selected based on relevance to the subject area of intelligent control systems in rehabilitation robotics. It was found that the most common use of intelligent algorithms for control is improving traditional control strategies with optimization and learning techniques. Intelligent algorithms are also commonly used in sensor output mapping, model construction, and for various data learning purposes. Experimental results show that intelligent controllers consistently outperform non-intelligent controllers in terms of transparency, tracking accuracy, and adaptability. Active participation of the patients and lowered interaction forces are consistently mentioned as important factors in improving the rehabilitation outcome as well as the patient experience. However, there are limited examples of studies presenting experimental results with impaired participants suffering limited range of motion, so the effectiveness of therapy provided by these systems is often difficult to quantify. A lack of universal evaluation criteria also makes it difficult to compare control systems outside of articles which use their own comparison criteria.**

***Index Terms*— Control systems, human joints, machine intelligence, physical human-robot interaction, rehabilitation robots.**

I. Introduction

STROKE, other neurological diseases, and debilitating injuries can cause major, often lifelong, problems for their sufferers in the form of decreased mobility. Between the years 1990 and 2019 there were more than 12.2 million new stroke cases each year, and by 2019 over 101 million people live post-stroke according to the 2022 global stroke factsheet [1]. Studies have shown that physical impairment is a frequent effect of acute stroke, reporting that up to 80% of acute stroke victims experience some form of limb impairment [2]. The most prevalent and effective method to treat stroke-related motor disability is physical therapy led by a physiotherapist, but the ever-increasing number of stroke patients puts more and more pressure on healthcare services. According to the NIH, standard inpatient treatment involves 3 hours of intensive treatment 5-6 days a week for up to 3 weeks, while outpatient treatment requires frequent hospital presence for several hours up to 3 days a week [3]. While stroke victims comprise the majority of patients requiring this kind of treatment, there are many other diseases and injuries which require similarly intensive rehabilitation, including but not limited to drop foot, osteoarthritis, muscular dystrophy, various sporting injuries like sprains or fractures, and recovery from other medical procedures like joint replacements.

With the ever-increasing burden on therapists caused by the labor-intensive nature of treatment for physically impaired patients, robotic rehabilitation is an open research field focused on developing systems to aid in the physical therapy of joints. This can be achieved by reducing the workload on therapists, providing more accurate therapeutic exercises guided by the robot, and increasing safety for both the therapist and their patient [4]. Many different systems have been developed in this field to be used for various joint exercises such as gait, ankle, and wrist rehabilitation [5], [6], [7], as well as specific research into the actuation and control of these systems [8]. The effectiveness of these systems is reliant on their ability to perform rehabilitation exercises accurately and repetitively. The safety of using these robots is also paramount as direct human-robot interaction is implicit in their design.

A number of reviews exist concerning rehabilitation robotics generally [9], [10] as well as specific applications of rehabilitation robotics [11], [13], and control techniques used in the field [12], [14]. This paper aims to systematically search and review articles focusing on machine intelligence used in control systems for physical rehabilitation robotics. The

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relative effectiveness of these systems in terms of rehabilitation outcomes will be discussed and compared, important factors in improving rehabilitation outcome will be determined, and any notable research trends found will be established. In particular, the benefits and shortcomings of commonly used intelligent controllers will be discussed in the context of rehabilitation robotics.

A comprehensive search and discussion of literature focused on intelligent control of rehabilitation robotics, published in the years 2015 to 2022 to ensure up to date research, will be presented. Experimental and clinical data published as part of these articles will be examined and analyzed.

II. Method

A. Search Strategy

This review was limited to articles, including journal articles, conference proceedings and book chapters, published online in English. This includes articles not originally published in English which have since been translated into English. The search only includes articles published between the years 2015 – 2022. As the field of machine intelligence is rapidly increasing in popularity, the scope of this review is limited to the most recent publications and advances in the field.

Seven electronic databases were chosen for this review based on relevance to the subject area of medical engineering and volume of articles available: PubMed, ScienceDirect, Web of Science, DOAJ (Directory of Open Access Journals), Cochrane Library, Wiley Online Library, and IEEE Xplore. A free search of Google Scholar was also conducted to ensure the search was as thorough as possible and included relevant publications missed in the database search.

The search terms and search strings used for each database were tailored to the specifics of the database's search function to ensure each search was as comprehensive and relevant to the research question as possible. The general search terms used were "Robot∗" AND "joint∗" AND ("rehabilitat∗" OR "treat∗") AND "control∗" AND ("system∗" OR "algorithm∗").

B. Inclusion/Exclusion Criteria

Robotics has been defined as "The application of electronic, computerized control systems to mechanical devices designed to perform human functions [15]", while a control system or control strategy is "a system of devices or set of devices, that manages, commands, directs or regulates the behavior of other device(s) or system(s) to achieve desire results [16]". This review will consider software control systems to be defined as "devices" in this nature, and thus any article utilizing a software control system will be included. Any robot not using a control system that is in some way automatic will be excluded. Articles that focus on bioelectric feedback such as surface electromyography will be included only if they also include comparison or reference to other control systems, as this constitutes a sensing system rather than a control system.

A Rehabilitation robot will be defined as any robot designed to aid in the physical therapeutic recovery of a person suffering from neurological or physical injury. As the aim of this review is to determine important factors in improving rehabilitation outcome, articles on purely assistive robots such as assistive exoskeletons or prosthetics will be excluded as their purpose is not rehabilitation of the targeted limb, rather assisting their motion for day-to-day tasks. As the review focusses on the rehabilitation outcome and control schemes used, there will be no intentional bias or exclusion criteria concerning which limb or joint is targeted for rehabilitation.

Articles including clinical trials of rehabilitation robots as well as simulation results will be included, so long as there is sufficient mention of the control system used.

This review focuses on intelligent control strategies used in rehabilitation robotics. Machine intelligence is notoriously difficult to define [87] with multiple conflicting definitions in literature [88], so here intelligent control systems will be defined as any which use machine learning or data-driven adaptation to adjust any control parameters, either during use or for optimisation of the control system parameters. Any article concerning the type of intelligent control system used in a rehabilitation robot will be included, with a particular focus on those which quantify the effectiveness of any control strategies mentioned. Articles not mentioning a control system, or those with no particular focus on the control system used, will be excluded, as well as articles which present traditional control strategies lacking intelligence.

C. Stages of Review

After searching each database, the articles were collated in a document for screening. Identical articles found in multiple databases were removed. The article titles were then screened for relevance to the research question, and some were removed based on the inclusion/exclusion criteria.

The abstracts of the remaining papers were then read, and the papers further screened for relevance with more thorough exclusion criteria. The full text of the final articles in review were then read and organized based on relevant research for discussion and data extraction. Articles found during the Google Scholar free search were included at the abstract screening stage as they were initially selected based on title relevance during the search.

D. Search Results

A total of 635 articles were found using the search method detailed in the previous section. 123 of these were found to be duplicates from different databases and were removed, resulting in 512 unique articles. 196 of these articles were removed based on their titles due to the exclusion criteria, mostly due to irrelevance in the subject area of control systems and rehabilitation robotics. 68 articles were excluded based on reading their abstracts due to lack of focus on control systems in favor of the mechanical design of the robot instead. Several literature review articles were also excluded at this stage. 248 articles met the inclusion criteria based on their abstracts, while 17 further articles were found during the Google Scholar free search which met the inclusion criteria.

After reading the full text, 48 of the remaining articles were excluded from review due to having little or no relevant discussion concerning control systems, a further 91 were excluded later due to lack of unique or relevant data and discussion points, and 56 were excluded due to exclusively using traditional controllers with no intelligence. 70 articles met the inclusion criteria for this review, discussing intelligent control systems used in various types and models of rehabilitation robots and their relevant successes/failings.

III. Results

Intelligent control systems have become a major focus of research for rehabilitation robotics in recent years given their ability to adapt to patient specific needs, enhancing safety and effectiveness of treatment. Most articles making use of an intelligent controller focus on it as a specific subject of research, some alongside the development of a rehabilitation robot, but others apply the controller to an existing robot.

Figure 1 shows a generalised control system diagram for a rehabilitation robot, including both feedforward and feedback loop, as well as the potential usage of various sensors and sources of noise and disturbances to the system. Not all features shown in the diagram will be present in all developed systems depending on the type of controller and its intended specific use case. The labeled control system section of the diagram will differ greatly from study to study. As such figures 2 and 3 present more specific controller cases, which are discussed in detail in later sections.

Two main control paradigms are present in terms of rehabilitation robotics control, being passive and active control. Passive control focuses on position, with the robot guiding a patient's joint through a series of predetermined motions with little or no sensing or human input to guide the training. This sort of control is suitable for patients with little motor function in the targeted joint but is inherently non-compliant and therefore the motion must be carefully regulated to ensure proper training is achieved and safety is ensured. Active control regulates the applied torques of the robotic joint to assist or resist the motion of the patient, in order to either guide motion to build muscle plasticity or provide resistance to improve strength. Certain control schemes are more suitable for either passive or active training, depending on their ability to react to disturbance or sensor input and whether they are specifically designed to follow trajectories or to provide torque outputs. Many articles present both passive and active training methods, often with different control schemes used for each.

A. Control Optimisation

Proportional Integral Derivative (PID) and Proportional Derivative (PD) controls are often used as the baseline controller for many robotic systems. These traditional control schemes use gain parameters for the input, its integral function, and derivative depending on the implementation to calculate control signals. Some research has gone into optimizing traditional control algorithms by applying intelligent algorithms to adjust the control gain parameters, allowing the linear controllers to perform more dynamically and more effectively reject disturbances to the system by dynamically responding to error. Particle swarm algorithms are used to optimize PID parameters in [60], [77], [78], and [80], with [78] developing a novel artificial bee colony algorithm for parameter optimisation. Particle swarm algorithms use a number of agents referred to as 'particles' in a search space of dimensions equal to the number of parameters and use an iterative process to move these particles towards an optimal solution for some objective function. Sharing of information between particles allows the 'swarm' to behave as a group, which speeds up the process. Adaptive simulated annealing method is used for parameter optimisation in [59]. Zeigler-Nichols is used in some articles for optimisation but is only mentioned briefly and is rarely a topic of focused research, however [78] does compare two intelligent optimisation techniques with Zeigler-Nichols as a baseline. This optimisation method is specific to PID control and relies on raising the proportional gain value until the system is unstable, then calculating the integral and derivative gains based on the resulting oscillations. Results from these articles show that optimised versions of the controller consistently have better motion tracking accuracy and robustness to external disturbances and noise. The comparison results from [78] found that the developed artificial bee colony optimisation method performed better than swarm optimisation and Ziegler Nichols in terms of error correction and settling time but had a slower response time.

Genetic Algorithms (GA) are used in several cases for optimisation of different control schemes. This optimisation method generates a population of solutions and iteratively 'evolves' them based on the objective function by sharing traits and randomly assigning new ones. GAs are used to optimize the respective control strategies in [40], [53], [54], [55], and [56], while [52] uses GA to estimate friction for the robot dynamic model. GA is used to optimize joint angle and velocity parameters in a control system with a multi-layer perceptron neural network in [40]. A GA presented in [53] is used to determine and optimize impedance parameters. This controller was validated in an experiment with a patient to provide good compliance and low patient-machine interaction torques. GA is used to optimize PD control in [54], and for Sliding Mode Control (SMC) in [55] and [56].

B. Fuzzy Logic Control

Despite existing for decades, fuzzy logic has become a popular logic structure for controllers in recent years with many articles utilizing it for controller development since 2015. Fuzzy logic is considered a subset of AI given its ability to make decisions by grouping continuous data into discrete subsets. This allows for many inputs/outputs to be accommodated and can assist with modelling nonlinear systems. Fuzzy logic is often applied to non-intelligent controllers such as PID as a method to improve their functionality. Fuzzy PID controllers are used in [17] and [25], with [18] using fuzzy PD control. Fuzzy SMC is used for motion control in [19], [20], [21], [22], [27], [28], and [29]. Fuzzy logic is used for impedance control in [20], [26], and [30] and for admittance control in [21] and [29]. Impedance control uses the ratio of position and force to

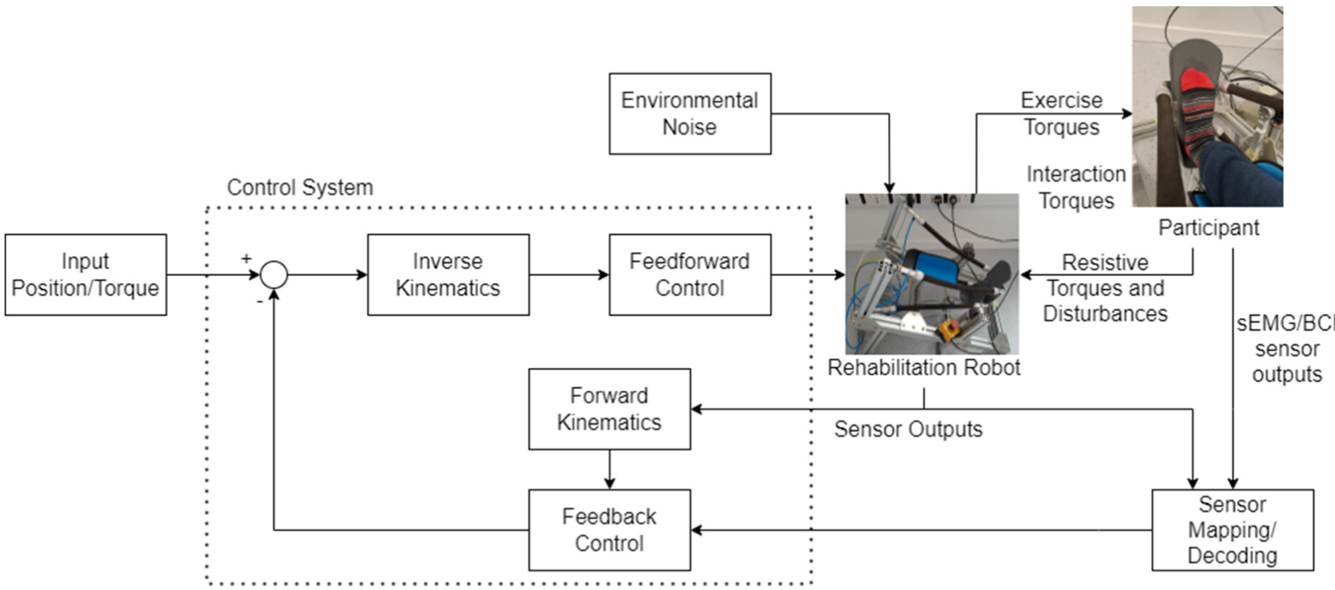

Fig. 1. A generalised diagram for control of a rehabilitation robot. An ankle rehabilitation robot is used as an example.

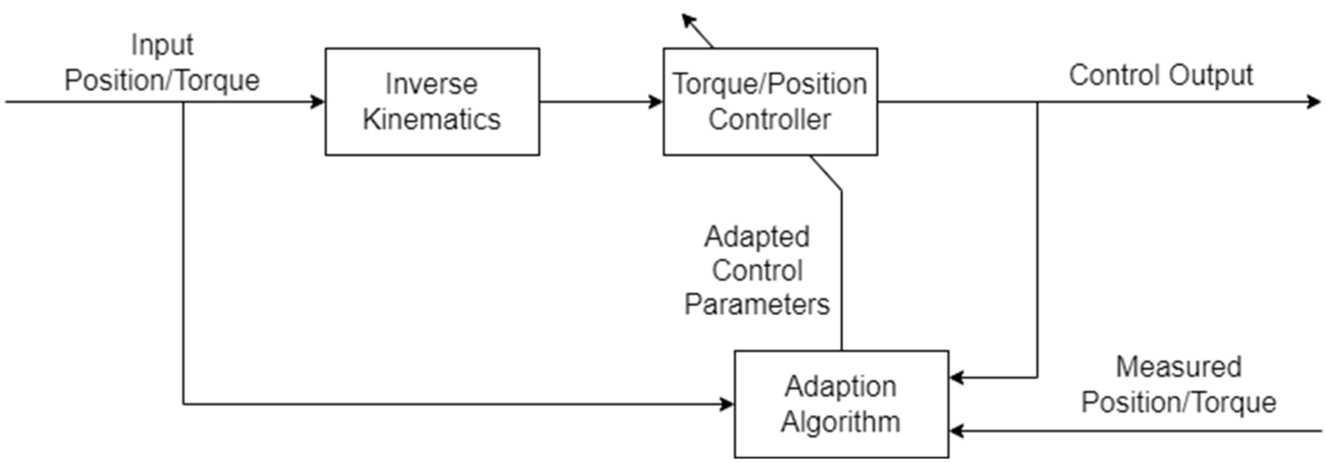

Fig. 2. A generalised adaptive controller diagram. The Adaption Algorithm block includes the adaptive law for the system and represents the use of intelligence in adaptive controllers. The adaptive law is typically unique to the controller/study it is presented with. Some examples of adaptive laws presented in this review include interaction torque-based adaption, adaptive simulated annealing, particle swarm optimisation-based adaption, adaption based on error back-propagation, and haptic feedback-based adaption.

control the force output by the system, while admittance control uses this ratio to control the position output. Collectively these methods are sometimes referred to as compliance control. Control algorithms simply referred to as fuzzy control are used in [23] and [24]. Experimental data is presented in [17] comparing a proposed fuzzy PID controller to standard PID with an unimpaired participant. The results show both controllers have overall acceptable tracking performance, but the fuzzy controller performed better. Fuzzy SMC with adaptive gain is used in [19] and is experimentally verified in both passive and active control modes. A proposed Integral sliding mode impedance control with fuzzy adjustment (IFSMIC-TDE) is experimentally compared with model-based sliding mode control in [20] with three participants. All three experiments show the superiority of the fuzzy-based controller, with smaller time delays, less chattering, and smaller impedance errors than the model-based method. Fuzzy SMC using PID-based sliding surfaces is developed in [27] and is compared with a standard PID controller in an experiment with an unimpaired participant, and the results show the proposed controller has improved tracking performance and reduced chattering. An experiment with 10 stroke patients is presented in [24] in which 5 patients use the proposed lower limb rehabilitation robot and controller for training in 20 15-minute sessions over the course of four weeks, and 5 patients designated the control group were treated with conventional post-stroke rehabilitation. Of the patients who used the robot, 3 exhibited improvements in their lower limb recovery, while none in the control group did. Experiments are presented in [22], [26], and [29] to validate their respective fuzzy controllers, each finding them to have accurate motion control with minimal tracking error.

C. Adaptive Controllers

A focus of intelligent control in rehabilitation robotics is to make the robot more adaptive, allowing it to reject

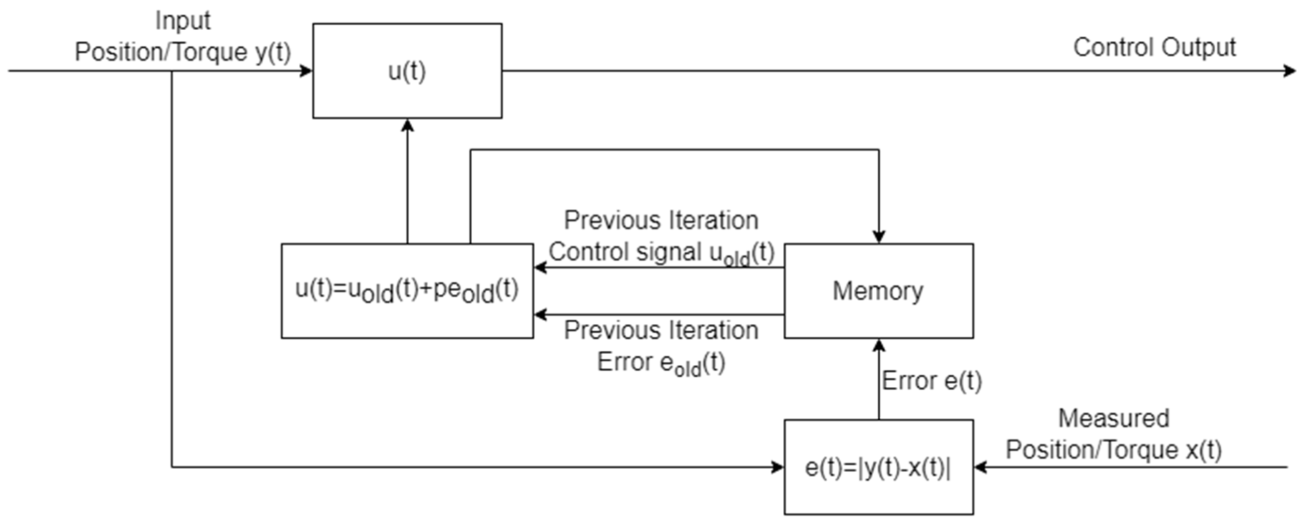

Fig. 3. A generalised Iterative Learning Controller diagram. y(t) is the input values to the system, u(t) is the control function, uold(t) is the control function from the previous iteration, e(t) is the error between the desired and actual output, eold(t) is the error form the previous iteration, and P is the learning rate.

disturbances and adjust training or control parameters to better suit different patients or sensor inputs dynamically. Adaptability can also help provide safer and more comfortable rehabilitation by reducing the interaction torque between user and machine, also referred to as improving the transparency of the system. Figure 2 shows a general diagram of an adaptive control system, as an example of a specific application of the Control System section shown in figure 1. The torque/position control block will differ depending on the specific use case from study to study. While adaptability is the aim of most intelligent controllers mentioned here, several articles specifically mention the use of adaptive controllers [18], [19], [20], [21], [22], [23], [25], [30], [33], [42], [43], [50], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [89], [90]. Most of these apply adaptive algorithms to other control schemes such as PID or SMC. Fuzzy logic is also often used in adaptive controllers to help approximate system models and plants which are impossible to define with purely mathematical models. Among the articles presenting an adaptive controller, the most numerous is adaptive SMC. Adaptive PID and PD are also present, with a few using adaptive impedance and admittance control. Many of these controllers use fuzzy logic in their adaptive algorithms, while some use neural networks which will be discussed in more detail in a later section. Adaptive Iterative Learning Control is presented in [33], while [64] presents adaptive state-space control, and [71] develops a wholly novel adaptive controller based on motor primitives. The hybrid shared controller developed in [89] uses both a Mode Insertion Gradient algorithm and Optimal Controller Inner Product to adaptively adjust impedance parameters in response to user input. Another novel adaptive controller is presented in [90], with a Minimal Assist As Needed (mAAN) control scheme. This algorithm uses sensorless torque estimation to dynamically react to user inputs and adjust torque parameters accordingly. The paper also presents a bound modification algorithm for adjusting allowable error, and a decayed disturbance rejection algorithm for encouraging voluntary movement during training. Generally, the purpose of adaptive algorithms in control is to dynamically adjust the control parameters during exercises based on sensor feedback or learned behaviors to provide better rehabilitation care, improve patient comfort, and optimize the output of the system. Experimental results from these articles consistently prove that adaptive control is fit for purpose. In comparative studies, it outperforms non-adaptive controllers in terms of tracking performance and stiffness control, exhibiting lower error values.

D. Learning Control

Iterative learning control (ILC) is used in a number of articles in this review. It is a tracking algorithm that relies on the system repeating a pre-set series of movements or impedances, depending on the operating mode, and iteratively adjusting parameters to better fit the required motion given the resulting sensor outputs. This allows for very accurate and repeatable motion but requires several repetitions to converge properly, meaning initially the movement is typically inaccurate. Figure 3 shows a general diagram for implementation of ILC in a rehabilitation robot as an example of a learning control loop. This diagram is an example of a specific application of the Control System section shown in figure 1. ILC is used for motion control in [31], [32], [33], [34], [35], [36], [37], and [38]. Experimental results are presented in [32], [35], and [37] validating their respective implementation of ILC. The results in [32] show the iterative learning impedance controller is capable of consistently converging error to 0 in response to interaction torques. Experiments with 8 unimpaired subjects are presented in [35], the results of which show stable and safe interaction forces between subject and robot, as well as adaptable parameters allowing for training exercises of different difficulties. The results presented in [37] from experiments with 3 unimpaired subjects show that the tracking error of the joint movements become smaller with increasing numbers of repetitions. Results comparing ILC with other controllers are presented in [34], [36], and [38]. Active Disturbance Rejection Control (ADRC) and PID are each compared with ILC combined with ADRC in an experiment with one participant in [34]. ILC-ADRC showed faster response time and better disturbance rejection than PID, and better tracking performance than standard ILC, consistently proving it the most suitable of the tested controllers. ILC based on PID is compared with ILC based on nonlinear control in [36]. Both controllers decrease in error over more iterations, but the overall error of the PID-based controller was larger. The nonlinear method has better performance with negligible increase in required torque. Two algorithms are proposed in [38], norm-optimal ILC (NOILC) and Optimization-based proportional-type ILC (OPILC). Both controllers converged to the reference trajectory with OPILC having a more damped response.

Intelligent controllers in the literature often make use of neural networks in various applications, some applied directly to the controller to learn parameter settings, some used for sensor feedback, as well as for disturbance compensation and value estimation. Many types of neural network exist but all operate on similar principles, with a network of 'neurons' which activate on a certain input threshold determined by gain parameters learned through training and pass the data on to the next layer of neurons. The different possible activation functions and limitless configurations make neural networks applicable to nearly any computational problem. Neural networks are used in software design in articles [18], [34], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [86]. The types of networks used in the literature discussed here are backpropagation and convolutional neural networks, Radial Basis Function networks (RBF), as well as long-short term memory networks (LSTM). RBF networks are used mostly for compensation for disturbances and unknown values, and there are no examples in this review of RBF networks being used for motion prediction or classification. A reinforcement learning neural network is used in [42], and a central pattern generator neural network is used in [41], both used as the basis of the motion controller proposed in their respective articles. Some of these articles compare their proposed controller's network with other types, and [47] develops and tests both LSTM and convolutional neural networks for joint position prediction but does not compare the two. Results from articles with experiments or simulations consistently prove that the network used is fit for purpose, and those which compare neural networks with other algorithms and methods prove that the network performs better. Two different neural networks are compared in the same application in [44], [45], and [48]. A LSTM neural network is used to create a motion perception model for control of an upper limb exoskeleton in [44], and through experiments compared to backpropagation neural network, finding that the LSTM had better performance with lower prediction error. An experiment comparing the effectiveness of several algorithms for a motion classification system is presented in [45], including perceptron and convolutional neural networks. The convolutional neural network performed the worst of the tested algorithms in terms of classification accuracy. A backpropagation neural network is used for mapping relationships between surface electromyography (EMG) sensors and knee joint angle in [48], finding through experiments that it is superior to LSTM neural network as well as Support Vector Regression methods. The results from [44] and [48] seem to suggest that LSTM neural networks are better suited for motion intention prediction, while backpropagation is better suited for mapping sensor outputs. Several articles [45], [48], [49], [50] compare different methods or algorithms incorporating the same type of neural network.

E. Other Controllers

A nonlinear Model Predictive Controller (MPC) is presented in [83] for more compliant human-robot interaction. MPC uses a model of the dynamic system as well as knowledge of future input values to predict future states, allowing for optimal control with future system states taken into account. The system is simulated with input torques mimicking an unimpaired and an impaired subject. In both cases the controller performs as expected, properly guiding trajectories in response to interaction torques.

K-nearest neighbors, another learning algorithm which uses proximity to make classifications and predictions, is used for motion control in [81] based on sEMG sensors by identifying motion intention. This method is experimentally validated to have a good identification accuracy rate but becomes less accurate the greater the applied load to the system. A probabilistic trajectory tracking algorithm for passive mode control and a system identification model to adapt and adjust an impedance controller in response to the user's anatomical stiffness in the active mode are both presented in [82]. Data gathered from a passive mode experiment was used to estimate anatomical stiffness for the active mode. In active mode the forces applied by the robot were considerably higher towards the extremities, and concerns for system instability in highly unstable environments were raised. It is noted that these two experiments constitute some of the only results in this review which critically evaluate their respective controllers, raising valid concerns for their functionality, rather than just concluding that they are fit for purpose.

F. Controller Comparisons

While most articles in this review use a single controller for their respective rehabilitation strategy, several experiments and simulations have been done comparing different controllers using the same platform to determine which performs best under certain conditions. Most of these comparisons are done to validate the controller developed in the article by presenting its superior qualities over more traditional controllers, most often PID, but some develop multiple controllers and compare them against each other to determine which is the most suitable for the application. All articles which compare multiple controllers using the same robotic platform either experimentally or in simulation are presented in table II. In all cases where a new controller is designed and compared with a more common classical controller such as PID, the new

TABLE I
ALGORITHM ADVANTAGES AND DISADVANTAGES

Algorithm	Article Count	Advantages	Disadvantages	Application Scope
Proportional Integral Derivative	32	Computationally efficient, easy to implement, universally used and documented	Nonlinear and time-invariant, often inaccurate, no intelligence without additional algorithms	Applicable to any control problem but with limited effectiveness on complex systems
Sliding Mode Control	15	Nonlinear control functionality, effective at mitigating uncertainties and disturbances	Susceptible to chattering	Wide applicability to various control problems especially those with system uncertainties and bounded disturbances
Particle Swarm Optimisation	4	Applicable to any dimensional search space/optimisation function	Poor initial accuracy due to learning period, does not guarantee global optimal solutions	Optimisation method suitable for many applications including controller parameters and system modelling
Genetic Algorithm	5	Capable of optimizing very large and complex datasets, applicable to cases where traditional optimisation methods struggle	High complexity causes inefficiency for simpler optimisation problems, high computation times	Complex, nonlinear, nondifferentiable optimisation problems in many applications
Adaptive Algorithms	34	Improved response to system and sensor inputs over time	Increases computational complexity of the applied algorithm	Improvement to other algorithms to allow for improved functionality over time
Fuzzy Logic	14	Allows for heuristic decision making in data processing	Can lose some data accuracy, requires thorough testing and verification	Improved decision making functionality in many algorithms
Iterative Learning Control	8	Model-free control of any system complexity, approaches optimal tracking control over time	Poor initial accuracy due to learning period, can result in overfitting, requires repeated input	Control of any system with repeated input function
Neural Networks	17	Deep learning allows for advanced decision making based on learned data values	Requires large amounts of training data for effective decision making	Applicable to all manner of computational decision making
Model Predictive Control	2	Optimal control for current and future timeslots	Requires a system model and future input values	Optimal control of systems with known mathematical models and input functions
Impedance Control	16	Force control helps provide safe human-robot interaction	Limited in scope to systems with required force outputs and position sensors	Applicable to systems where output force must be accurately maintained and controlled
Admittance Control	7	Position control allows for intuitive human-robot interaction	Reactive control method, cannot be used as standalone position/force controller	Applicable where interaction forces with the system should guide its motion, such as in encouraging motion in therapeutic exercises
Assist-As-Needed	1	Encourages user participation in exercises, can improve rehabilitation outcomes	Limited to use in rehabilitation robotics, requires a system model	Improved user participation in rehabilitation and assistive motion systems

TABLE II
EXPERIMENTAL RESULTS WITH PARTICIPANTS WITH LIMB IMPAIRMENT

Article	Subject Characteristics	Age	Rehab/Experiment Type	Control System	Measures	Outcomes and observations
Huang, YC et al. 2021 [24]	10 stroke patients	Not specified	Lower limb rehabilitation	Fuzzy	Brunnstrom motor recovery status	Control group did not improve, 3/5 in training group improved
Miao, M.d. et al. 2022 [39]	1 unimpaired, 1 patient (Pathology not specified)	Unimpaired 26, patient 52	Gait rehabilitation	SMC with RBF NN adaption	Motion trajectory, control torque, gain coefficients	Good coherence on straight track. Curved track had errors. Unimpaired subject affected better than patient
J. Chen et al. 2021 [53]	1 patient (Pathology not specified)	Not specified	Active training with lower limb exoskeleton	Genetic impedance and SMPIC	Joint angle, torque, GA fitness values, joint position	GA gives good interaction. Controller has good robustness and tracking
M. Zhang et al. 2017 [58]	1 ankle sprain, 1 drop foot due to stroke	Ankle sprain 29, drop foot 68	Ankle rehabilitation	PID low-level, adaptive admittance high-level	Passive ankle torque, joint position	Adaptive control has greater compliance than fixed
Asín-Prieto G et al. 2020 [62]	10 unimpaired, 1 post-stroke	Unimpaired 29.80 ± 6.32, post-stroke 37	Ankle rehabilitation with video game visual feedback and EMG	PID	Joint torque, RMSE, video game SCORE, ROM, joint velocity	Subjects satisfied. Unimpaired subjects improved, impaired subject ROM decreased initially, improved later
Maggioni S et al. 2018 [65]	5 unimpaired, 1 complete spinal cord injury	Unimpaired 27 ± 4.7, impaired 37	Gait rehabilitation	Adaptive hybrid PD and D	Normalised adaptive stiffness	Hybrid controller stiffness adapted to error over time
Rajasekaran V et al. 2018 [67]	4 incomplete spinal cord injury	21-49	Gait assistance robot with brain-machine interface	Volition adaptive impedance	Joint angle, stiffness, interaction torque	Error decreased each session. Participants showed improvement
Liu Q et al. 2017 [68]	3 unimpaired, 1 cerebral palsy	Unimpaired 27-31, impaired 42	Ankle rehabilitation	Adaptive compliance	Joint angle, torque, actuator pressure, admittance, force	Accuracy and compliance trade-off controlled by actuator pressure. Movement worse at higher stiffness
M. Zhang et al. 2019 [69]	1 ankle sprain two months prior	29	Ankle rehabilitation	Adaptive trajectory tracking	Joint position, joint force, actuator force	Good tracking performance. Small sample size means best training method cannot be proven

controller is found to be superior in performance, with the most common measure being trajectory tracking. In cases where an intelligent controller is compared to a non-intelligent controller, the intelligent controller invariably performs better. Due to the abundance of novel controllers in literature there are many comparisons missing. This makes it practically

TABLE III
ARTICLES COMPARING CONTROL SYSTEMS

Articles	Control systems compared	Relevant results/ conclusions
Q. Wu et al. 2019 [20]	Integral Fuzzy SMIC with Time-Delay Estimation (IFSMIC-TDE), Model-Based SMIC	IFSMIC-TDE has smaller error and chattering degree in multiple tests
T. Goyal et al. 2022 [23]	Fuzzy, Adaptive fuzzy	Adaptive controller has significantly smaller tracking error
Q. Wu et al. 2019 [43]	Adaptive Admittance Control with NN Disturbance Observer (AACNDO), Fuzzy cascade PID	AACNDO has smaller tracking errors and better adaptability than FCPID
Z. -Q. Ling et al. 2021 [48]	BPNN position estimation, SVR, LSTMNN	BPNN had lowest error and closest fit to motion curves. LSTMNN had partial deviation. SVR had worst performance
Xiu-Feng Zhang et al. 2018 [49]	Pattern recognition using PSO BPNN, BPNN	Network recognition rate increased across all measurements when optimised. Response time is fast
P. Zhang et al. 2020 [50]	RBFNN-based adaptive SMC, Variable SMC, PID, RBFNN, Continuous terminal SMC, Decentralized adaptive robust control	Variable SMC had severe chattering. This was reduced with RBFNN-based. RBFNN-based also had best tracking performance
W. Qian et al. 2021 [63]	Adaptive SMIC, PD impedance, SMIC	Adaptive SMIC had smallest error. Parameters converged after 20s
Wilian M. et al. 2019 [66]	Optimal impedance via model predictive control, Impedance control	Model predictive controller adaptively adjusts stiffness. Impedance has bad stability at low impedance, forces patient motion at high impedance
G. Ding et al. 2018 [73]	Adaptive proxy-based SMC, PID, Adaptive PID, Proxy-based SMC	Adaptive controllers have superior performance. APSMC maintains performance with different users where PID and PSMC do not
M. Ketelhut et al. 2020 [38]	Norm-Optimal ILC, Optimization-based Proportional-type ILC	Both controllers converge after six iterations. Norm-Optimal has low frequency oscillation after five iterations. Optimization-based has more damped response
Y. Li et al. 2020 [72]	Model Free Adaptive Control (MFAC), Improved MFAC (IMFAC)	IMFAC has better control performance, robustness, stability than MFAC
J. Liu et al. 2018 [75]	Adaptive SMC, SMC, PID	Both SMC have good tracking performance. Classical SMC shows chattering. PID has worse tracking performance than ASMC
Z. Shen 2018 [17], Q. Wu 2015 [27], L. Cheng 2018 [34], J. Li 2022 [57], Shen, Z. 2019 [76], Xiaohong Cui 2021 [35], S. Zhang 2016 [25], Y. Wang 2021 [30], X. Zhu 2015 [36], A. M. M. Ali 2021 [74]	Fuzzy PID, Fuzzy SMC with PID-based sliding surfaces, ILC with ADRC, Adaptive gain function with cascade PID, Adaptive robust position admittance, ADRC, Fuzzy adaptive impedance, Nonlinear ILC, Model Reference Adaptive control, each compared with PID	PID used as comparative baseline. All controllers have superior characteristics in respective experiments. Tracking performance, response time, interaction force, stability all worse with PID
J. Wang et al. 2019 [28]	Fuzzy compensation SMC, PD	PD showed tracking errors, movement delays, fluctuation under disturbance. FCSMC improves on these

SMC = Sliding Mode Control, SMIC = Sliding Mode Impedance Control, BP = Backpropagation, LSTM = Long-Short Term, RBF = Radial Basis Function, NN = Neural Network, SVR = Support Vector Regression, PSO = Particle Swarm Optimisation, ILC = Iterative Learning Control, ADRC = Active Disturbance Rejection Control

impossible to determine which controller is objectively the best for different aspects of rehabilitation such as transparency, personalization, or different control modes.

IV. Discussion

A. Summary of Results

A summary of the algorithms used in the literature reviewed here is presented in table I, alongside observed advantages, disadvantages, and general application scope for each. Some of the most used controllers such as PID and SMC have recently been used as the basis for intelligent controllers through adaptive algorithms to dynamically adjust control parameters, optimisation techniques, and sensor feedback systems. Passive and active control schemes are used in equal number and most rehabilitation systems are designed to accommodate both, as they are necessary for different stages of the rehabilitation process, and this often requires multiple different control systems. Intelligent controllers have become more prevalent, making use of adaptive algorithms, neural networks, fuzzy logic, and other decision-making processes to allow rehabilitation robots to react to different patient needs and data training. This allows for improved tracking accuracy, robustness to disturbance and noise, as well as more personalized training exercises over non-intelligent systems. These improvements are presented in comparative experiments and simulations, as summarized in table III. Many articles present results comparing controllers on the same platform, with PID being the most used controller for comparison and generally considered the baseline to improve upon. In recent years compliance control and assist-as-needed control have become popular in the field of rehabilitation robots. Given the specific need for accurate force output and safe human-machine interaction, impedance and admittance control schemes prove highly effective at providing active control. Assist-as-needed control has similar usage in rehabilitation but specifically provides the minimal amount of assistance for the required task to be completed. These control methods have been shown to improve active participation in exercises, which is connected in many cases with improved rehabilitation outcomes.

B. Safety and Ethical Considerations

While the focus of many articles in this field is on the accuracy of motion and torque control, most also discuss transparency and human-robot interaction. This is essential to any robot which directly interacts with a human, and especially in rehabilitation robots as the interaction is prolonged and typically with an injured or impaired limb. The interaction force between robot and human must be kept low enough as to not injure the user but must also still be able to guide movement or provide sufficient resistance. Many experiments presented in these articles measure interaction torques to determine transparency of the system.

The compliance of the robot is another important consideration in terms of safety in rehabilitation. Solid driven actuators are inherently noncompliant, meaning motion of the user's joints are forced along the motion path of the robot. While this may assist in the efficiency of training and help promote more motion in the joint, it is unsafe in the case of rapid or unplanned movement on the user's part. This could cause injury or damage to the patient and the robot. Some systems instead opt to use compliant actuators, some of the more popular being artificial pneumatic muscles and series elastic actuators. These actuators allow for some patient-driven movement in multiple axis making them safer, but present problems in control as this inherent compliance can impact the tracking accuracy of the system. More complicated dynamic models are required to control systems based on these actuators.

Patient safety is the most discussed ethical concern in relation to robot-assisted rehabilitation, yet as an automated healthcare system more considerations are present which are less mentioned in the literature. Loss of human interaction could impact the effectiveness of rehabilitation as the improvement of these systems allows for more at-home treatment without the need for a therapist. Accountability is another ethical consideration which is related to safety, as in the case of an injury with an automated system the person or groups responsible is often nebulous. One aspect which is addressed by intelligent control is the potential loss of personalized care. In treatment with a specialist rehabilitation therapist, the condition suffered by the patient can be treated with specialized exercises, and this is lost in the case of predefined trajectories or impedance tasks. Intelligent systems can be applied to learn the needs of the patient and allow for more personalized care, and this is the topic of research in many articles focusing on machine learning control strategies. However, machine intelligence introduces another ethical dilemma. A machine learning system requires a large quantity of data to properly learn required joint torques and movements for rehabilitation exercises, and the collection of such large datasets could result in privacy issues as the incentive for data collection campaigns increases.

Risks are introduced by giving an automated system the free reign to alter larger aspects of the training, and these high-level decisions should always be made by a therapist, as errors in the machine's judgment could have serious ramifications on both the patient and the medical body responsible [85].

C. Meta-Analysis and Evaluation

After extracting data from all articles presenting experiments with human participants, it was found that the vast majority of these experiments did not include impaired subjects in their participants, with only 9 articles presenting results from experiments with impaired subjects. The results of these experiments are summarized in table II. Some of these results focus on the performance of the controller, but those which focus on the rehabilitation outcome all find that impaired subjects improve in motion range or accuracy. Unfortunately, there were no studies in this review in which different control strategies are used for rehabilitation of impaired subjects and their effectiveness compared.

While there are other examples of experiments with participants, these are unimpaired and therefore present less useful data for this review. The effectiveness of rehabilitation is only properly measurable with a subject able to benefit from it, however the purpose of these experiments can help realise important factors in validating these systems. The most prominent of these factors is the tracking and/or torque accuracy of the control scheme used as this is the most common measure in experiments. Specifically, the most common measure in experiments is joint angle and Root-Mean-Squared Error (RMSE) in terms of deviation from the reference trajectory provided by software. Some experiments also measure the output directly from the controller or sensors to check their functionality and directly compare with the system outputs. In articles which utilize EMG the force estimation from those sensors are typically presented as well.

As each article typically focuses on a different rehabilitation robot platform for different joints and applied with different training motion exercises, comparison between them given the data presented in experiments is made difficult. Every article presents data suggesting the controller proposed is suitable for the application, and every article comparing a developed controller experimentally to others shows that it is superior to all others used. The only consensus between articles is that those which use intelligence in the controller consistently outperform those which do not, typically in terms of motion tracking error or torque output error, and rejection of disturbances to the system. The importance of these measures in clinical practice is that lower motion tracking or torque output error allow for more repeatable and accurate therapeutic exercises, and better disturbance rejection helps keep the patient's motion in line with the expected exercise motion.

Participant comfort is only explicitly mentioned in [58]. It mentions comfort in terms of robot compliance and that the interaction forces of the robot must be set to ensure patients feel comfortable using it. Comfort is an important factor in rehabilitation as it can help patients actively engage in training and not distract or impair it further, which is an issue that can be solved with improved compliance and better transparency, but also physically more comfortable surfaces between the robot and the patient. There is an inherent loss in patient feedback, especially patient comfort, when using robotic assisted therapy with no attending physiotherapist, and no articles reviewed here attempt to rectify this by incorporating user-input feedback systems or intelligence designed to detect patient comfort.

The most important factors in a rehabilitation system as determined by the literature are tracking performance of motion or force application; safety of human-robot interaction achieved by transparency, low interaction force, and compliance of the machine; and active and engaged participation of the subject. Patient engagement is a subject discussed in greater depth in [84]. A robust controller is essential for good tracking performance, but this can be achieved by most conventional controllers with good optimisation and parameter tuning. Compliance of the machine is a uniquely physical property that is best implemented with inherently compliant actuators. Intelligent control can allow for improved transparency, as well as more engaging and personalized training motions, and safer interaction forces.

D. Gaps and Opportunities

There exists some gaps in the literature regarding intelligent controllers used in rehabilitation robotics. The effectiveness of the training on patients who would require it in a clinical setting is not well represented, with very few articles presenting experiments with impaired participants and even fewer showing long-term effects of the training. Critical evaluation of newly developed control schemes is also lacking. Most articles presenting a novel controller conclude from their results that it is fit for purpose and meets evaluation criteria, but they rarely discuss shortcomings or potential improvements to be made. Articles [81], [82] are exceptions to this, and it is noted they do not use conventional control schemes in their development, rather developing novel algorithms. To determine which algorithms or control schemes are most appropriate for certain situations, or which is the best comparatively, articles should include any failings of the system or limitations of the results presented to allow for critical analysis of the research.

More recent studies published in the past year give a good insight into the future directions of the field. The system presented in [91] uses brain-computer interface (BCI) for improved control of a lower limb rehabilitation robot, with a CNN trained to classify sensor inputs and motion intention. This system is tested online with two subjects to verify its functionality. The article includes significant insight into future work, mentioning improved feedback, greater training data diversity to improve generalization, and optimisation of algorithms to improve response times. A bio-inspired control design based on the function of the cerebellum in mammals is presented in [92]. This novel neural network design is used to control an upper limb rehabilitation robot actuated by an antagonistic pair of pneumatic muscles. In simulation this control method was compared with traditional controllers and shown to effectively compensate uncertainties and disturbances. An adaptive sliding mode controller designed to improve safety in upper limb rehabilitation exercises is presented in [93]. The system uses interaction force estimation to adjust training dynamically. The article recommends that the system cannot quickly evaluate additional information such as stiffness and damping, and suggests future work be done to improve the system in this regard as well as using the system in robots without force sensors in order to reduce cost.

Recent work, as well as the research trends in the other literature reviewed here, suggests that intelligent control design is quickly becoming the focus in the area. Novel controllers frequently make use of computational decision-making processes like neural networks and fuzzy logic in various aspects, including intention detection, motion prediction, and sensor input mapping. There is also a focus on making rehabilitation systems more intuitive, comfortable, and safe to use, alongside the typical focus of tracking accuracy and robustness in these studies.

V. Conclusion

The consensus among the literature is that the adaptability and personalization offered by intelligent controllers make them superior to non-intelligent control in all control modes. They also outperform non-intelligent controllers in all comparative experiments in terms of error, rejection of disturbances to the system, and interaction torques with the user. However, it is important to note that while this seems the case in published literature, there exists a publication bias especially in emergent fields such as machine intelligence in physical applications. Any intelligent controllers which did not perform properly or were generally worse than traditional controllers would likely not be published, so this conclusion must not be taken as true globally without specific evidence.

Actual comparison between the controllers is generally limited to only what is presented in individual articles, as the results are specific to each robotic platform, movement exercises, and experiment duration. There is no universal metric for effectiveness, nor a standardized set of experiments, to quantifiably determine the effectiveness of each controller. The same can be said of other aspects of the rehabilitation robot such as actuators, sensor systems and hybrid rehabilitation systems, as while these have been extensively researched in the literature there are few experimental results demonstrating their effectiveness over more traditional methods.

While the comparative effectiveness of controllers is difficult to determine, the overall important factors in terms of rehabilitation remain similar throughout the literature. Active participation in exercise is consistently mentioned as having a great impact on the effectiveness of treatment. Transparency is often measured in experiments to ensure the robots have safe and comfortable interaction with the human participant. Transparency can, and has been, improved by intelligent control. Active participation of the subject can be encouraged with personalized exercises and the system's ability to adapt to their specific needs. However, the most common measure of success is tracking accuracy. While accuracy of motion is important for any controller, the ability to follow reference paths with minimal error is not as important to rehabilitation outcome as the patient's experience and engagement in the training. The ability of the system to reject or compensate for disturbances is another common measurement, as it impacts the safety of the patient and generally improves training effectiveness. Other aspects such as compliance or weight of the robot itself are important as well but are more difficult to directly improve with better controllers.

To further the research and fill gaps presented in the literature, comparative experiments between commonly used controllers should be done, as well as tests over longer periods and with impaired patients, to determine their effect on the rehabilitation outcome and give conclusive results on which performs best under certain conditions. Comparing novel intelligent controllers to state-of-the-art algorithms in the field should also become more of a priority, as comparisons to traditional controllers like PID and SMC are becoming increasingly obsolete with the rapid development of more accurate and robust controllers. Feedback from participants in the experiments should also be gathered frequently, as the patient's experience is a crucial factor when undergoing physical therapy.

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