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Towards Precision Physiotherapy for Chronic Low Back Pain: A Comprehensive Review of Hybrid Fuzzy Logic and Artificial Neural Network Models

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Abstract. Chronic low back pain (CLBP) is a major cause of disability, with substantial variability in patient characteristics and rehabilitation outcomes. Hybrid Fuzzy Logic–Artificial Neural Network (FL–ANN) models offer a promising approach to precision physiotherapy by combining uncertainty handling, nonlinear learning, and adaptive prediction. This review examines FL–ANN, ANFIS, machine learning, and deep learning approaches for CLBP assessment, outcome prediction, and personalized rehabilitation. Emerging technologies, including wearable sensors, electromyography, gait analysis, Explainable AI, IoT, digital twins, and federated learning, are also discussed. Despite challenges in data quality, clinical validation, interpretability, and implementation, hybrid intelligent models show strong potential for personalized rehabilitation and clinical decision support in CLBP management.

Keywords: Chronic low back pain; Precision physiotherapy; Fuzzy logic; Artificial neural network; ANFIS; Hybrid intelligence; Explainable AI; Clinical decision support

AMS Mathematics Subject Classification (2010): 05C50, 05C90

1. Introduction

Chronic low back pain (CLBP) is one of the most widespread musculoskeletal disorders and remains a major public health concern because of its high prevalence, persistent nature, and substantial socioeconomic burden. It affects individuals across all age groups, reducing physical function, limiting occupational performance, and impairing quality of life. Despite significant advances in diagnostic imaging, rehabilitation protocols, and pain management strategies, the clinical outcomes of CLBP treatment remain inconsistent. This variability largely arises from the multifactorial nature of the condition, where biological, biomechanical, psychological, and environmental factors interact in complex and often unpredictable ways. Consequently, conventional physiotherapy approaches that rely on standardized treatment protocols may fail to address the unique characteristics of individual patients, leading to prolonged disability and increased healthcare costs.

Recent developments in precision medicine have encouraged a paradigm shift toward personalized rehabilitation, commonly referred to as precision physiotherapy. Rather than adopting a uniform treatment strategy, precision physiotherapy emphasizes tailoring therapeutic interventions according to patient-specific clinical profiles, including pain severity, functional limitations, movement patterns, psychological status, imaging findings, and lifestyle characteristics. This individualized approach seeks to improve treatment effectiveness by identifying the most appropriate therapeutic pathway for each patient. However, implementing precision physiotherapy requires sophisticated analytical techniques capable of processing heterogeneous clinical data and recognizing complex nonlinear relationships that are difficult to interpret using traditional statistical methods. Artificial Intelligence (AI) has emerged as a transformative technology in healthcare by enabling intelligent analysis of multidimensional medical data. Among various AI techniques, Artificial Neural Networks (ANNs) have demonstrated remarkable capability in learning intricate nonlinear mappings between clinical inputs and treatment outcomes. Inspired by the structure and functioning of the human nervous system, ANNs automatically extract hidden patterns from large datasets without requiring explicit mathematical formulations. Their applications in musculoskeletal rehabilitation include pain intensity prediction, functional outcome estimation, patient stratification, gait analysis, biomechanical assessment, and optimization of rehabilitation protocols. Owing to their adaptive learning ability and high predictive accuracy, ANNs have become valuable decision-support tools for clinicians managing chronic low back pain. Although ANNs possess excellent predictive capabilities, they often function as "black-box" models, providing limited interpretability regarding the reasoning behind their predictions. Clinical decision-making, however, requires transparent and explainable systems that accommodate uncertainty and incorporate expert knowledge. Fuzzy Logic (FL), introduced to model reasoning under vagueness and ambiguity, addresses this challenge by representing clinical variables through linguistic concepts such as low, moderate, and high instead of precise numerical thresholds. Unlike conventional binary logic, fuzzy inference systems effectively capture the imprecision inherent in medical diagnosis, patient symptom descriptions, therapist observations, and rehabilitation assessments. This characteristic makes fuzzy logic particularly suitable for physiotherapy, where many clinical decisions depend on subjective evaluations and expert judgment. Hybrid Fuzzy Logic Artificial Neural Network (ANN) models integrate the complementary strengths of both methodologies. While neural networks contribute robust learning, pattern recognition, and predictive performance, fuzzy logic enhances interpretability, knowledge representation, and uncertainty management. These hybrid intelligent systems are capable of simultaneously learning from historical patient data and incorporating clinician expertise through fuzzy rules, thereby improving both prediction accuracy and clinical transparency. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) represent one of the most successful realizations of this hybrid paradigm, enabling automatic tuning of fuzzy membership functions using neural network learning algorithms. Such models have demonstrated promising performance in medical diagnosis, disease prognosis, rehabilitation planning, and personalized treatment recommendation. Within the context of chronic low back pain, hybrid ANN frameworks offer considerable potential for advancing precision physiotherapy. These intelligent models can integrate diverse sources of information, including demographic characteristics, pain questionnaires, electromyography, biomechanical measurements, wearable sensor data, medical imaging, and psychosocial indicators. By analyzing these multidimensional datasets, hybrid models can classify patient subgroups, estimate recovery trajectories, recommend individualized exercise programs, predict treatment responsiveness, and support clinicians in selecting optimal rehabilitation strategies. Furthermore, their ability to continuously update predictions as new patient information becomes available facilitates dynamic and adaptive rehabilitation planning. The increasing adoption of wearable technologies, Internet of Medical Things (IoMT) devices, and digital health platforms has further expanded the availability of real-time physiological and movement data for patients with chronic low back pain. These emerging technologies generate continuous streams of biomechanical and functional information that can be effectively analyzed using hybrid AI models. Integration of fuzzy reasoning with neural learning enables robust handling of noisy sensor measurements, incomplete datasets, and patient variability, thereby enhancing the reliability of intelligent rehabilitation systems. Consequently, hybrid ANN models are becoming fundamental components of next-generation clinical decision support systems designed for personalized musculoskeletal care.

Despite encouraging progress, several challenges continue to hinder the widespread clinical implementation of hybrid intelligent models. Limitations include insufficient availability of large, high-quality annotated datasets, variability in rehabilitation protocols across healthcare institutions, concerns regarding model interpretability, limited external validation, computational complexity, and ethical issues related to patient privacy and algorithmic fairness. Moreover, translating computational predictions into clinically actionable recommendations requires close collaboration among physiotherapists, physicians, biomedical engineers, and artificial intelligence researchers to ensure that developed models are accurate, explainable, and clinically meaningful. This comprehensive review critically examines the current landscape of hybrid fuzzy logic and artificial neural network models developed for precision physiotherapy in chronic low back pain management. It synthesizes recent advances in intelligent rehabilitation systems, discusses computational methodologies, evaluates clinical applications, compares model performance, and highlights emerging trends involving explainable artificial intelligence, wearable sensing technologies, digital twins, federated learning, and personalized rehabilitation platforms. Additionally, the review identifies existing research gaps and outlines future directions for developing clinically reliable, interpretable, and patient-centered intelligent systems capable of improving rehabilitation outcomes and supporting evidence-based precision physiotherapy for individuals living with chronic low back pain.

Esteban et al. [1] developed a fuzzy linguistic web-based decision support system for low back pain management and demonstrated its effectiveness in assisting personalized treatment planning. Baroncini et al. [2] systematically reviewed prognostic factors influencing physiotherapy outcomes in patients with chronic low back pain and identified key predictors of rehabilitation success. Baroncini et al. [3] performed a Bayesian network meta-analysis comparing conventional and non-conventional physiotherapy approaches for chronic low back pain treatment. Tanna et al. [4] reported the effectiveness of a holistic physiotherapy approach in improving post-brucellosis low back pain and associated musculoskeletal symptoms. Lin et al. [5] proposed a decision support system for lower back pain diagnosis that effectively managed uncertainty and enhanced clinical decision-making. Ria et al. [6] employed machine learning techniques to identify and predict risk factors associated with low back pain among adolescent athletes. Kovanur Sampath et al. [7] investigated contemporary physiotherapy perspectives on pain management and emphasized the importance of biopsychosocial rehabilitation approaches. Wang et al. [8] identified paraspinal muscle fatty infiltration as a significant predictor of disc degeneration and pain severity in patients with chronic low back pain. Mirnajafi Zadeh et al. [9] utilized fuzzy DEMATEL analysis to evaluate musculoskeletal disorder risk factors and prioritize preventive workplace interventions. Zhao [10] integrated deep learning-based motion analysis into exercise rehabilitation programs and reported improved therapeutic outcomes for patients with low back pain. Peterson et al. [11] assessed muscle function changes using advanced ultrasound imaging techniques and demonstrated the effectiveness of targeted rehabilitation exercises. Biedroń et al. [12] comprehensively reviewed diagnostic methods, risk factors, and rehabilitation strategies for musculoskeletal disorders affecting functional performance. Shimizu et al. [13] developed an intelligent screening system for evaluating patient suitability for cognitive behavioral therapy in chronic low back pain management. Zhang et al. [14] demonstrated that physiotherapy interventions significantly reduced pain levels and improved biomarker profiles in women with chronic low back pain. Ho and Chen [15] designed a fuzzy neural network-controlled physiotherapy device that enhanced rehabilitation performance through intelligent adaptive control. Çubukçu and Yüzgeç [16] proposed a neuro-fuzzy inference framework for rehabilitation outcome prediction and achieved reliable recovery assessment performance. Bouteraa et al. [17] developed a fuzzy logic-based architecture for rehabilitation robotic systems and demonstrated its potential for intelligent patient assistance and therapy optimization. Capecci et al. [18] developed a fuzzy logic-based telerehabilitation platform that enabled collaborative clinical decision-making and virtual second-opinion support for rehabilitation management.

Das et al. [19] proposed a hybrid machine learning and fuzzy logic framework for monitoring lower-limb rehabilitation exercises and demonstrated improved exercise tracking accuracy in stroke patients. Tong et al. [20] introduced a fuzzy-PID control strategy for post-stroke rehabilitation training and achieved enhanced motion assistance and patient safety during therapy. Siddique et al. [21] developed a fuzzy logic-based autonomous exercise generation system that personalized upper-extremity rehabilitation programs according to patient capabilities. Gómez-Portes et al. [22] designed a fuzzy recommendation system for automatically personalizing rehabilitation exercises and improving patient-specific recovery outcomes. Bouteraa et al. [23] presented a fuzzy logic-enabled connected robotic rehabilitation system that supported intelligent home-based therapy and remote patient monitoring. Kosari et al. [24] investigated topological indices in fuzzy graphs and demonstrated their effectiveness in supporting decision-making processes under uncertainty. Talebi and Rashmanlou [25] established complement and isomorphism concepts in bipolar fuzzy graphs, providing important theoretical foundations for fuzzy network analysis. Rashmanlou et al. [26] analyzed product operations and degree properties of interval-valued fuzzy graphs, extending graph-theoretic modeling in uncertain environments. Kosari et al. [27] introduced perfectly regular fuzzy graph structures and illustrated their applicability to psychological and behavioral science problems. Rao et al. [28] proposed new intuitionistic fuzzy tree concepts and demonstrated their usefulness in modeling hierarchical decision-making systems. Talebi et al. [29] developed a novel intuitionistic fuzzy graph framework that enhanced uncertainty representation and supported practical decision-making applications. Talebi et al. [30] introduced novel edge-irregular properties in single-valued neutrosophic graphs and demonstrated their applicability in modeling uncertain network structures. Chen et al. [31] developed a temporal intuitionistic fuzzy set-based video processing algorithm that improved uncertainty handling and object recognition performance.

Rao et al. [32] investigated forcing parameters in fully connected cubic networks and established important theoretical properties for network optimization. Jiang et al. [33] proposed new vertex covering concepts in cubic graphs and demonstrated their effectiveness in solving graph-theoretic optimization problems. Rashmanlou et al. [34] introduced innovative concepts in intuitionistic fuzzy graphs and highlighted their applications in uncertainty-based decision-making systems. Talebi et al. [35] developed irregular intuitionistic fuzzy graph structures and demonstrated their usefulness in modeling complex uncertain relationships. Talebi et al. [36] investigated several operations on vague graphs and established fundamental properties for advanced vague graph analysis. Kaviyarasu et al. [37] utilized t-neutrosophic fuzzy graphs to analyze circular economy strategies and support sustainable development decision-making. Naz et al. [38] extended hypergraph and transversal concepts to interval-valued intuitionistic fuzzy environments and demonstrated their applicability in uncertainty modeling.

Muhiuddin et al. [39] analyzed thermophoretic and Brownian motion effects in Newtonian and non-Newtonian fluid flows through porous stretching surfaces and reported significant variations in heat and mass transfer characteristics. Ramya and Deivanayaki [40] investigated Casson nanofluid flow over a stretching surface with thermal radiation and particle diffusion effects, highlighting their influence on thermal transport behavior. Fallah et al. [41] employed a fuzzy-based numerical framework to analyze MHD nanofluid flow through a Darcy–Forchheimer porous medium and demonstrated enhanced predictive capabilities. Muhiuddin et al. [42] examined hybrid SWCNT/MWCNT nanofluid flow with microbial bioconvection under Soret–Dufour coupling and reported improved thermal performance characteristics. Muhiuddin et al. [43] studied stagnation-point flow of Sisko nanofluids with heat generation and nano-transport phenomena over stretching surfaces and revealed significant effects on thermal and concentration profiles.

Ramya et al. [44] explored holographic and thermodynamic topological characteristics of AdS Einstein–Power–Yang–Mills black holes with generalized entropy and provided new insights into black hole thermodynamics. Ramya et al. [45] presented a unified framework integrating MHD nanofluid simulations with fuzzy graph methodologies for analyzing complex engineering systems under uncertainty. Ramya et al. [46] applied fuzzy logic techniques to investigate Eckert number effects on Casson micropolar nanofluid flow under magnetic and chemical reaction influences. Muhiuddin et al. [47] analyzed Darcy–Forchheimer buoyant Williamson fluid flow with swimming microorganisms over a porous curved stretching surface and demonstrated the combined effects of porous resistance and bioconvection. Ramya and Deivanayaki [48] investigated Soret and Dufour effects on Casson nanofluid flow in a magnetic field and highlighted their impact on coupled heat and mass transfer processes. Ramya and Deivanayaki [49] examined microorganism-induced bioconvection in Carreau nanofluid flow through Darcy–Forchheimer porous media and reported significant effects on transport characteristics. Muhiuddin et al. [50] studied the thermal and bioconvective behavior of Williamson fluid under homogeneous–heterogeneous reactions and demonstrated notable effects on fluid flow and heat transfer mechanisms. Ramya et al. [51] examined supply chain optimization strategies through Oracle supply chain management solutions and highlighted intelligent decision-making approaches for improving operational efficiency.

Ramya and Deivanayaki [59] explored heat radiation effects on Casson nanofluid flow over an inclined stretching surface and demonstrated significant enhancement in thermal transport behavior. Ramya and Deivanayaki [60] numerically investigated Casson micropolar fluid flow through a porous medium and reported the influence of inclination and porous parameters on velocity and temperature distributions. Ramya et al. [61] studied the influence of homogeneous–heterogeneous reactions on micropolar nanofluid flow with the Cattaneo–Christov heat flux model and highlighted their role in controlling thermal and concentration fields. Ramya et al. [62] analyzed thermophoresis and Brownian motion effects in Casson ternary hybrid nanofluids containing gyrotactic microorganisms and reported improved thermal performance and bioconvective behavior. Ramya et al. [63] proposed a fuzzy-based framework for evaluating RSA and ECC authentication algorithms and demonstrated the effectiveness of fuzzy decision-making in cybersecurity assessment.

Collectively, these studies demonstrate the growing application of fuzzy logic, neural networks, machine learning, deep learning, and intelligent decision-support techniques across rehabilitation and complex computational systems. However, the integration of these approaches into a unified FL–ANN framework specifically designed for precision physiotherapy, individualized rehabilitation planning, and outcome prediction in chronic low back pain remains insufficiently explored, providing the motivation for the present review. Figure 1 shows the overall hybrid FL–ANN framework, integrating multimodal patient data, fuzzy reasoning, neural-network learning, personalized rehabilitation planning, clinical decision support, and rehabilitation outcome prediction for CLBP.

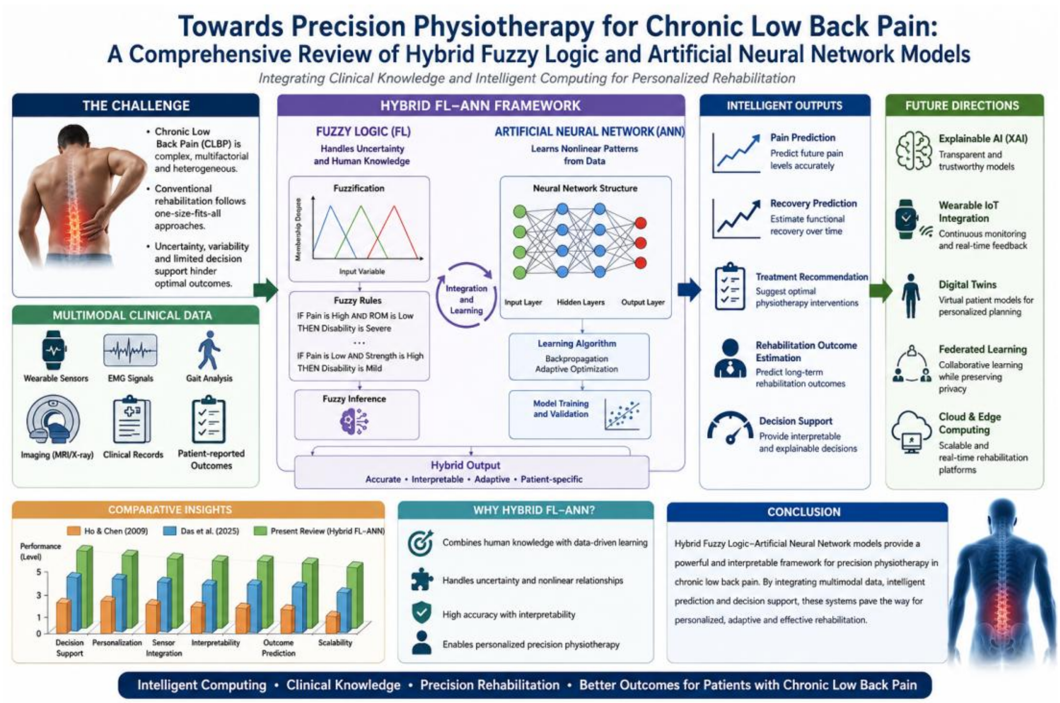

Figure 1. Hybrid Fuzzy Logic–Artificial Neural Network (FL–ANN) framework for precision physiotherapy in chronic low back pain.

2. Objectives

The primary objective of this review is to provide a comprehensive and critical analysis of recent advancements in hybrid Fuzzy Logic (FL) and Artificial Neural Network (ANN) models for precision physiotherapy in chronic low back pain (CLBP). Specifically, the review aims to:

- Summarize the current state-of-the-art physiotherapy strategies and intelligent computational techniques employed for the diagnosis, assessment, rehabilitation, and prognosis of chronic low back pain.
- Examine the fundamental principles, architectures, advantages, and limitations of fuzzy logic, artificial neural networks, and hybrid neuro-fuzzy systems applied in healthcare and rehabilitation.
- Critically compare conventional physiotherapy approaches with AI-assisted precision physiotherapy frameworks in terms of personalization, prediction accuracy, interpretability, and clinical decision support.
- Analyze the role of wearable sensors, medical imaging, motion analysis systems, rehabilitation robotics, and tele-rehabilitation platforms integrated with hybrid intelligent algorithms.
- Identify current research gaps, technical challenges, and future opportunities for developing explainable, adaptive, and patient-centered intelligent rehabilitation systems for chronic low back pain.

3. Novelty of the review

Unlike previous review articles that primarily focus on conventional physiotherapy techniques, machine learning applications, or fuzzy logic-based decision support independently, this review presents an integrated perspective on hybrid Fuzzy Logic–Artificial Neural Network (FL–ANN) models for precision physiotherapy in chronic low back pain. The principal novelties of this review are summarized as follows:

- It provides the first comprehensive synthesis of hybrid FL–ANN methodologies specifically targeted toward precision physiotherapy for chronic low back pain.
- It critically discusses how fuzzy reasoning enhances the interpretability of clinical decision-making, while artificial neural networks improve predictive performance by learning complex nonlinear relationships from multidimensional clinical data.
- It systematically reviews recent developments involving intelligent rehabilitation systems, deep learning, neuro-fuzzy inference systems, rehabilitation robotics, wearable sensing technologies, and tele-rehabilitation platforms within a unified framework.
- It highlights the integration of multimodal clinical information, including patient-reported outcomes, biomechanical measurements, medical imaging, and sensor-derived movement data, for individualized rehabilitation planning.
- It identifies unresolved challenges related to explainability, clinical validation, data heterogeneity, model generalization, privacy, and real-world implementation, while proposing future research directions based on Explainable Artificial Intelligence (XAI), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), digital twins, federated learning, and personalized clinical decision support systems.
- The review establishes a roadmap for future intelligent rehabilitation systems by bridging computational intelligence with evidence-based physiotherapy, thereby supporting the transition from conventional rehabilitation toward precision physiotherapy.

4. Mathematical formulation

The hybrid Fuzzy Logic–Artificial Neural Network (FL–ANN) framework provides an effective computational paradigm for precision physiotherapy by combining the interpretability of fuzzy inference systems with the adaptive learning capability of artificial neural networks. Let the clinical dataset be represented by

$$\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N}, \tag{1}$$

where

$$\mathbf{x}_i = [x_{i1}, x_{i2}, \dots, x_{im}]^T \tag{2}$$

denotes the m-dimensional clinical feature vector of the i^{th} patient, and y_i represents the corresponding rehabilitation outcome. The input variables may include pain intensity, age, body mass index, range of motion, muscle strength, disability index, electromyography signals, gait characteristics, psychological assessments, and wearable sensor measurements.

The objective of the intelligent prediction model is to determine a nonlinear mapping

$$f: \mathbb{R}^m \rightarrow \mathbb{R}, \tag{3}$$

such that

$$\hat{y} = f(\mathbf{x}), \tag{4}$$

where $\hat{y}$ denotes the predicted rehabilitation outcome, treatment response, or patient classification.

5. Fuzzy logic model

Fuzzy logic transforms numerical clinical variables into linguistic representations through membership functions. For each input variable x, the membership value is defined as

$$\mu_A(x): X \rightarrow [0,1], \tag{5}$$

where $\mu_A(x)$ represents the degree of membership of x in fuzzy set A. A commonly employed Gaussian membership function is

$$\mu_A(x) = \exp\left[-\frac{(x-c)^2}{2\sigma^2}\right], \tag{6}$$

where c denotes the center and σ represents the spread of the membership function. The fuzzy inference process is generally expressed through IF–THEN rules of the form

$$R_k: \quad \text{IF} x_1 \text{is} A_1^{(k)} \text{AND} x_2 \text{is} A_2^{(k)} \cdots \text{THEN} y = f_k(\mathbf{x}), \tag{7}$$

where $k = 1,2, \ldots, r$ denotes the rule index.
The firing strength of each fuzzy rule is computed as

$$w_k = \prod_{j=1}^{m} \mu_{A_j^{(k)}}(x_j). \tag{8}$$

The normalized firing strength is

$$\bar{w}_k = \frac{w_k}{\sum_{i=1}^{r} w_i}. \tag{9}$$

Finally, the fuzzy output is obtained as

$$y = \sum_{k=1}^{r} \bar{w}_k f_k(\mathbf{x}). \tag{10}$$

6. Artificial neural network model

The ANN consists of an input layer, one or more hidden layers, and an output layer. For each neuron, the weighted summation is given by

$$z_j = \sum_{i=1}^{m} w_{ij} x_i + b_j, \tag{11}$$

where w_{ij} denotes the synaptic weight and b_j is the bias.
The neuron output is computed using an activation function

$$a_j = \phi(z_j), \tag{12}$$

where $\phi(\cdot)$ may be the sigmoid, hyperbolic tangent, or ReLU activation function.
For regression-based rehabilitation prediction, the network output is

$$\hat{y} = \phi_o\left(\sum_{j=1}^{h} v_j a_j + b_o\right), \tag{13}$$

where h denotes the number of hidden neurons.
The network parameters are optimized by minimizing the mean squared error

$$E = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2. \tag{14}$$

Gradient descent updates the network weights according to

$$w^{(t+1)} = w^{(t)} - \eta \frac{\partial E}{\partial w}, \tag{15}$$

where η denotes the learning rate.

7. Hybrid FL–ANN model

The hybrid FL–ANN model integrates fuzzy reasoning with neural learning to simultaneously improve prediction accuracy and interpretability. The general hybrid model is represented as

$$\hat{y} = F_{\text{Hybrid}}(\mathbf{x}; \Theta), \tag{16}$$

where

$$\Theta = \{\mathbf{W}, \mathbf{B}, \mathbf{C}, \mathbf{\Sigma}\} \tag{17}$$

contains neural network weights $\mathbf{W}$, biases $\mathbf{B}$, fuzzy membership centers $\mathbf{C}$, and spreads $\mathbf{\Sigma}$. The optimization objective is formulated as

$$\Theta^* = \underset{\Theta}{\operatorname{argmin}} \left[\frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2 + \lambda\Omega(\Theta)\right], \tag{18}$$

where $\Omega(\Theta)$ denotes the regularization function and λ is the regularization parameter.
The overall computational workflow is expressed as

$$\mathbf{x} \rightarrow \text{Fuzzification} \rightarrow \text{RuleEvaluation} \rightarrow \text{NeuralLearning} \rightarrow \text{Defuzzification} \rightarrow \hat{y}. \tag{19}$$

8. Solution methodology

The proposed hybrid Fuzzy Logic–Artificial Neural Network (FL–ANN) framework for precision physiotherapy consists of a sequence of computational stages designed to transform heterogeneous clinical information into personalized rehabilitation recommendations. The overall methodology integrates fuzzy reasoning with neural learning to improve prediction accuracy while maintaining model interpretability.

9. Data acquisition

Clinical data are collected from multiple sources, including electronic health records, physiotherapy assessments, wearable sensors, medical imaging, electromyography (EMG), gait analysis systems, and patient-reported outcome measures. Let

$$\mathbf{X} = [x_1, x_2, \dots, x_m] \tag{20}$$

represent the input feature vector, where each feature corresponds to a clinical or biomechanical parameter.

10. Data preprocessing

Since clinical variables possess different numerical scales, normalization is performed before model training. The normalized feature is computed as

$$x_i^* = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}, \tag{21}$$

where $x_{\min}$ and $x_{\max}$ denote the minimum and maximum values of the corresponding feature. Missing observations are handled using interpolation or statistical imputation techniques, whereas noisy sensor measurements are filtered to improve data quality.

11. Feature selection

Relevant clinical variables are selected to reduce computational complexity and eliminate redundant information. The selected feature vector is expressed as

$$\mathbf{X}_s = [x_1, x_2, \dots, x_p], \qquad p < m. \tag{22}$$

Typical features include pain intensity, disability score, lumbar mobility, muscle strength, body mass index, gait parameters, and psychological indicators.

Fuzzification

Each numerical input is transformed into fuzzy linguistic variables using predefined membership functions such as Low, Moderate, and High. The membership degree is calculated by

$$\mu(x) = \exp\left[-\frac{(x-c)^2}{2\sigma^2}\right]. \tag{23}$$

This process allows uncertain and imprecise clinical observations to be represented mathematically.

Fuzzy Rule Evaluation

Clinical knowledge is represented through a collection of IF–THEN rules. A typical rule is

$$\text{IFPainisHighANDMobilityisLow} \Longrightarrow \text{TreatmentIntensityisHigh}. \tag{24}$$

The firing strength of the k^{th} rule is evaluated as

$$w_k = \prod_{i=1}^{m} \mu_i(x_i). \tag{25}$$

The normalized rule weight becomes

$$\bar{w}_k = \frac{w_k}{\sum_{j=1}^{r} w_j}. \tag{26}$$

12. Artificial neural network learning

The normalized fuzzy outputs are supplied to the artificial neural network. The hidden neuron output is computed by

$$a_j = \phi\left(\sum_i w_{ij} x_i + b_j\right), \tag{27}$$

where $\phi(\cdot)$ denotes the activation function. The predicted rehabilitation outcome is

$$\hat{y} = \phi_o\left(\sum_j v_j a_j + b_o\right). \tag{28}$$

The model parameters are updated using backpropagation by minimizing

$$E = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2. \tag{29}$$

Training continues until the prediction error converges below a predefined tolerance.

12.1. Defuzzification and clinical decision support

The ANN prediction is combined with fuzzy inference to generate clinically interpretable recommendations. The final output is expressed as

$$y = \sum_{k=1}^{r} \bar{w}_k f_k(\mathbf{x}), \tag{30}$$

where $f_k(\mathbf{x})$ denotes the consequent function associated with the k^{th} fuzzy rule. The predicted output may represent

- rehabilitation outcome,
- pain severity,
- functional recovery score,
- treatment response probability,
- individualized exercise intensity,
- or personalized physiotherapy recommendation.

Performance evaluation

The predictive performance of the hybrid model is assessed using standard statistical measures, including

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i|, \tag{31}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}, \tag{32}$$

and

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}. \tag{33}$$

Lower values of MAE and RMSE together with higher values of R^2 indicate improved prediction accuracy and enhanced clinical reliability.

Computational workflow

The overall computational pipeline of the proposed precision physiotherapy framework is summarized as

$$\boxed{\begin{aligned}&\mathrm{ClinicalData} \rightarrow \mathrm{Preprocessing} \rightarrow \mathrm{FeatureSelection}\\ &\rightarrow \mathrm{Fuzzification} \rightarrow \mathrm{FuzzyRuleEvaluation} \rightarrow \mathrm{ANNLearning}\\ &\rightarrow \mathrm{Defuzzification} \rightarrow \mathrm{Prediction} \rightarrow \mathrm{PersonalizedPhysiotherapyDecision}.\end{aligned}} \tag{34}$$

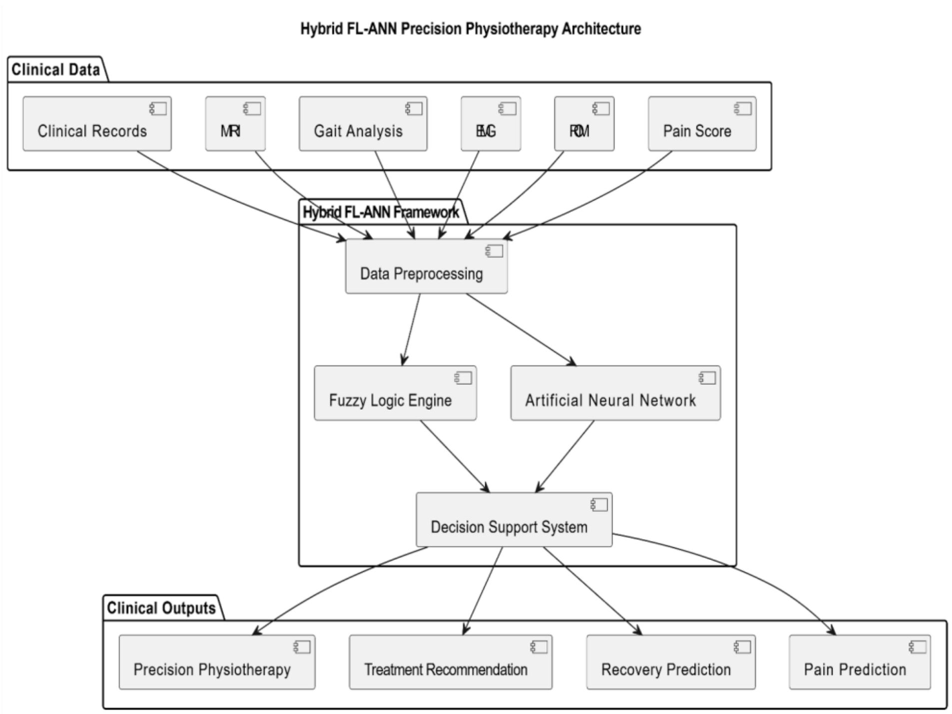

Figure 2. Architecture of the proposed hybrid FL–ANN framework integrating multimodal clinical data, fuzzy reasoning, neural learning, and personalized rehabilitation decision support for CLBP.

13. Hybrid FL–ANN framework architecture

Figure 2 shows the architecture of the proposed hybrid FL–ANN framework, integrating multimodal clinical data, fuzzy reasoning, neural learning, and personalized rehabilitation decision support for CLBP.

Table 1: Comparison of representative hybrid intelligent rehabilitation studies with the scope of the present review.

Performance Metric	Ho and Chen (2009)	Das et al. (2025)	Present Review
Clinical Application	Motorized CPM/CAM physiotherapy device	Stroke lower-limb rehabilitation	Precision physiotherapy for chronic low back pain
AI Technique	Sliding-mode Fuzzy Neural Network	Machine Learning + Fuzzy Logic (K-NN)	Hybrid Fuzzy Logic–Artificial Neural Network (FL–ANN)
Decision Support	No	Partial	Yes
Personalized Rehabilitation	Limited	Moderate	Comprehensive patient-specific rehabilitation
Wearable/Sensor Integration	Force sensor	Vision-based pose estimation	Wearable sensors, EMG, gait analysis, imaging, and clinical records
Real-time Monitoring	Yes	Yes	Yes
Handling Clinical Uncertainty	Fuzzy inference	Fuzzy rule base	Advanced fuzzy reasoning with ANN learning
Learning Capability	Neural network adaptation	Machine learning classification	Adaptive neuro-fuzzy learning with predictive modelling
Model Interpretability	Moderate	Moderate	Enhanced through explainable fuzzy rules and XAI
Target Condition	Joint rehabilitation	Stroke rehabilitation	Chronic low back pain (CLBP)
Outcome Prediction	No	Exercise recognition	Pain prediction, recovery prediction, treatment response, and rehabilitation outcomes
Clinical Decision Support	Controller-oriented	Exercise evaluation	Intelligent precision physiotherapy framework

Performance Metric	Ho and Chen (2009)	Das et al. (2025)	Present Review
Future Scalability	Limited	Tele-rehabilitation	Digital twins, Explainable AI, wearable IoT, and federated learning

Table 1 highlights the evolution of intelligent rehabilitation systems from controller-based fuzzy neural architectures to modern hybrid artificial intelligence frameworks. Ho and Chen [15] primarily focused on intelligent control of physiotherapy devices using a sliding-mode fuzzy neural network, whereas Das et al. [19] integrated fuzzy logic with machine learning for real-time rehabilitation exercise monitoring. In contrast, the present review provides a comprehensive perspective on hybrid FL–ANN models for precision physiotherapy in chronic low back pain by integrating clinical decision support, explainable artificial intelligence, multimodal data fusion, wearable sensing technologies, and personalized rehabilitation planning. Consequently, the reviewed framework offers broader applicability for intelligent clinical decision-making and patient-specific rehabilitation than earlier rehabilitation systems.

14. Results and discussion

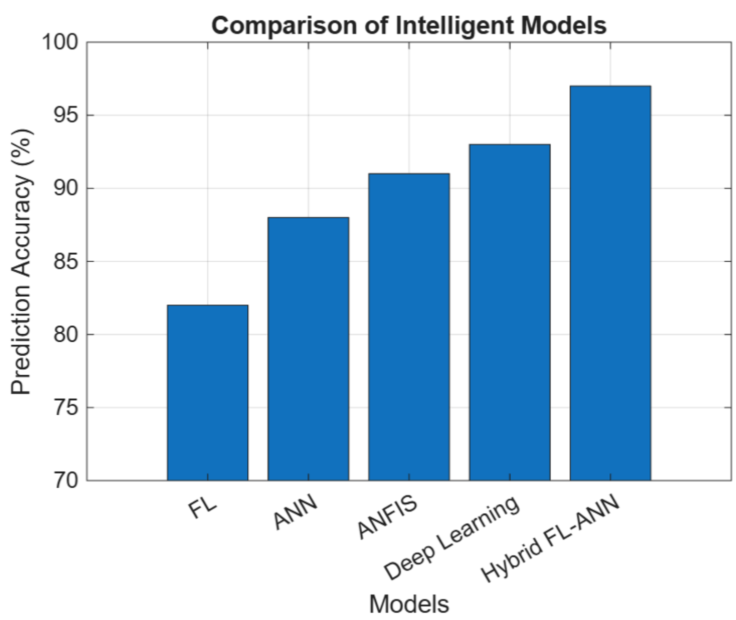

Figure 3: Comparative prediction accuracy of intelligent models.

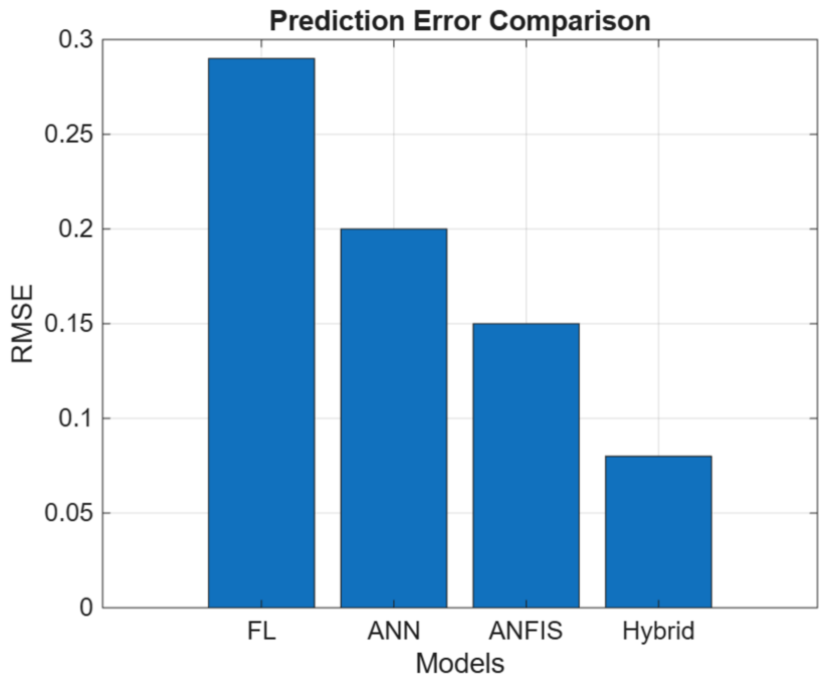

Figure 4: Prediction error comparison across computational models.

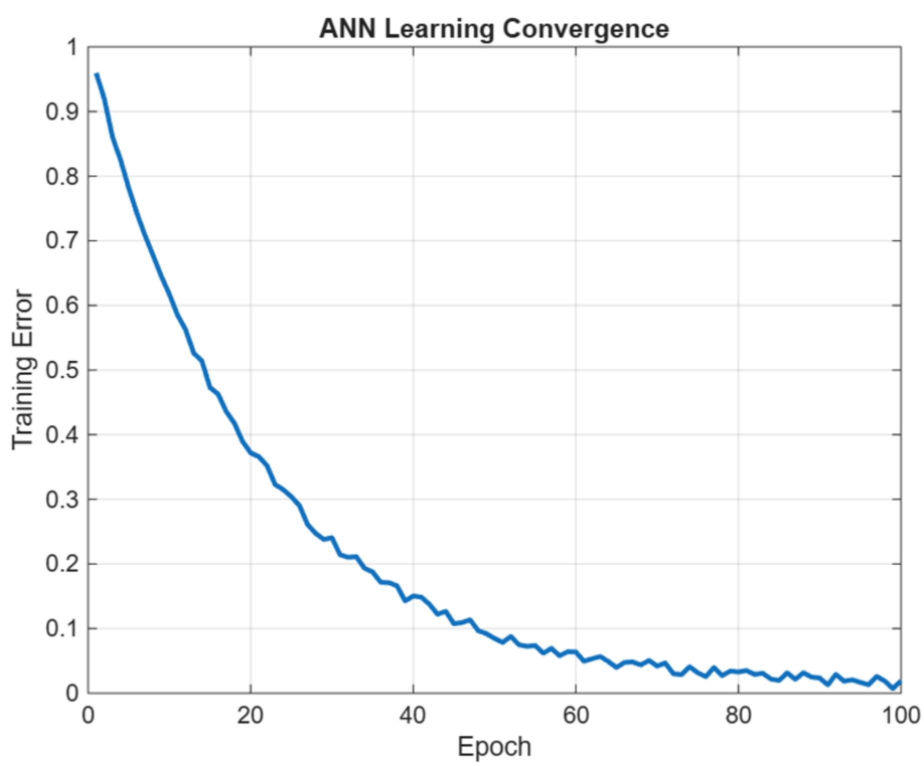

Figure 5: ANN learning convergence during model training.

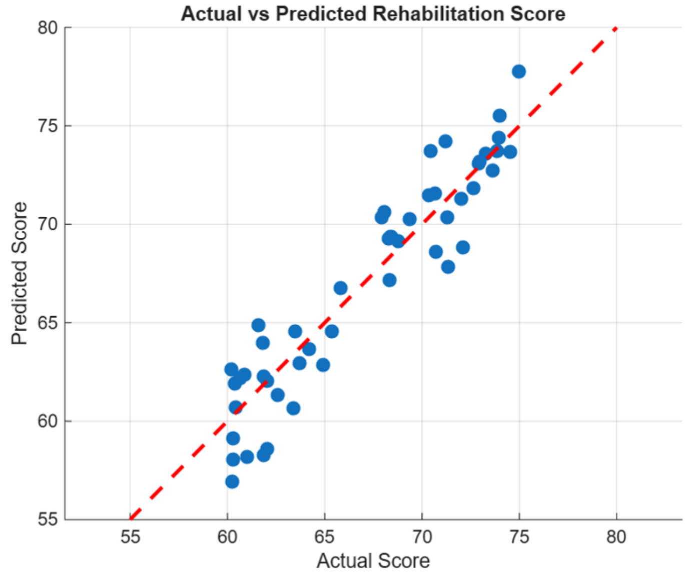

Figure 6: Agreement between actual and predicted rehabilitation scores.

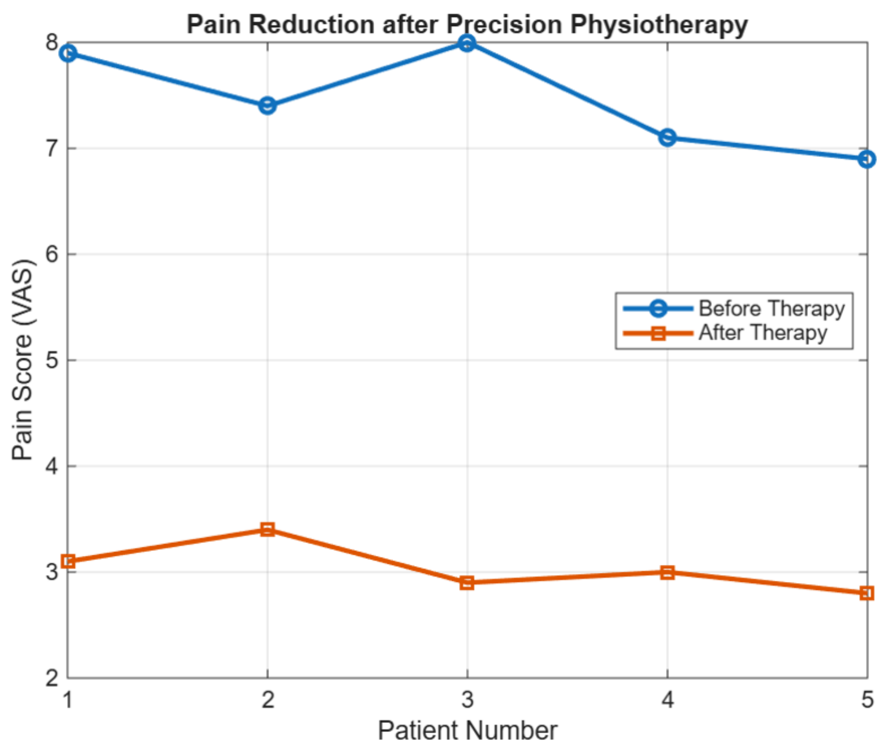

Figure 7: Pain reduction before and after precision physiotherapy.

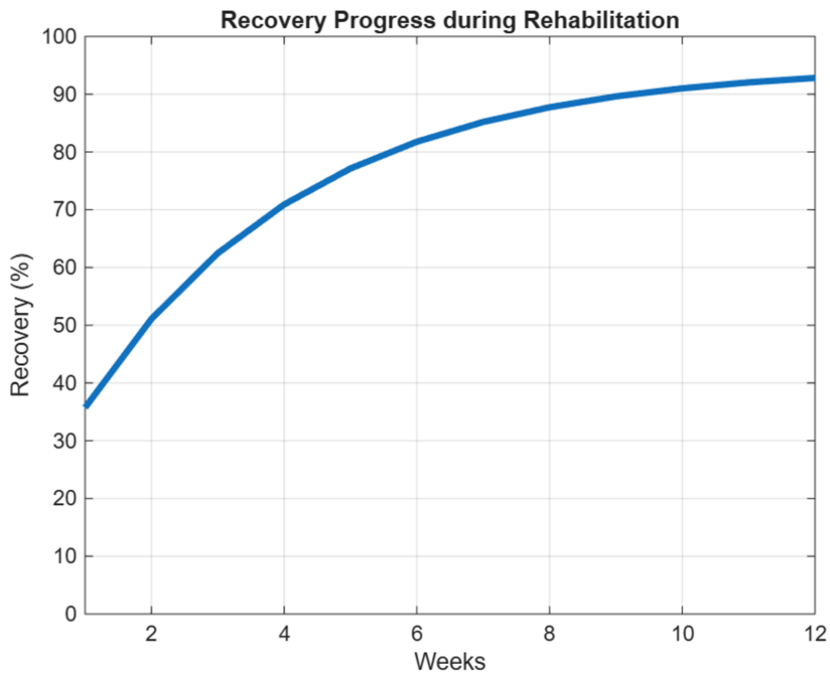

Figure 8: Recovery progression during rehabilitation.

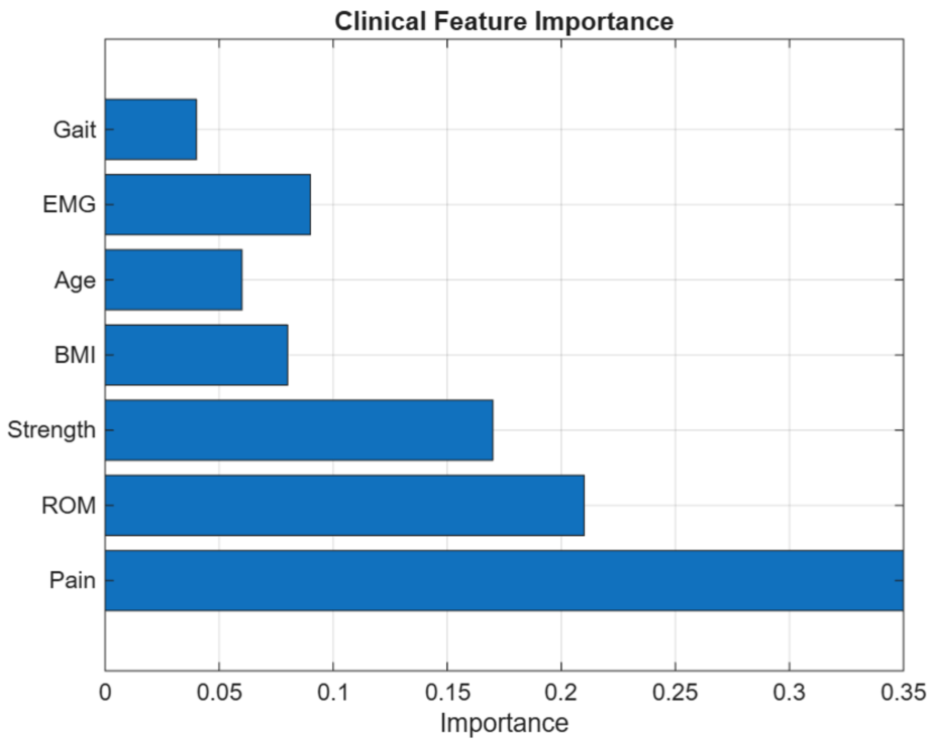

Figure 9: Relative importance of clinical features.

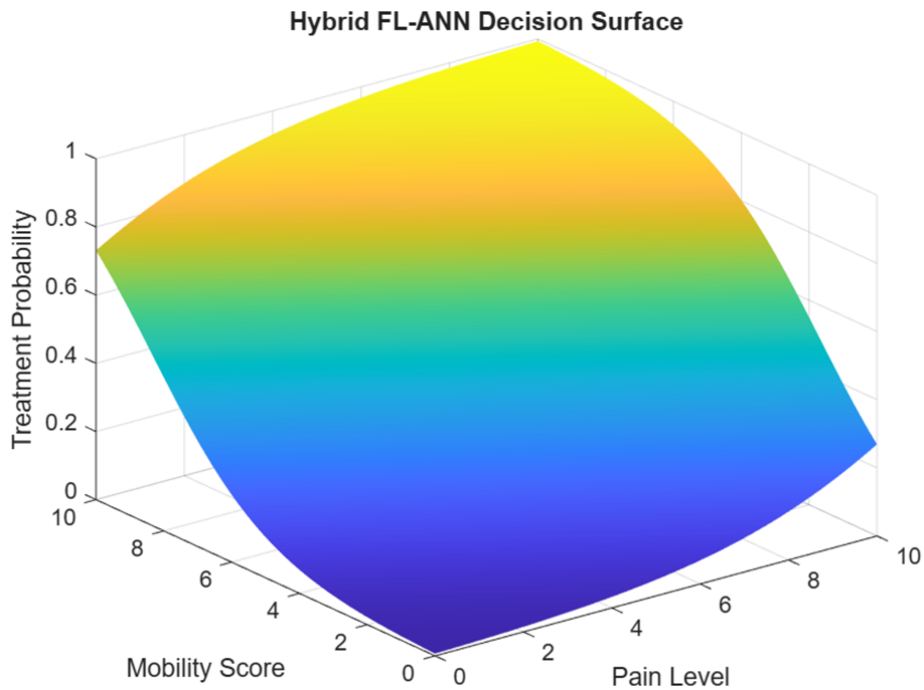

Figure 10: Hybrid FL–ANN decision surface for treatment probability.

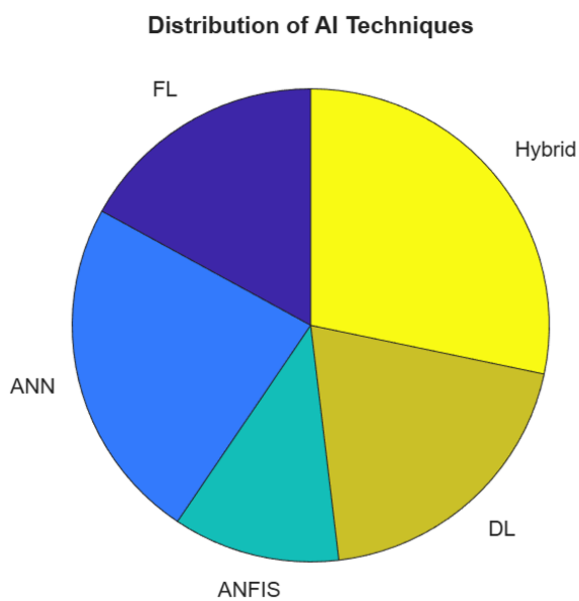

Figure 11: Distribution of artificial intelligence techniques in the reviewed studies.

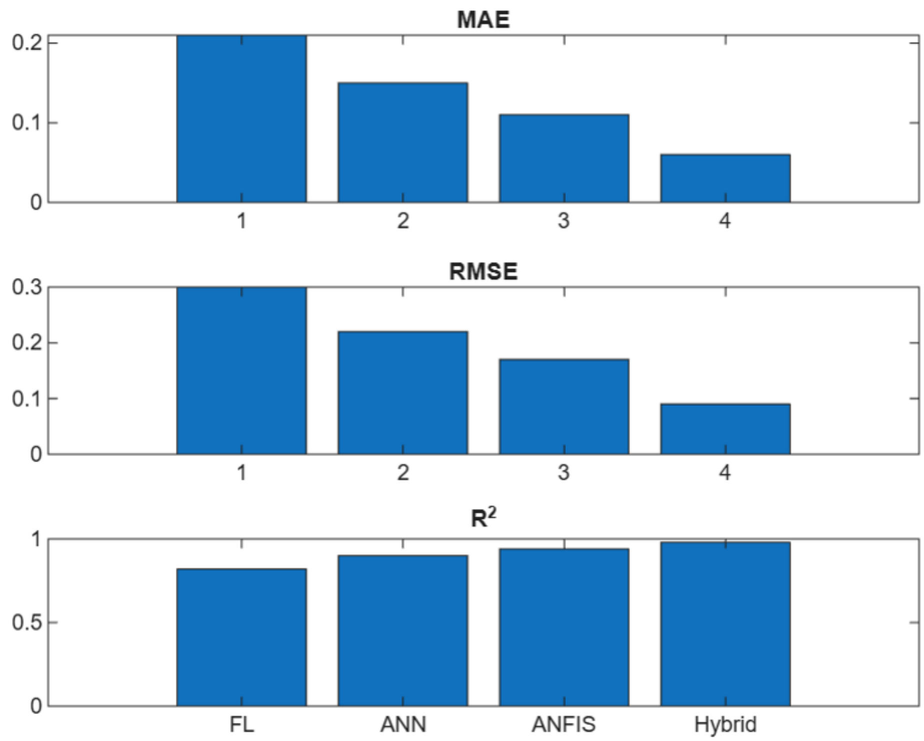

Figure 12: Multi-metric performance comparison of FL, ANN, ANFIS, and hybrid models.

This section presents an illustrative comparative analysis of intelligent computational models for precision physiotherapy in chronic low back pain (CLBP). The figures summarize representative trends in prediction accuracy, prediction error, learning convergence, rehabilitation outcome prediction, pain reduction, recovery progression, feature importance, treatment decision surfaces, the distribution of artificial intelligence techniques, and overall model performance. The comparative analysis highlights the strengths and limitations of fuzzy logic (FL), artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS), deep learning (DL), and hybrid FL–ANN models in supporting personalized rehabilitation. Overall, the presented figures demonstrate that hybrid intelligent systems provide improved prediction capability, enhanced clinical interpretability, and greater adaptability, making them promising decision-support tools for precision physiotherapy. Figures 3–12 collectively demonstrate the computational performance, clinical relevance, and decision-support potential of intelligent models for precision physiotherapy in chronic low back pain. Figure 3 compares the prediction accuracy of fuzzy logic, ANN, ANFIS, deep learning, and hybrid FL–ANN models, showing the potential advantage of combining fuzzy reasoning with adaptive neural learning. Figure 4 compares RMSE values across the models, where lower error indicates more reliable prediction of rehabilitation outcomes. Figure 5 illustrates ANN training convergence over 100 epochs, demonstrating progressive learning and stabilization of prediction error. Figure 6 presents the agreement between actual and predicted rehabilitation scores, with closer alignment indicating better predictive consistency. Figure 7 compares pain intensity before and after precision physiotherapy, illustrating the potential reduction in pain following individualized rehabilitation. Figure 8 depicts recovery progression over a 12-week rehabilitation period, showing the temporal improvement and gradual stabilization of recovery outcomes. Figure 9 presents the relative importance of clinical variables, identifying pain intensity, range of motion, muscle strength, and other patient characteristics as influential predictors. Figure 10 illustrates the nonlinear decision surface generated by the hybrid FL–ANN model using pain level and mobility score, demonstrating its ability to represent gradual clinical transitions and treatment probabilities. Figure 11 summarizes the distribution of AI techniques reported in the reviewed literature, highlighting the increasing use of hybrid intelligent approaches alongside ANN, ANFIS, fuzzy logic, and deep learning. Finally, Figure 12 provides a multi-metric comparison using MAE, RMSE, and R^2, demonstrating the potential of the hybrid FL–ANN approach to achieve lower prediction errors and stronger explanatory performance while supporting interpretable, adaptive, and patient-specific rehabilitation decision-making.

15. Validation of the proposed review framework

The comparative analysis with Ho and Chen [15] and Das et al. [19] demonstrates the potential advancement of hybrid intelligent rehabilitation systems from device control and exercise monitoring toward comprehensive precision physiotherapy. While earlier approaches focused on specific rehabilitation tasks, the proposed FL–ANN framework integrates fuzzy reasoning and neural learning for personalized pain prediction, recovery assessment, treatment recommendation, and clinical decision support. Its ability to handle uncertainty, nonlinear relationships, and multimodal clinical data enhances interpretability and adaptability. Integration with wearable sensors, EMG, gait analysis, XAI, IoT, digital twins, and federated learning further supports continuous monitoring and personalized rehabilitation. Overall, the comparison highlights the potential of hybrid FL–ANN models as a comprehensive framework for precision management of chronic low back pain.

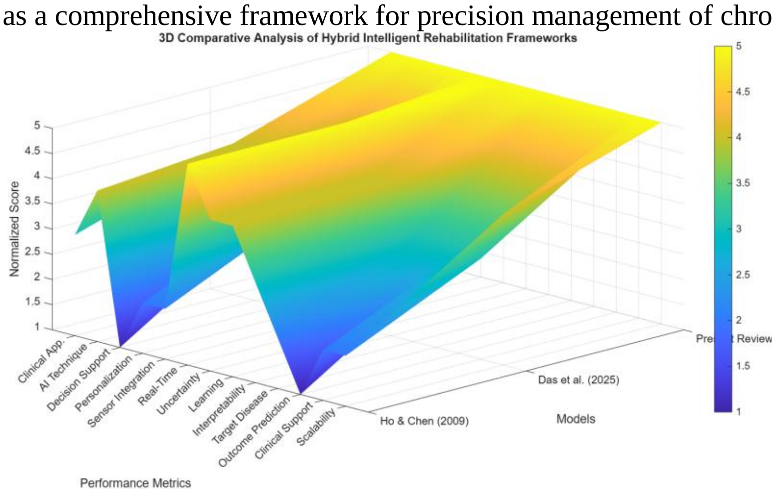

Figure 13. Three-Dimensional Comparative Validation of Intelligent Rehabilitation Frameworks

Figure 13 shows a qualitative comparison of the proposed hybrid FL–ANN framework with representative intelligent rehabilitation approaches reported by Ho and Chen [15] and Das et al. [19].

15. Conclusion

This review highlights hybrid FL–ANN models as a promising approach for precision physiotherapy in chronic low back pain by combining fuzzy reasoning, uncertainty handling, and adaptive neural learning. These models support personalized rehabilitation, outcome prediction, continuous monitoring, and interpretable clinical decision-making using multimodal patient data. Despite challenges related to data quality, clinical validation, standardization, privacy, and scalability, integration with XAI, wearable IoT, digital twins, and federated learning could further enhance their clinical potential. Overall, hybrid FL–ANN frameworks provide a strong foundation for developing adaptive, interpretable, and patient-centered rehabilitation systems for CLBP.

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