Health and Metabolism

Review

Artificial Intelligence Empowers Monitoring, Assessment, and Management in Exercise

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Abstract: The rapid development of artificial intelligence (AI) is a powerful catalyst for personalized exercise monitoring and management. This narrative review examines how exercise and physiological indicators are used in health surveillance and disease management and evaluates the integration of AI in these domains. Accumulating evidence demonstrates strong associations between indicators such as gait, electromyography, and cardiorespiratory fitness with disease outcomes and overall health. AI methods are increasingly being applied to improve monitoring, diagnosis, and personalized exercise prescription, offering greater precision compared with traditional approaches. Nevertheless, challenges persist, including limited data quality, lack of multimodal integration, concerns with interpretability, and ethical issues surrounding privacy. Many studies still rely on small cohorts, limiting clinical applicability. We synthesize current findings, identify research gaps, and propose future directions to enhance the robustness and practical value of AI-driven approaches in exercise and health research.

Keywords: artificial intelligence; deep learning; exercise; healthcare; sports

1. Introduction

Exercise is widely regarded as the cornerstone for promoting health and disease management, extending across the entire life course. It can be broadly categorized based on the primary energy sources utilized during activity, including aerobic exercise, anaerobic exercise, and high-intensity interval training (HIIT). Several studies underscore the benefits of these exercise forms in enhancing well-being and managing health conditions. Aerobic exercise significantly improves cardiovascular health [1,2], alleviates symptoms of Parkinson's disease [3,4], mitigates asthma symptoms [5], eases arthritis pain and stiffness, enhances cognitive function [6,7] and improves sleep quality and overall quality of life [8,9]. Anaerobic exercise is particularly effective in increasing strength and muscle mass [10–13], while HIIT has been shown to promote weight loss [14,15], enhance metabolic function [16], and improve cardiorespiratory fitness [17,18]. Exercise facilitates vascular remodeling and reduces blood pressure by regulating endothelial cell activity and promoting the production of nitric oxide and endothelial nitric oxide synthase through well-defined molecular pathways [19]. Additionally, it mitigates insulin resistance, enhances responses to oxidative stress, decreases inflammation, reduces adiposity, upregulates the expression of insulin-dependent transporter proteins, and improves insulin signaling pathways [20]. Exercise also stimulates the release of endorphins and other neurotransmitters, which play key roles in countering depression [21].

The motor response itself is heterogeneous and is influenced by an individual's physiology, disease status, behavioral patterns and environmental factors. Therefore, exercise-related indicators have emerged as objective and quantifiable functional health indicators. Furthermore, In the late 1960s, the World Health Organization (WHO) officially adopted the term "exercise prescription. Scientifically based exercise prescriptions, tailored to various demographics and conditions, enable individuals to achieve their health objectives. Exercise prescriptions differ according to diseases [22]. For instance, the exercise prescription for diabetes recommends resistance exercise two

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to three times per week, in addition to at least thirty minutes of moderate-intensity aerobic exercise. However, individual implementation of the prescription requires modifications based on each person's unique situation [23].

With the advancement of technology, integrating artificial intelligence (AI) with exercise and health has become an increasingly prominent area for study and application. The advancement of wearable technology has enabled continuous daily health monitoring, activity categorization, and real-time data analysis to provide immediate health recommendations and feedback. Applying AI and a wrist-mounted accelerometer, Farrahi et al. [24] tracked and categorized 24-h activity behaviors like sleep and inactive behavior. To compare user-uploaded films and conventional posture, Qiu et al. [25] employed AI to provide real-time feedback and coaching for posture during rehabilitation training. AI provides a sophisticated method for predicting and alerting potential health hazards and diagnoses through deep learning algorithms. By integrating gait data and AI, Kaur et al. [26] and Meyer et al. [27] have made substantial progress in the diagnosis of multiple sclerosis (MS) and fall risk. Xia et al. [28] proved that force data may be used to detect the gait of individuals with Parkinson's disease accurately. The application of AI technology is especially important for certain diseases and demands. It holds the potential to refine individualized exercise prescriptions by integrating patients' medical information, physiological indicators, and exercise preferences, thereby aiming for improved safety and precision. For instance, individuals can design a personalized workout plan by interacting with ChatGPT and providing their exercise preferences and physiological data. The integration of such smart technologies has significantly advanced the healthcare industry. Given the increasing importance of exercise indicators and the growing potential of artificial intelligence (AI) in health research, this narrative review aims to critically synthesize current evidence on two key aspects: (1) the role of exercise and physiological indicators in the management of health and disease, and (2) the application and effectiveness of AI in integrating these indicators for improved monitoring and assessment. In addition, this review highlights the existing challenges in the field and outlines potential directions for future research.

2. Categories of Exercise-Related Indicators and Their Associations with Health and Diseases

Exercise indicators are important quantitative tools used to objectively represent an individual's exercise performance and physiological responses. Their value is not only reflected in the assessment of exercise capacity, but also plays a key role in health monitoring, disease risk assessment and individualized exercise intervention. They provide reliable quantitative means to identify potential health risks, predict disease onset and progression, as well as optimize personalized exercise treatments (Figure 1). Exercise indicators reflect the comprehensive regulatory status among the skeletal muscle system, cardiovascular system, respiratory system and metabolic system. Their clinical significance depends not only on measurability but also on their sensitivity to changes in functional status. Based on principles from physiology [29], exercise science [30], and health management [31], as well as their measurability and clinical applicability, this study focuses on BMI, muscle mass, bone density, muscular strength, balance, lung function, heart rate, blood pressure, and metabolic rate as core exercise metrics. These indicators are quantifiable across various domains and collectively encompass body composition, physical performance, cardiovascular function, and metabolic status, forming a fundamental basis for evaluating individual health status (Table 1). The application of these individual exercise indicators to assess disease health is detailed below.

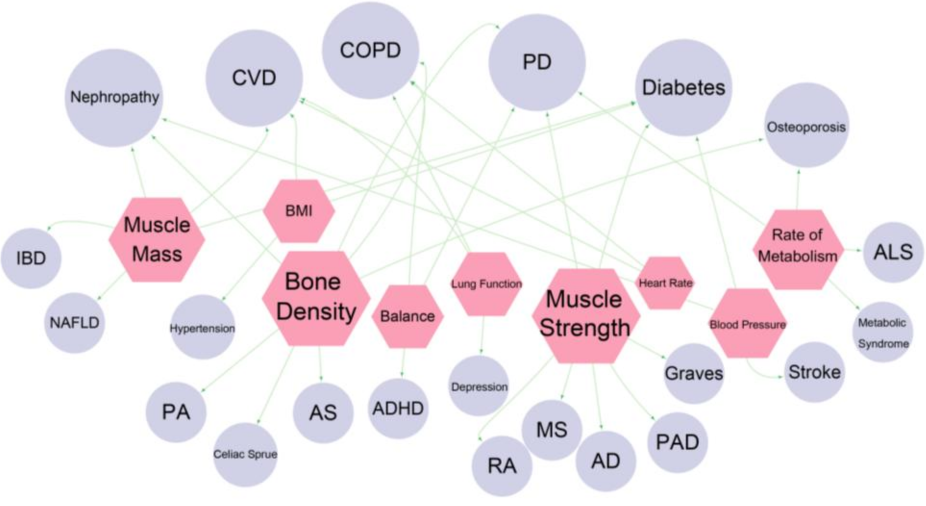

Figure 1. Mapping the pleiotropic effects of physical exercise indicators across various disease categories.

Table 1. Exercise indicators and diseases.

Indicator	Disease	Performance	Literature
Body Composition Indicators			
BMI			
	CVD, Diabetes	Prediction	[32]
	Hypertension	Health Monitoring	[33]
Muscle Mass			
	Diabetes	Diagnosis	[34]
	Nephropathy	Diagnosis, Health Monitoring	[35]
	NAFLD	Prediction	[36,37]
	CVD	Prediction	[38]
	IBD	Health Monitoring	[39]
Bone Density			
	Arthritis	Diagnosis	[40,41]
	COPD	Diagnosis	[42]
	Nephropathy	Prediction	[43]
	Celiac Sprue	Diagnosis	[44]
	Osteoporosis	Prediction	[45]
Indicators of Exercise Capacity			
Muscle Strength			
	PD	Diagnosis, Prediction	[46–48]
	AD	Prediction	[49]
	Multiple Sclerosis	Diagnosis	[50]
	Graves	Diagnosis	[51]
	PAD	Diagnosis	[52]
	Arthritis	Diagnosis, Prediction	[53–55]
	Diabetes	Diagnosis	[56]
Balance			
	PD	Prediction	[57]
	ADHD	Diagnosis	[58]
	COPD	Diagnosis	[59]
Lung Function			
	COPD	Prediction	[60,61]
	CVD	Prediction	[62]
	Depression	Health Monitoring	[63]
Cardiovascular health indicators			
Heart Rate and Blood Pressure			
	CVD	Prediction	[64,65]
	COPD	Diagnosis	[66]
	Nephropathy	Prediction	[67]
	Stroke	Prediction	[68]
	Diabetes	Prediction	[69]
Metabolic Indicators			
Rate of Metabolism			
	Metabolic Syndrome	Health Monitoring	[70]
	Osteoporosis	Prediction	[71]
	PD	Health Monitoring	[72]
	ALS	Prediction	[73]

CVD: Cardiovascular Disease; NAFLD: Non-Alcoholic Fatty Liver Disease; IBD: Inflammatory Bowel Disease; COPD: Chronic Obstructive Pulmonary Disease; PD: Parkinson's Disease; AD: Alzheimer's Disease; PAD: Peripheral Artery Disease; ADHD: Attention Deficit Hyperactivity Disorder; ALS: Amyotrophic Lateral Sclerosis.

2.1. Body Composition Indicators

2.1.1. BMI

BMI (weight/height^2, kg/m^2) is the most widely used body composition index [74]. High BMI accounts for approximately 58% of the global burden of type 2 diabetes [75]. Elevated BMI was associated with increased CVD risk and mortality, with risk increasing with obesity duration [76].

The impact of a high BMI runs through a person's entire life. In adolescent populations, high BMI substantially increased risks later in life: among diabetic youth, high BMI was associated with diabetes progression (HR: 2.76, 95% CI: 2.11–3.58) and coronary heart disease (HR: 5.43, 95% CI: 2.77–10.62); these associations persisted after adjustment for adult BMI (HR: 6.85, 95% CI: 3.3–14.21) [32]. At the population level, BMI also demonstrated a strong ability to distinguish common cardiovascular metabolic risk factors. Prevalence of hypertension and hypercholesterolemia rose markedly with BMI (for BMI < 25: 3.5% and 13.0%; for BMI > 30: 24.6% and 22.0%) [33].

2.1.2. Muscle Mass

Skeletal muscle mass (measured by Dual-Energy X-ray Absorptiometry or Bioelectrical Impedance Analysis) is central to posture, exercise, and balance [77]. Patients with diabetes showed decreased lower-limb muscle density ($p < 0.05$) [34]; among CKD patients, 47% of non-dialysis patients experienced deterioration in muscle quality within one year (vs. 25% hemodialysis, 35% peritoneal dialysis) [35]. Muscle mass inversely correlates with NAFLD risk (OR: 2.57, 95% CI: 2.03–3.25, $p < 0.001$) [36].

Longitudinal and cross-sectional study evidence further supports the negative correlation between muscle mass and the risk of metabolic diseases. Higher SMI predicted lower incident NAFLD (HR: 0.44, 95% CI: 0.38–0.51, $p < 0.001$), and individuals with the largest SMI increases had lower new-NAFLD risk (HR: 0.69, 95% CI: 0.59–0.82, $p < 0.001$) [37].

A similar effect has been seen in patients with CVD (HR: 0.19, 95% CI: 0.04–0.85) [38] and inflammatory bowel disease (IBD) [39]. These findings collectively highlight the importance of maintaining and monitoring muscle mass in the management of various diseases.

2.1.3. Bone Mineral Density

Bone Mineral Density (BMD) is a critical measure reflecting bone mineral content, strength and structural integrity [78]. BMD declined with age—more pronounced in women (37.5%) than men (22.9%) [79]. Integrating BMD measurements with other risk factors has been shown to enhance the accuracy of fracture risk predictions in osteoporosis assessments [80]. In rheumatoid arthritis, osteoporosis probabilities were 6.5% at the femoral neck and 12.6% at the spine, with bone volume reductions of ~18% and ~20.7% respectively [40]. COPD patients displayed lower overall bone density (Z-score: –0.5; 95% CI: –0.8 to –0.2; $p < 0.001$) [42]. In adolescents with renal failure, average BMD Z-scores were 2.12 ± 1.4 for the lumbar spine and 1.77 ± 1.4 for the femoral neck, indicating a significant risk of early adult fractures [43]. Both untreated ($p < 0.001$) and treated ($p < 0.05$) celiac disease patients exhibited significantly lower BMD compared to healthy individuals [44]. Older women with Parkinson's disease demonstrated lower proximal femur (0.66 ± 0.11) and hand BMD (0.34 ± 0.03) vs. controls (0.75 ± 0.09 and 0.38 ± 0.03) [45]; ankylosing spondylitis patients showed lower peripheral bone density (thumb $p = 0.007$; tibia $p = 0.033$) [41].

The utility of body composition indicators is constrained by methodological and interpretative limitations. BMI does not distinguish between fat and lean mass, muscle mass quantification provides little insight into functional performance, and BMD measures density without capturing microarchitectural quality. To enhance predictive validity, future research should refine measurement standards, incorporate qualitative dimensions such as muscle density and bone microstructure, and explore composite indices that integrate fat distribution, muscle functionality, and skeletal integrity for more precise disease risk stratification.

2.2. Indicators of Exercise Capacity

2.2.1. Muscle Strength

Muscle strength, commonly assessed via handgrip and lower-limb force measurements, captures the force-generating capacity of skeletal muscle and serves as a practical indicator of functional status. Declines in muscle strength were closely linked to age-related reductions in muscle mass [81,82], although strength loss frequently exceeds what would be expected from muscle atrophy alone, suggesting contributions from neuromuscular dysfunction. PD patients (unmedicated) showed reduced hip extension torque (0.76 vs. 0.96 Nm/kg), knee extension torque (1.00 vs. 1.18 Nm/kg) and slightly prolonged sit-to-stand time (1.97s vs. 1.89s) [46,47]. Low grip strength (lowest 25%) was associated with higher PD risk (HR: 1.6, 95% CI: 1.42–1.79) vs. moderate strength [48]; each 0.05 kg increase in relative grip strength reduced all-cause dementia incidence by 8.2% [49]. Leg strength differences were significant in MS ($p < 0.001$) [50]. Deficits were also reported in Graves' disease (hand grip $p = 0.012$), PAD ($p < 0.005$), and rheumatoid arthritis [51–54]. Quadriceps weakness rose knee osteoarthritis risk in women (OR: 1.47, 95% CI: 1.1–1.96) [55]. In type 2 diabetes, lower-limb strength was reduced by ~16–22% despite similar upper-limb strength to controls [56].

2.2.2. Balance

Balance refers to the ability to maintain body stability and prevent falls during both static and dynamic movements. It is crucial for daily activities, athletic performance, and fall prevention. Clinically, the Berg Balance Scale (BBS) is a commonly used tool for assessing balance ability. According to standard scoring criteria, a BBS score of 41–56 is considered indicative of normal balance, while a score of ≤40 suggests a high risk of falling, warranting further intervention to reduce fall incidence. PD patients with postural-instability gait disorder showed faster cognitive decline and higher dementia risk ($p = 0.003$) [57]. ADHD children demonstrated impaired balance vs. controls ($p < 0.001$) [58]. COPD patients had worse balance scores, longer frontal-perturbation reaction times ($p = 0.027$), and increased foot-contact duration ($p = 0.008$) [59].

2.2.3. Lung Function

Lung function indicators are linked to various alterations in health and illness [83]. Vital capacity (VC), FEV1/FVC and VO_2max assess pulmonary and cardiorespiratory capacity. The normal range for VC: ≥4.8 L (adult males), ≥3.2 L (adult females). Childhood FEV1/FVC in the lowest quartile (<96.5%) predicted COPD at age 45 (OR: 5.76, 95% CI: 1.9–17.4) and ACOS (OR: 16.3, 95% CI: 7–55.9) [60].

In contrast, achieving normal FEV_1 in early adulthood did not completely eliminate future risks, as normal early lung function was still associated with an increased incidence of COPD in later life (HR: 1.15, 95% CI: 0.68–1.94) [61], highlighting the importance of longitudinal trajectory over a single measurement.

In heart failure, low FEV1 (HR: 0.86, 95% CI: 0.8–0.92, $p < 0.001$), low FVC (HR: 0.87, 95% CI: 0.8–1.04, $p < 0.001$) and low FEV1/FVC (HR: 0.88, 95% CI: 0.8–0.96, $p = 0.01$) predicted all-cause mortality [62]. Low VO_2max was associated with higher depressive symptomatology (lowest 25% VO_2max OR: 3.42, 95% CI: 1.65–7.09) [63].

Exercise capacity measures capture dimensions of functional health that static indices cannot. However, most existing evidence is cross-sectional, limiting the ability to assess temporal dynamics. Longitudinal investigations are warranted to monitor progressive changes in muscle strength, balance, and VO_2max, thereby enabling early identification of functional decline and disease onset. Moreover, the development of multidimensional performance scores that synthesize strength, balance, and cardiorespiratory fitness may provide a more comprehensive assessment of overall functional reserve.

2.3. Cardiovascular Health Indicators

Heart Rate and Blood Pressure

Heart rate refers to the number of times the heart beats per minute. Variations in the heart rate at rest are a significant cardiovascular disease risk factor [84]. An increase of 15 bpm in RHR was associated with higher CVD mortality for men (OR: 1.24, 95% CI: 1.11–1.4) and women (OR: 1.32, 95% CI: 1.08–1.6) [64]. Low heart rate variability, predicted coronary artery disease ($p < 0.001$) [65]. Furthermore, an elevated resting heart rate was correlated with the severity of COPD and was strongly associated with cardiovascular mortality at all stages of the disease ($p < 0.001$) [66].

Blood pressure (SBP/DBP) remains a cornerstone predictor, with optimal levels typically defined by a threshold of SBP <120 mmHg and DBP <80 mmHg . Men with stage-4 hypertension had markedly greater odds of end-stage renal disease (OR: 22.1, $p < 0.001$) [67]. Baseline hypertension increased risk of cerebrovascular events and reducing BP lowers stroke risk in extensive cerebrovascular disease [68]. Elevated baseline BP predicted incident CVD and type 2 diabetes (HR: 2.39, 95% CI: 1.95–2.93, $p < 0.0001$) [85]. Lastly, increased systolic blood pressure was also negatively correlated with cognitive function ($\beta = -0.291$, $p < 0.005$) [69].

Although heart rate and blood pressure are readily obtainable and widely applied in both clinical and research contexts, their substantial variability undermines reliability when assessed in isolation. Future studies should prioritize dynamic monitoring approaches that capture intra-individual fluctuations, circadian rhythms, and variability across clinical visits. Such analyses are likely to yield more accurate prognostic information than reliance on static thresholds alone, particularly in relation to cardiovascular risk and cognitive outcomes.

2.4. Metabolic Indicators

Metabolic Rate

Metabolic rate is the total amount of energy used by metabolic activity per unit of time. Basal metabolic rate (BMR) reflects resting energy expenditure. WHO normal ranges: ~1500–1800 kcal/day (men) and ~1200–1500 kcal/day (women). Obesity with metabolic syndrome often involved reduced resting metabolic rate ($p < 0.01$) [70]. Lower BMR was associated with higher osteoporosis incidence (OR: 0.99, 95% CI: 0.98–0.99, $p < 0.001$) [71]. Elevated BMR (>36.4 kcal/($m^2 \cdot h$)) in older adults related to higher mortality (HR: 1.53, 95% CI: 1.19–1.96) [86]. Disease-specific patterns further highlight metabolic heterogeneity. The duration of PD was significantly correlated with an increased basal metabolic rate in unmedicated patients ($r^2 = 0.31$, $F = 3.6$; $p = 0.0045$) [72]. High metabolism was commonly observed in patients with amyotrophic lateral sclerosis (ALS) and was associated with an increased risk of ALS-related death (HR: 3.2, 95% CI: 1.1–9.4, $p = 0.03$) [73].

Metabolic indicators exhibit pronounced heterogeneity, being influenced by demographic characteristics, body composition, and endocrine factors. Interpretation of absolute values without contextualization may lead to misclassification. A more appropriate approach is to consider individualized baselines and longitudinal trajectories of metabolic rate. Integrating metabolic measures with biochemical or metabolomic markers could provide a more nuanced understanding of the interplay between metabolism and disease vulnerability, offering opportunities for personalized risk profiling.

2.5. Interactions among Exercise Indicators

Exercise-related indicators interact across multiple physiological systems, forming a tightly coupled network that underlies health and disease. For instance, skeletal muscle helps maintain bone health by applying mechanical loads that stimulate bone mineralization [87–89]. Muscle strength and muscle mass are also closely correlated; higher strength is frequently accompanied by greater muscle mass, which enhances metabolic rate [90,91]. Body composition and metabolic abnormalities are tightly linked: elevated BMI and adiposity are strongly associated with hyperglycaemia, dyslipidaemia, systemic inflammation, and atherogenesis. [92–95], while low muscle mass frequently coexists with excess adiposity and constitutes an independent risk factor for adverse outcomes [96]. Bone density has been reported to correlate with CVD risk, though the association is weaker and likely reflects overall health deterioration [97]. Epidemiological data further report associations between low bone mineral density and increased cardiovascular event rates [98]. Despite these observations, a substantial proportion of the literature treats exercise-related measures independently, which may obscure mediating, compensatory, or bidirectional mechanisms. For example, BMI conflates adipose and lean tissue, complicating interpretation of metabolic and cardiovascular associations; similarly, observed links between BMD and cardiovascular disease may, in some contexts, reflect frailty or systemic inflammation rather than direct causality [99].

The above evidence highlights the need for research frameworks that capture the interplay of multiple domains. Future investigations should employ causal mediation and multi-state transition models to clarify whether observed associations. At the same time, findings on the combined effects of adiposity, muscle mass, and metabolic dysregulation suggest the utility of constructing composite indices that integrate structural and functional components. Moreover, stratified analyses across demographic and clinical subgroups will be essential to identify heterogeneity and to guide targeted prevention strategies.

3. Intelligent Health Monitoring and Assessment by Exercise and Physiological Indicators

Artificial intelligence (AI) was coined in the 1950s to describe the human-like intellect demonstrated by machines. AI technology now has a wide range of applications, including health monitoring, disease diagnosis, rehabilitation therapy, and sports. The rapid advancements in AI technologies have significantly enhanced the precision and efficiency in these fields [100]. AI can leverage wearable devices, sensors, smartphones, and computer vision technologies to collect and process real-time physiological and movement metrics, such as heart rate, blood pressure, and movement trajectories, enabling comprehensive health monitoring. Various algorithms facilitate disease diagnosis and prediction, improving diagnostic accuracy and efficiency for healthcare professionals (Figure 2). Additionally, reinforcement learning techniques can optimize personalized exercise prescriptions, providing intelligent guidance for achieving optimal health management. Here, we have reviewed several applications in combination of monitoring, assessment, and management with health, disease diagnosis/prediction, rehabilitation, and sports (Table 2).

Table 2. Health management by indicators and intelligent models.

Classification	Purpose	AI Paradigm	Training Datasets	AI or Deep Model	Performance	Literature
Disease Diagnosis and Prediction	MS gait differentiation	Discriminative	Gait data; MS patients and HC ($n = 40$)	ResNet	ACC = 82.9%, AUC = 81.3%	[26]
	MS fall risk classification	Discriminative	Gait data; 37 MS patients	BiLSTM	ACC = 86%, AUC = 88%	[27]
	PD gait quantification	Discriminative	Vertical ground reaction force in Gait; 93 PD and 73 HC	CNN, LSTM	ACC = 99.07%, AUC = 99.6%	[28]
	Dementia CI classification	Discriminative	Path image of walking; 10 CI	CNN	ACC = 87.38%	[101]
	Sarcopenia risk prediction	Discriminative	Exercise and health data; 108,304 older adults	DNN	ACC = 87.55%	[102]
	MS/PD gait dysfunction prediction	Discriminative	Gait data; 10 MS, 9 PD, 14 HC	CNN	ACC = 89.34%	[103]
	Early CP screening	Discriminative	Joint coordinates; 1127 infants	Transformer	AUC = 96.7%	[104]
	ITW gait recognition	Discriminative	Gait data; 36 children	CNN	ACC = 79.3%, AUC = 93%	[105]
	Multi-modal NDD diagnosis	Discriminative	Gait data and images; NDD	CorrMNN	ACC = 96%, AUC = 95%	[106]
Rehabilitation	Stroke rehab exercise recognition	Discriminative	Exercise acceleration and angular velocity values; from patients	CNN	ACC = 98.8%	[107]
	Rehab exercise scoring	Discriminative	Joint coordinates; 15 HC	AE	Separability = 0.515 *	[108]
	Shoulder rehab monitoring	Discriminative	Exercise acceleration and angular velocity values; 58 patients with shoulder pain	MLP	ACC = 92.5%	[109]
	Stroke arm movement classification	Discriminative	Exercise acceleration and angular velocity values; 14 stroke survivors	CNN	ACC = 88.87%	[110]
	sEMG motion classification	Discriminative	Electromyography signals of exercise; HC	BP-LSTM	ACC = 92%	[111]
	Action quality assessment	Discriminative	Exercise poses images; from standard and patients	MS-CNN, STN	ACC = 70.02%	[25]
	Post-stroke muscle assistance	Discriminative	Exercise electroencephalography and electromyography signals; stroke patients	AI-based predictive model	ACC = 88%	[112]
	Locomotion intent prediction	Discriminative	Gait data and electromyography signals; 10 HC	CNN	ACC = 94.59%	[113]
	Exoskeleton gait analysis	Discriminative	Walking poses images; HC	CNN	ACC = 97.18%	[114]
Health monitoring and Exercise prescription	Exercise prescription	Generative	Basic information	ChatGPT	ChatGPT	[115]
	Personalized elderly exercise	Discriminative	Exercise data; 300 community-dwelling older adults (aged ≥ 65)	ResNet	NR	[116]
	Mental health exercise prescription	Discriminative	Mental health and exercise data; clinical trial participants	Generative AI tool	NR	[117]
	Personalized fitness recommendation	Discriminative	Exercise data; public fitness datasets	MLP, BiLSTM	NR	[118]
	24-h activity classification	Discriminative	Accelerometer data; 151 participants (18–91 years)	BiLSTM	ACC = 98.2%	[24]
	Minor gait alteration detection	Discriminative	Gait data; 12 able-bodied participants	LSTM	ACC = 82%	[119]
	Walking posture identification	Discriminative	Exercise pose images; Young adults	CNN	ACC = 86%	[120]
	VO_2max estimation	Discriminative	The 20-m run result and basic information; 267 adolescents	ANN	$p = 0.654$	[121]
	Exercise thermal analysis	Discriminative	1,107,855 thermals images in exercise	CNN	IoU: 0.7 *	[122]

Table 2. *Cont.*

Classification	Purpose	AI Paradigm	Training Datasets	AI or Deep Model	Performance	Literature
Sports monitoring and prediction	Football player detection	Discriminative	Features in competition footage; Video	CNN	AP = 93.2% *	[90]
	Multi-athlete tracking	Discriminative	Features in competition footage; APIDIS, NCAA Basketball, and VolleyTrack datasets	LSTM	F1 = 0.915, MOTA = 0.902 *	[91]
	Volleyball activity recognition	Discriminative	Accelerometer data; 10 professional players	CNN	ACC = 83.2%	[123]
	Sports achievement prediction	Discriminative	Basic information	BPNN	MSE = 0.0013 *	[124]
	Athlete performance prediction (EEG)	Discriminative	Electroencephalography signals; 36 elite archery athletes	CNN, LSTM	ACC = 96.7%	[125]
	Knee injury risk monitoring	Discriminative	Exercise data; 13 semi-professional athletes	CNN	ACC = 88.95%	[126]

Area Under the Curve (AUC), Accuracy (ACC): Accuracy of classification models; Mean Squared Error (MSE); Average Precision (AP): Model performance in object detection tasks; Separability: Measures the separability of different classes in the feature space; Multiple Object Tracking Accuracy (MOTA), F1 Score: Model performance in multi-task tracking tasks; Intersection over Union (IoU): Used in computer vision to measure the overlap between predicted results and ground truth; Multiple Sclerosis (MS), Parkinson's Disease (PD), Healthy Controls (HC), Cognitive impairment (CI), Cerebral Palsy (CP), Idiopathic Toe Walking (ITW), Neurodegenerative Diseases (NDD), Surface Electromyography (sEMG), Maximal Oxygen Uptake (VO2max), Electroencephalogram (EEG). *: The best performance reported in the respective studies. NR: Not reported in the original study.

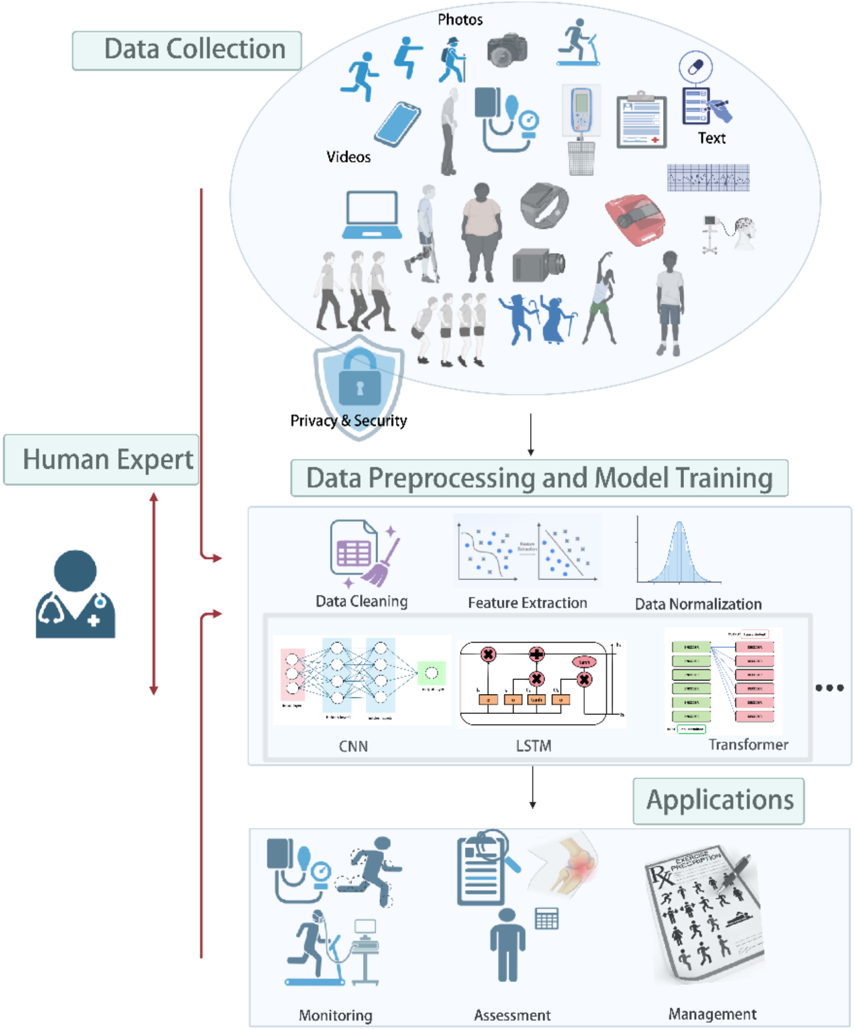

Figure 2. A multi-stage deep learning framework for comprehensive health monitoring, assessment, and personalized exercise management. (Figure created with BioRender.com.).

3.1. Health, Exercise Monitoring and Remote Coaching

3.1.1. Health Monitoring

AI-enabled wearable sensing systems have proven to be highly accurate in continuously monitoring physiological and movement-related behaviors, especially when jointly modeling temporal and spatial features.

Recent studies have shown that combining wearable sensors with deep learning architectures can reliably capture activity patterns and motion states in real-world scenarios. Farrahi et al. [24] combined wrist-worn accelerometry with a bidirectional LSTM, achieving 98.2% accuracy in classifying 24-h activities.

3.1.2. Exercise Monitoring

In the sports domain, exercise indicators have been leveraged for detection, tracking and performance analysis. Wang et al. [90] designed a parameter-efficient deep CNN for football player detection, reaching AP = 0.932 and outperforming YOLO while reducing complexity. Kong et al. [91] introduced a multimodal LSTM architecture for basketball action recognition (movement, passing, dribbling, shooting), achieving MOTA = 90.2% and IDF1 = 91.5%.

The method based on wearable devices further demonstrates the feasibility of motion classification in unrestricted environments. Kautz et al. [119] applied a DCNN to classify beach-volleyball actions from accelerometer data (US, OS, SP, DG), obtaining an accuracy of 83.2% and surpassing traditional classifiers. These results collectively indicate that AI-driven models can effectively capture the motion characteristics of specific movements under different sensing modes.

Through the motion recognition model, abnormal motion patterns can be detected, allowing athletes to correct these problems during regular training and prevent the accumulation of incorrect techniques. These technologies provide coaches with more refined data support, helping to improve training effectiveness and reducing the risk of injuries.

Despite these advances, translation to injury prevention and training optimization requires integration of exercise monitoring with workload, fatigue, and recovery indicators. Longitudinal studies assessing predictive validity for injury occurrence and evaluations of diverse competitive and environmental conditions remain essential for real-world implementation.

3.1.3. Remote Coaching

Rehabilitation

Methods based on sensor data analysis and deep learning modeling can effectively monitor, classify, guide, and assess the quality of rehabilitation movements, thus enabling efficient remote rehabilitation training guidance. Zhang et al. [120] proposed SSRER, a CNN-based system mapping sensor signals to a 0–1 execution score, which achieved near-clinician agreement (98.8 points over 50 tests). Liao et al. [123] used 3D motion capture with autoencoders and Gaussian mixture models to assess ten rehabilitation movements (Separability = 0.515).

The classification-based method has also demonstrated excellent performance. Lee et al. [107] classified 11 shoulder rehabilitation exercises from IMU data using a multi-layer perceptron with 92.5% accuracy. Qiu et al. compared standard postures to learner postures using an attention-based multi-scale CNN and a spatial transformer network (STN), providing real-time feedback and coaching during rehabilitative training posture [25]. The system consists of two primary elements, each with an average posture accuracy rate of 70.02%.

These studies are critical for precisely evaluating and monitoring rehabilitation training, not only enhancing its quality but also optimizing the training process. It also improves the efficacy of home rehabilitation by allowing patients to rehabilitate at home, considerably enhancing treatment efficiency and effectiveness while also providing more convenient rehabilitation experiences. However, the use of AI for remote rehabilitation assessment and guidance is not without risks. Over-reliance on AI systems introduces significant concerns about clinical safety and muddies the definition of medical responsibility. Errors in algorithm classification or motion analysis can provide inappropriate feedback, potentially reinforce incorrect movements and leading to a cascade of negative outcomes, such as heightened injury risk or unsatisfactory recovery. These dangers are amplified in unsupervised home environments lacking professional oversight. Since optimal rehabilitation requires supervision by trained clinicians, the adoption of AI must be accompanied by rigorous scrutiny of its ethical and legal dimensions, particularly concerning liability, data privacy, and informed consent.

Regular Exercise Training

Regular exercise training can also be effectively monitored and guided remotely. Panwar et al. [108] used three-axis acceleration data to classify joint movements of the forearm using a two-layer CNN based on the "Rehab-Net" model, achieving an accuracy rate of 88.87% in a natural environment (where participants performed arbitrary upper limb movements). Wang et al. [109] used an enhanced deep backpropagation LSTM to assess surface electromyography (EMG) signals on the upper limb and automate upper limb movement analysis, obtaining a 92% accuracy.

These studies confirm the feasibility of remote, home-based exercise assessment using AI-enabled sensing and modeling approaches. However, further progress depends on validation against clinically meaningful outcomes, development of adaptive and individualized feedback mechanisms, and rigorous evaluation in real-world settings characterized by variable sensor placement, user compliance, and environmental conditions.

3.2. Diagnosis and Prediction

Intelligent computing methods based on gait characteristics, movement data, and physiological signals have shown promising results in the diagnosis and prediction of various diseases. Kaur et al. [26] applied a CNN ("Rehab-Net") to treadmill gait data, classifying multiple sclerosis with ACC = 82.9% and AUC = 0.813. Meyer et al. [27] used accelerometers and a BiLSTM to identify MS patients at risk of falls, achieving ACC = 86% and AUC = 0.88. Similarly, Xia et al. [28] combined in-shoe pressure sensors with attention-based LSTM to recognize Parkinsonian gait, reaching 99.07% accuracy. Faruk et al. [110] developed a CNN for cognitive impairment detection from positional images, yielding ACC = 87.38%. Furthermore, Bae et al. [111] predicted sarcopenia risk from anthropometric and functional indicators using a four-layer neural network, with ACC = 87.55%. Meanwhile, Chen et al. [101] built a convolutional model with attention for idiopathic toe walking detection, achieving 89.34% accuracy. Furthermore, Gao et al. [102] created a motor assessment model for infant cerebral palsy screening, reporting AUC = 96.7%. In conclusion, these deep learning models that analyze walking data, the combination and application of exercise and health data, and motion features in images and videos have significantly improved disease diagnosis accuracy and opened up new avenues for disease early detection and intervention.

In addition to using movement characteristics to guide the diagnosis of individual diseases, multiple studies have achieved promising results in capturing subtle features of disease phenotypes in patients. For example, research has explored gait characteristics associated with different neurodegenerative diseases. Specifically, the gait traits of neurodegenerative illnesses differ, and AI technology is effective at distinguishing them. Kaur et al. [103] classified MS, PD and healthy controls using CNN with ACC = 79.3% and AUC = 0.93. Zhao et al. [104] used gait data and image information from multiple sensors to design a dual-channel memory neural network that distinguished and quantified PD, Huntington's disease, and ALS with excellent performance (ACC > 96%, AUC > 0.95). By combining joint information, gait data and multimodal feature fusion, the deep learning model can analyze the gait features and distinguish between different diseases, even when these diseases have very similar phenotypes. The models are capable of capturing the specific characteristics and making accurate diagnoses.

AI can also help anticipate athletic performance. Hou et al. [105] used a BP neural network to predict 3000 m steeplechase performance (runtime 0.0276 s, MSE = 0.0013). Tsai et al. [106] analysed EEG signals with a hybrid model to predict athletic performance (accuracy up to 96.70%). R. Ruiz et al. [124] employed adolescents' 20-m shuttle run performance and basic physiological parameters(such as weight, height) to estimate the maximum oxygen uptake (VO2max) using an Artificial Neural Network (ANN) and compare it to actual data, showing a mean difference of 0.5 mL/(kg min) between measured and estimated VO2max, which was not statistically significant ($p = 0.654$). Hillen et al. [125] created an automatic analysis method based on CNN for analyzing thermal imaging images captured during exercise to ensure accurate measurement of skin surface radiant temperature, with an average intersection over union (IoU) of 0.7 and an average measured value difference of 0.01 °C (SD = 0.08 °C). By analyzing physiological data, monitoring neural signals, and utilizing intelligent image recognition, training plans can be optimized to enhance training effectiveness and enable precise fatigue monitoring during exercise.

Every athlete might experience injuries to some extent in their career. Therefore, it would be beneficial if we could foresee in advance and prevent it. Methods based on biomechanical modeling and deep learning can effectively help us do this. Johnson et al.'s study [121] showed us a CNN simulation of 3D knee moments can predict injuries associated with gait, runing and lateral lacomotion. Their findings demonstrate that the correlation with actual measured values is greater than 0.8 in several movement tasks, with lateral walking showing the highest prediction accuracy (0.85 or above). This enables athletes to determine whether they are carrying an excessive moment load during specific motions and provides early warning of knee injury risk.

Meanwhile, the combination of deep learning, bio-signal analysis and robotics has also shown good results in the application of rehabilitation therapy. Using deep learning to classify and predict movement intentions is extremely suitable for building rehabilitation assistive devices. Jacob et al. [122] translated EEG into muscle activity, classifying six hand postures with 88% accuracy. Zhang et al. [126] integrated IMU and EMG with CNN for movement-intention prediction (accuracy 94.59%). This enabled more precise robotic control during training assistance. Furthermore, when employing robots for rehabilitation training, it is important to be aware of the wrong gait. Wang et al. [112] collected gait posture data from numerous angles and utilized a CNN for joint recognition to predict the posture of the human lower limbs while walking. The results showed an accuracy of 97.18%. These studies not only improve the effectiveness and quality of rehabilitation training by increasing precision and efficiency, but they also demonstrate that current AI has advanced to a stage where machines can reliably analyze movement patterns and infer specific goals involved in rehabilitation training. These well-trained rehabilitation models can be integrated with other large-scale models to augment the capabilities of healthcare professionals in monitoring and guiding rehabilitation exercises. They can function as supplementary components of postoperative rehabilitation assessment systems, potentially alleviating the workload of clinicians while providing continuous patient oversight.

3.3. Development of Exercise Prescription

With the advancement of deep learning, multimodal data analysis, and other AI technologies, the formulation of personalized exercise prescriptions based on individual physiological characteristics and exercise metrics has become a reality. Notable examples include use of large language and generative models as interfaces (e.g., ChatGPT) for conversational guidance and prescription generation [113]. Studies have demonstrated that smartphone-derived signals can inform effective prescription: a 1D-ResNet model applied to smartphone sensor data produced individualized exercise programmes that improved balance and strength in older adults compared with controls [114]. Tan et al. [115]gave personalized exercise prescriptions to participants using a multi-modal data-driven AI system. The results showed that the experimental group performed better on assessments of cognitive function, mental health, and sleep quality. Furthermore, Liu et al. [116] employed the user's training records, multi-layer perceptrons, and multi-layer BiLSTM networks to generate high-precision tailored fitness recommendations that accurately predicted training distance, speed, and heart rate.

However, both fitness exercise prescriptions and medical exercise prescriptions should follow standardized medical prescription principles, particularly the FITT-VP framework, which includes exercise frequency, intensity, type, time, volume, and progression. In the context of artificial intelligence assisted exercise prescription, especially for populations with chronic diseases, adherence to the FITT-VP framework becomes even more critical. Exercise prescriptions must be developed within clearly defined safety ranges, taking into account disease severity, comorbidities, functional limitations, and potential adverse risks.

3.4. Implementation of AI Technologies

3.4.1. Data Acquisition

The performance of AI models is fundamentally shaped by the quality and type of data used for training. Data acquisition approaches can be divided into invasive and non-invasive strategies.

Invasive devices include accelerometers, gyroscopes, heart rate monitors, and electromyography (EMG) sensors, which provide accurate physiological and kinematic data such as step frequency, velocity, and muscle activation [117,118,127]. Their advantage lies in high signal fidelity, but they can restrict natural movement, cause discomfort, and are generally limited to short-term or laboratory-based use. By contrast, non-invasive methods, including video-based recordings and markerless motion capture, extract gait, joint trajectories, and posture in naturalistic environments [128–130]. Even heart rate can be estimated remotely from video footage [131]. Although scalable and user-friendly, these approaches are vulnerable to external confounds such as lighting, occlusion, and resolution.

Major research employing deep learning technology concentrates on gathering data with a single kind of device; however, future studies can adopt multimodal integrationto enhance the precision and comprehensiveness of data collection, as well as the impact of data analysis and model training that follows. There is also a significant benefit to enhancing portable wearable devices (e.g., smart wristbands), which are not only easy to transport but also store a large amount of data with high generalization value once a system for deep learning applications is effectively constructed. We also found that when combining exercise, disease, and health, the indicators used to distinguish a decline in disease or health status are mostly movement postures such as gait and joint position. Those diseases or health statuses are mostly significantly associated with such externalizing phenotypes or cause similar symptoms, such as PD and MS. This leads to the conclusion that such predictions and diagnoses may be of limited utility for illness management and treatment because by the time such phenotypes appear, the disease has already happened or progressed to some level. Studies that do not use physiological and biochemical markers, as well as indicators of bodily function (e.g., VO2 max, oxygen saturation, heart rate, etc.), as inputs are frequently able to forecast potential progression and onset from earlier time dimensions.

3.4.2. Model Architectures and Training Strategies

Selecting and optimizing the appropriate model architecture is the most critical step in translating data into actionable insights. The choice of model is dictated by the nature of the input data and the specific task at hand.

For sequential time-series data captured by sensors (e.g., gait cycles, heart rate variability), Long Short-Term Memory (LSTM) networks are commonly employed due to their ability to learn long-range dependencies. Interestingly, some studies have found that Convolutional Neural Networks (CNNs), which excel at identifying spatial patterns, can also be effectively applied to time-series data and may even outperform LSTMs in certain scenarios [132]. For image and video data analysis, CNNs are the dominant architecture owing to their proficiency in extracting hierarchical spatial features.

To enhance performance, researchers are increasingly experimenting with hybrid models that combine the strengths of multiple architectures (e.g., CNN-LSTM networks) [133,134], yielding superior outcomes. Beyond these common models, innovative approaches are being explored. For instance, Gaussian Mixture Models (GMMs) have been integrated into frameworks to model the complex distribution of standard movement patterns. By calculating the log-likelihood of a new movement sequence against the GMM of "normal" movements, researchers can achieve an unsupervised quantitative assessment of movement quality [123]. Similarly, the concept of adversarial learning, through Generative Adversarial Networks (GANs), has been applied both for predicting movement intention (a discrimination task) and for generating realistic movement trajectories (a generation task) [91,108]. This technique helps in categorizing unlabeled data and improving model generalization.

3.4.3. Emerging Deep Learning Models

In recent years, advancements in deep learning architecture have begun to further expand the modeling capabilities of complex exercise and physiological data. Self-supervised learning frameworks are increasingly attracting attention in wearable devices and exercise data analysis because they can perform representation learning from large-scale unlabeled datasets. For instance, a model pre-trained on over 700,000 person-days of accelerometer data from the UK Biobank through self-supervised learning demonstrated significant improvements in generalization and activity recognition performance across multiple benchmark datasets, particularly when labeled data was limited [135].

Meanwhile, an increasing number of Transformer-based architectures and attention mechanisms have been introduced into practice modeling. SETransformer, combined global self-attention with adaptive channel feature weighting to capture complex motion patterns over a longer time window [136]. MoPFormer demonstrated a stronger cross-dataset generalization ability by dividing inertial data into "motion primitives" and conducting self-supervised pre-training [137]. Graph neural networks and their fusion architecture with Transformer can simultaneously capture spatio-temporal dependencies, demonstrating advantages in skeleton action recognition and spatial structure modeling, and are conducive to action pattern classification and anomaly detection.

Emerging architectures such as self-supervised learning and Transformer-based models are gradually integrating with traditional deep models. Their applications are expected to enhance the robustness, scalability, and interpretability of motion-related artificial intelligence systems, thereby supporting more reliable health monitoring and personalized intervention.

3.4.4. The Paradigm Shift: From Discriminative to Generative AI

At present, most AI systems applied in exercise and health research are still based on the discriminative modeling paradigm, mainly focusing on tasks such as classification, regression, and risk prediction. Although these methods have demonstrated good performance in activity recognition, disease classification and outcome prediction, they still have inherent limitations in simulating complex movement scenarios, deducing multiple intervention pathways and supporting interactive decision-making.

In recent years, generative AI has gradually emerged, enabling models not only to analyze existing data but also to generate new representations, motion trajectories, and intervention suggestions. Generative methods represented by large language models (LLM) and basic models have the potential to integrate multi-source heterogeneous information, including physiological signals, exercise data, clinical records, and individual situational factors, thereby constructing a more coherent and adaptive reasoning framework.

Apart from interactive guidance, one of the most transformative potentials of generative AI in medical and sports-related applications lies in data synthesis. Generative models can be used to simulate real but artificial patient data, thereby alleviating the common model training limitations, privacy restrictions and class imbalance in clinical populations. Meanwhile, advancements in prompt engineering and reasoning strategies, such as structured prompts and React-style reasoning, have provided new approaches to enhancing the transparency and controllability of generative models. By clearly decomposing the decision-making steps and correlating the generated outputs with the intermediate reasoning process, these methods may partially alleviate the "black box" nature of artificial intelligence systems and enhance the interpretability of health-related decision support.

In the field of exercise science and rehabilitation, this paradigm shift offers new possibilities for the formulation of individualized exercise programs, the simulation of alternative training or rehabilitation pathways, and context-aware guidance. However, the effective integration of generative models and discriminative models, as well as their application under the premise of clinical safety, are still in the exploratory stage. How to enable artificial intelligence systems to continuously monitor individual states, integrate multimodal inputs and propose reasonable intervention suggestions under the conditions of ensuring safety, controllability and clear responsibility boundaries still requires further research.

4. Challenges and Future Directions

Despite promising progress, the application of AI in exercise health remains constrained by several technical, methodological, and ethical challenges. A primary limitation is data quality and availability: many studies are based on relatively small, homogeneous, or selectively recruited cohorts, leading to restricted generalizability of findings. Dataset scale and diversity directly determine model robustness and translational potential. Beyond technical limitations, ethical issues, particularly data privacy are paramount. AI systems in this domain often rely on sensitive lifestyle, physiological, and continuous movement data, making secure storage, privacy protection, and responsible governance indispensable requirements for implementation.

In terms of methodological scope, most current applications of deep learning in sports and health emphasize classification tasks such as activity recognition, intensity categorization, or disease diagnosis. By contrast, relatively few models address continuous regression problems, such as VO_2max estimation, long-term performance forecasting, or quantitative assessment of physiological reserve. This imbalance limits the potential of AI to deliver fine-grained and clinically actionable insights. Moreover, the "black box" nature of complex deep models hampers interpretability and trust. Without transparent mechanisms for explaining predictions, clinical adoption and user confidence remain limited.

In addition, the existing reviews and research on AI for exercise and health still mainly focus on the post-event analysis paradigm, that is, uploading, processing and interpreting the collected exercise and physiological data after the exercise is completed. Although such retrospective analyses have significant value in the assessment of exercise performance and the identification of risk factors, they often overlook the crucial role of real-time biofeedback in exercise correction and injury prevention. However, achieving true real-time feedback poses significant technical challenges. Traditional cloud architecture requires data transmission, remote processing and feedback, which may cause significant delays that cannot be ignored. The emergence of edge computing has solved this difficulty. Through model compression and quantization techniques, researchers can directly deploy the streamlined lightweight deep learning model locally on edge devices such as smartwatches, mobile phones or dedicated sensors. At present, some wearable devices and fitness applications are already capable of providing immediate feedback, but their applications are mostly concentrated in the fields of fitness and daily health management. The evidence of their clinical effectiveness in medical or rehabilitation scenarios remains limited. Also, real-time feedback systems impose stricter requirements on the verification of algorithm latency, stability and security in medical environments. Incorrect or inappropriate immediate guidance may bring potential risks. Therefore, in clinical and rehabilitation applications, real-time artificial intelligence systems still need to emphasize a human-centered design concept, ensuring the supervision and intervention of professionals in key decision-making processes to guarantee safety and controllability.

Future models should address these gaps by expanding the feature space and analytical scope. Multimodal integration, incorporating not only gait, electromyography, heart rate and oxygen saturation but also muscle strength, metabolic profiles, and additional physiological parameters, will allow more comprehensive assessment of exercise performance and health status. Increasing model complexity, when balanced with interpretability, may enhance long-term predictive accuracy, especially for outcomes that suffer from information decay over extended monitoring. Techniques such as self-supervised and reinforcement learning could enable adaptive, personalized prescriptions that continuously refine exercise recommendations in response to real-world user feedback. Collectively, these advances will facilitate the transition from isolated task performance to dynamic, individualized exercise health management. Based on these advancements, future research should also go beyond the main post-event analysis paradigm and shift towards real-time, closed-loop exercise health systems. Although multimodal modeling and adaptive learning can achieve increasingly accurate predictions, their clinical and rehabilitation value will ultimately depend on the ability to provide timely and safe feedback during movement execution. Such real-time systems should adopt the "human-in-the-loop" framework, in which the feedback generated by artificial intelligence will be constantly supervised and calibrated, and rewritten by healthcare professionals when necessary.

Another limitation of this review is that it does not provide detailed comparisons of technical aspects such as hyperparameter tuning, generalizability, or overfitting risks. Such analyses would require raw training scripts and parameter logs, which are rarely disclosed in published studies. More importantly, the purpose of this review is to present a conceptual overview for clinicians and exercise scientists, rather than to benchmark algorithms at a technical level.

5. Conclusions

The review emphasizes the importance of exercise-related indicators in health monitoring, disease diagnosis, and individualized intervention, as well as how AI technologies have been used to exploit these markers. While existing techniques show promise for accuracy and feasibility, they are hampered by dataset quality, methodological heterogeneity, and insufficient external validation. We identified key gaps—such as the reliance on overt motor phenotypes, the limited use of multimodal physiological data, and the preference for classification over regression tasks—and proposed potential solutions, including multimodal integration, advanced temporal modeling, and interpretable architectures.

Future research should close these gaps to improve forecast accuracy, allow for early discovery of disease trajectories, and enable more effective management options. Importantly, interdisciplinary collaboration among physicians, computer scientists, engineers, and public health professionals will be required to transform these technical improvements into scalable, trustworthy, and therapeutically relevant solutions. AI-powered exercise health systems have great promise for developing customized medicine and preventative healthcare if methodological innovation and rigorous validation continue.

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Abbreviations

Acronym	Explanation
CVD	Cardiovascular disease
NAFLD	Non-Alcoholic fatty liver disease
IBD	Inflammatory bowel disease
COPD	Chronic obstructive pulmonary disease
PD	Parkinson's disease
AD	Alzheimer's disease
PAD	Peripheral artery disease
ADHD	Attention deficit hyperactivity disorder

ALS	Amyotrophic lateral sclerosis
MS	Multiple sclerosis
BMI	Body mass index
WHO	World Health Organization
DXA	Dual-Energy X-ray absorptiometry
BIA	Bioelectrical impedance analysis
CKD	Chronic kidney disease
SMI	Skeletal muscle mass index
BMD	Bone mineral density
BBS	Berg balance scale
VC	Vital capacity
VO_2max	Maximal oxygen consumption
ACOS	Asthma-COPD overlap syndrome
FEV1/FVC	Ratio of forced expiratory volume in 1 second to forced vital capacity
HF	Heart failure
ECG	Electrocardiography
DBP	Diastolic blood pressure
BMR	Basal metabolic rate
HRV	Heart rate variability
BiLSTM	Bidirectional long short-term memory network
CNN	Convolutional neural network
RNN	Recurrent neural network
AP	Average precision
MOTA	Multi-object tracking accuracy
SCNN	Sequential convolutional neural network
US	Underhand serve
OS	Overhand serve
SP	Spike
DG	Dig
IMU	Inertial measurement unit
STN	Spatial transformer network
EMG	Electromyography
BPNN	Backpropagation neural network
EEG	Electroencephalogram
ANN	Artificial neural network
IoU	Intersection over union
AUC	Area under the curve
AI	Artificial intelligence
ACC	Accuracy
MSE	Mean squared error

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