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A review of applications of artificial intelligence in cardiorespiratory rehabilitation

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ABSTRACT

Implementations of artificial intelligence and machine learning are becoming commonplace in multiple application domains. This is in part due to advancements in computing hardware that have helped outsource the computation of resource-intensive mathematics related to artificial intelligence and machine learning to the chips of multi-core and parallel computing architectures. Partly it is due to the widespread appeal of machine learning as a suite of handy tools to fix practical issues. Many fields have become beneficiaries of artificial intelligence and machine learning and cardiorespiratory rehabilitation is no exception.

The aim of this paper is to review the current state of the art of the applications of artificial intelligence and machine learning in cardiorespiratory rehabilitation. We have taken a multidimensional view to addressing the needs and utility of artificial intelligence and machine learning in cardiorespiratory rehabilitation. We start with the most primitive applications of machine learning reported in existing literature in making medical devices for analyzing heartbeats and respiratory functions. We then discuss more recent approaches including deep learning to analyze performance or suggest alternative choices for food or exercise. Applications and utility of most recent feats such as explainable artificial intelligence are also discussed and conclusions around the current state of the art and possible future directions are proposed.

1. Introduction

Exercise therapy is a proven way of prescribing a set of physical activitys (PAs) to aid the treatment of certain medical conditions and to recover from certain diseases [1]. The advent of AI and high-performance computing systems coupled with the enhanced ability to collect data has opened an opportunity in the health and fitness sector with the hope that AI may be able to aid in recovery as well as in the improvement of human health [2]. The overall scope of this paper is to review previous literature on the applications of AI/ML in multiple aspects of cardiac and pulmonary rehabilitation. Literature about developing RSs for developing PA and exercise suggestions is considered. Similarly, RSs for nutrition therapy in conjunction with PA are suggested. Applications of X-AI in the context of healthcare are also cited along with literature for developing adaptive AI systems. A number of studies related to applied AI for developing systems for ensuring a patient's adherence to medication and exercise is also reviewed.

Our main purpose in conducting this research was to figure out the wide gamut of factors that influence cardiorespiratory health, fitness, rehabilitation, and pre-habilitation. This knowledge, in turn, was necessary to understand what kind of data, features, and metrics are required to develop a software-based solution (such as an app or a system) to assist the general population to monitor, evaluate and improve their cardiorespiratory health. Currently, there is no software application available that takes a complete and holistic view of the various conditions that affect cardiorespiratory health. Common cardiorespiratory tools such as a Fitbit or a tracking app will typically take a few numerical inputs such as the heart rate or breathing rate to reflect on the overall heart and respiratory health of a user [3]. Consequently, a wider range of actual factors that affect cardiorespiratory health is not fed to the app. As a result, the readings given by the app are not true reflections of the actual health of the user.

As we performed this survey, we found that the academic literature on the factors affecting cardiorespiratory health was lacking in papers that collectively reflect on the factors affecting cardiorespiratory rehabilitation. To this end, this paper contributes to this area in revealing valuable information concerning the application of AI and ML to cardiorespiratory health.

The rest of this article is structured as follows. In Section 2 applications of AI/ML for cardiorespiratory rehabilitation are reviewed. Section 3 considers how AI/ML may be used to help patients engage with exercise and healthcare regimes. Some issues related to

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transparency and regulations around using AI/ML in healthcare are presented in Section 4. Finally, Section 6 presents some discussions for future works and conclusions.

2. AI in cardiorespiratory rehabilitation

Applications of AI/ML in the monitoring of cardiac and pulmonary health are not new. Advances in deep learning technologies have paved the way for more accurate monitoring of cardiac and pulmonary health, along with applications of traditional learning approaches such as those based on logistic regression, Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs).

2.1. AI in cardiac diagnosis/rehabilitation

Agliari et al. have proposed to compute biomarkers based on computing beat-to-beat variability in the heart rate [4]. The biomarkers are fed to a multi-layer feed-forward ANN to classify patients. They found that their approach could have benefits in terms of social costs. Moreover, they also found that the extension of their approach to other pathologies could be feasible, so long as suitable data-sets were available.

In [5], Hijazi et al. have proposed to filter patients' Electroencephelograms (ECGs) and to apply ML classifiers to estimate cardiac health risks and severity. The ML algorithms they used were SVM, Decision Trees (DTs), and k-Nearest Neighbors (K-NNs). Although there is no evidence that their work was commercialized, it is well-cited. Techniques that employ ECG signal analysis for cardiac health monitoring are useful as continuous ECG sensors are becoming commonplace [6]. A range of wearable and other sensors exist that can be used either for high efficiency or the comfort of use. Tripathy et al. have proposed a personalized health care system [7]. A salient feature of the proposed system is that it has a mobile heart-rate monitoring module. The data can be sent to a doctor and based upon that treatment can be prescribed remotely. Fu et al. have designed a hardware device that can collect high-quality ECG data from the human body [8]. The data is sent to a cloud-based deep-learning platform that can diagnose a cardiovascular condition. Twenty types of diagnostic items including sinus rhythm, tachyarrhythmia, and bradyarrhythmia are supported. The main author, Zhaoj Fu, is the founder of Anhui HeartVoice Medical Technology Co., a company dedicated to caring for the human heart using AI.

2.2. AI in pulmonary rehabilitation

Similarly, AI and ML have been used increasingly in pulmonary disease identification and rehabilitation in recent years. In [9], Blanc et al. proposed an ML and deep learning-based approach to pulmonary nodules using Computed Tomography (CT) scans. The proposed solution consisted of a fully functional software pipeline in which deep learning was initially applied for nodule detection. The nodule classification was later achieved by employing an SVM. The platform showed good performance for nodule detection and patient diagnosis. Exact statistics pertaining to the performance of the system are mentioned in a reputable peer-reviewed journal. Rao et al. have surveyed approaches for pulmonary diagnosis based on acoustic methods [10]. They have noted methods for monitoring and measurement of sounds related to Chronic Obstructive Pulmonary Disease (COPD) or asthma. Apart from the traditional measurement device, such as the stethoscope, various specialized microphones for acoustic measurement are discussed. Apart from this, ultrasound is described as a way to estimate disorders in the respiratory system. Signal processing algorithms for feature extraction are mentioned. These include the discrete Fourier transform, Mel Frequency Cepstral Coefficients (MFCCs) as well as the wavelet transform. Moreover, ML algorithms for the classification of pulmonary health conditions are also mentioned. These include SVMs, K-NN, ANNs, and Gaussian Mixture Models (GMMs). Jung et al. have proposed a scheme to classify lung sounds using depth-wise separable Convolutional Neural Networks (CNNs) using spectrograms computed with short time Fourier transform (STFT) and MFCCs [11]. The spectrograms are fed to CNN as image data. Their approach is based on fusing the feature data obtained from STFT and MFCCs. The results they achieved were better than using either STFT or MFCCs features alone. They reported that even though the performance of their proposed system was comparable with the state-of-the-art viz a viz accuracy of the model, the computational performance was much better.

Palaniappan et al. have used auscultation data collected from a stethoscope to compute MFCCs as features [12]. They use these features to train an SVM classifier and a K-NN classifier to perform diagnosis. They used auscultation audio data from a well-known database known as RALE [13]. They reported a very high classification accuracy for their proposed models.

A non-invasive method for measuring respiratory rate has been proposed in [14] using the WiFi signal. The fact that the WiFi signal undergoes an increase or decrease in amplitude while passing through the human body while the lungs are deflated or inflated during respiration has been exploited. Their work has not been adopted widely. Pulse oximetry is another way to measure oxygen saturation levels in the bloodstream. Oxygen saturation level has been used to reflect on cardiac and pulmonary health for a long time. Recent studies have also begun to develop more accurate oximeters using ML techniques, as shown by Venkat et al. [15].

In [16], Nicolo et al. have discussed the importance of measuring respiratory rate in different contexts and situations including sports and exercise. They have proposed a number of cases where there is a need to assess the respiratory rate. They also propose technological tools and sensors that are amenable to the measurement of respiratory rate in the situations they have mentioned. Challenges encountered during sports and exercise related to measurement in outdoor settings and moving bodies are addressed. Some of these are ever-changing atmospheric conditions due to rain, changing weather, different postures in different exercises, and contact sports. Most of the challenges are related to the calibration of the sensors and inaccurate readings due to environmental factors and rapidly changing orientations and positions of devices. Sensor fusion has been proposed as one of the possible solutions to address these issues. In sensor fusion, data is gathered from a bunch of sensors and fused together to make sense of it. However, making sense of a large amount of data from different sensors is a challenge and AI is seen as a possible cure for the future of fused sensor data.

Summary of Applications of AI/ML in Cardiorespiratory Rehabilitation

In this section we discussed applications of AI/ML in cardiorespiratory rehabilitation from a retrospective perspective. More specifically, we discussed the applications of AI/ML for:

- Diagnosis of and rehabilitation of cardiac health.
- Pulmonary rehabilitation.
- ML algorithms used to develop rehabilitation systems have been listed in Table 1.

3. AI for patient engagement

3.1. virtual reality (VR) applications for rehabilitation

In recent years there has been an interest in utilizing VR platforms for cardiac and pulmonary rehabilitation [17]. VR systems exploit the neuroplasticity of the human mind, which is the ability of the mind to adapt to different environments. The idea is to use VR systems in space-constrained environments, such as homes, where there is not enough space to conduct outdoor activities. Moreover, role-playing games using VR can be quite interesting as shown by Garcia et al. [18]. Instead of focusing on the details of an exercise program, the subject can focus on the challenges of the game and the exercise happens as a byproduct. Thus, games that require walking, running, hiking, or climbing a mountain can be played in VR. The user can exert themselves physically for the duration of the game while not feeling bored. VR augmented exercise systems have been found to be quite effective when compared with traditional modes of physical exercise, as shown by Da et al. [19]. In a related study, it was found that rehabilitation that incorporates VR is more effective than standard rehabilitation for improving walking speed, balance and stability after a stroke [20]. The effect of VR augmented pulmonary rehabilitation has been studied by Colombo et al. in [21] and it was found to be quite effective. A related and cheaper alternative to VR is exergaming in which there is a requirement to perform physical exercise inherent to a video game's structure, as proposed by Bond et al. [22].

3.2. RSs for exercise and rehabilitation

RSs in sports and exercise are also becoming common to help individuals achieve better health viz a viz heart and lungs. One of the key ideas in developing a good RS is to exploit the subliminal human desire to partake in challenging activities. In [23], Mahyari and Pirolli quote that human beings get motivated about goals only if they are challenging enough. Similarly, they abandon activities if they are too challenging. To this end, they have proposed an RS that divides exercise-related activities according to their difficulty level. A subject is recommended to perform something a bit more difficult if they have successfully finished tasks recommended by a prior difficulty level. On the other hand, if they fail to complete the tasks on a particular difficulty level, they are recommended to choose tasks from a lower difficulty level. The exercises and activities are also suggested by computing a probability that the subject shall be able to complete the task successfully. Their system is based on a Recurrent Neural Network (RNN). mHealth is another RS developed for the Android operating system as proposed by Wuttidittachotti et al. [24]. Ni et al. have proposed an RS that uses heart rate and activity data for making recommendations [25]. The system is based on a Long Short Term Memory (LSTM) network.

In a recent article [26], Sato et al. have shown that exercise benefits the body in different ways, depending on the time of the day. Given such a variance in the effect of exercise in different scenarios, it becomes incumbent upon a good RS to take such factors into account. Last but not least, the most recent and commendable RS for mHealth and physical exercise is proposed in [27]. The proposed system is developed using deep RNNs.

3.3. AI for adherence

Another important and interesting area of applied AI/ML in healthcare is to develop intelligent models that verify a subject's or a patient's adherence to a specific exercise program or medication. In a highly cited recent article by Emanuel et al. [28] the authors have argued that in order for AI to live up to its hype in the healthcare domain, it would be required to invent the so-called "the effector arm of AI". The term refers to the tangible tools and models developed using AI that affect the subject's behavior and bring about appropriate behavioral changes among users. The rationale is that there is poor adherence among people to behavioral suggestions. For instance, in [29], Nicolson et al. compared self-reporting of exercise adherence by people to data collected using accelerometers. It was found that there was a poor correlation between the two and the people mostly overestimated their exercise adherence. In a recent article [30], Bohlmann et al. have reviewed considerable literature in which ML has been applied to develop human competitive models to verify medication adherence. Burns et al. [31] developed models using various ML algorithms to verify that patients with shoulder injury adhere to physiotherapy exercises. In [32] Lo et al. studied the perceived benefits of an AI-embedded mobile app with evidence-based guidelines for the self-management of chronic neck and back pain. They reported a significant reduction in pain levels due to the use of the mobile app. In [33] Ferrante et al. proposed to employ socially assistive robots to increase motivation, engagement to treatment, and adherence among the patients of pediatric asthma. Adherence to home exercise can be poor due to various reasons such as a decline in motivation, disinterest, mundane exercise routines etc. In [34], Argent et al. explored how connected health technologies could offer numerous interventions to enhance adherence. They highlight how well-designed connected health technologies, such as the use of mobile devices, including mobile phones and tablets, as well as inertial measurement units, provide us with the opportunity to better support the patient and clinician, with a data-driven approach that incorporates features designed to increase adherence to exercise such as coaching, self-monitoring, and education, as well as remotely monitor adherence rates more objectively.

3.4. AI for compliance

AI has recently been employed to develop systems that verify users' compliance with prescribed exercise. To check whether a patient has performed the prescribed exercise correctly and accurately is quite important. This becomes a lot more important when the patient is conducting exercises or alone or at home. A physiotherapist or a coach cannot be present with a user all the time in all phases of diurnal life. Having systems that can reflect on a user's compliance with prescribed physical activity is a convenience for both patients as well as physicians. ML and the advent of deep learning have made it possible to develop such systems that verify user compliance with prescribed exercise. In [35], Kianifar et al. proposed a system for identifying dynamic knee valgus as a user performs a single leg squat. Their system uses data obtained from three inertial measurement units (IMUs) and treats the data with various ML algorithms before producing the result. The ML algorithms that showed the best performance were SVM, K-NN, and Naive Bayes (NB) algorithms. Bavan et al. [36] evaluated the feasibility of using a single inertial sensor to recognize and classify shoulder rehabilitation activity using supervised ML techniques. Liao et al. [37] have developed a deep learning framework to assess user adherence and compliance viz a viz physical rehabilitation exercise. Soellner et al. [38] found in their study that pairing AI and a physician in a hypothetical scenario in which a user is supposed to perform exercise is substantially beneficial as opposed to using AI alone for verifying compliance. Fisher et al. [39] proposed a method for power wheelchair exercise compliance. Their method employs spectral analysis as well as Hidden Markov Models (HMMs).

Applications for recognizing sport-specific movement are becoming commonplace [40]. Deep learning and ML are increasingly being applied to develop frameworks that are used to verify if prescribed exercise for rehabilitation is being done correctly or not [37]. There exist applications that employ sensor data from IMUs alone for verifying exercise compliance [41]. More sophisticated approaches also take image data in conjunction with movement sensors to solve a typical problem related to musculoskeletal or limbic movement by employing a computer-vision-based solution [42].

3.5. RSs for nutrition therapy

Prescribing nutrition therapy in conjunction with physical activity and an exercise regime for rehabilitation is also common [43]. Nakahara et al. [44] have proposed aggressive nutrition therapy to treat malnutrition and sarcopenia. The latter is marked as a medical condition for gradual, progressive, and generalized skeletal muscle disorder. Baguley et al. [45] have prescribed nutrition-exercise therapy to treat cancer-related fatigue and to enhance the quality of life in men with prostate cancer. Literature related to the link between nutrition, physical activity, and cardiovascular health is also not nonexistent. In a slightly old but highly cited article Igarro et al. [46] have reflected on the role of nutrition and physical activity in the prevention of cardiovascular disease (CVD).

A few RSs for suggesting appropriate nutrition and diet also exist. Just like any typical RS, the dietary RS suggests diets based on a person's medical history and other user-specified data. The other data, for instance, could be related to data coming from sensors that monitor physical activity. AI and ML schemes are employed to instill intelligence into the RS. A recent, highly cited, dietary RS is DIETOS, proposed by Agapito et al. [47]. Another food RS is proposed in [48] by Ge et al. It suggests recipes according to users' preferences as well as health data. Toledo et al. [49] have recently proposed a food RS that considers the nutritional needs as well as the preferences of a user to suggest food sources. They maintain a taxonomy of a myriad of food sources arranged according to their nutritional profiles. A multi-tier decision-making system employing optimization techniques as well as AI/ML algorithms is developed. PREFer is another recent food RS proposed by Bianchini et al. [50]. It uses a recipe dataset to generate menus based on both medical prescriptions and a user's short/long-term preferences. Nag et al. [51] propose a live personalized nutrition recommendation engine that uses multimodal contextual data including GPS location, barometer, and pedometer output to calculate a live estimate of the user's daily nutritional requirements, which are then used to rank the meals based on how well they fulfill the individual's nutritional needs. Ge et al. [48] proposed a food RS developed on a mobile platform, which not only offers recipe recommendations that suit the user's preference but is also able to take the user's health into account, supported by wearable technologies. A very recent and quite novel nutrition RS is MATURE [52]. This RS recommends items to users based on the nutritional profiles of food items depending on the nutrient constituents. It does not depend on a particular classification technique as such. However, they have provided their own complete algorithm for the system to work and that heavily leverages feature classification.

Summary of Transparency and Regulation

In this section, we discussed applications of AI/ML in developing systems for patient engagement. In this regard, we discussed utilization of AI/ML for developing:

- AI/ML for developing VR applications for rehabilitation.
- RSs for exercise and rehabilitation.
- applications for adherence.
- applications for compliance.
- RSs for nutrition therapy.
- ML algorithms employed by various studies have been tabulated in Table 1.

4. Transparency and regulation

4.1. X-AI in cardiorespiratory rehabilitation

Nowadays customers and clientele of AI applications expect to receive an explanation of the results produced by their AI tools. The same is true about the domains of medicine and healthcare [53]. The old days when the rather wizardly results of AI tools were accepted on face value are long gone. X-AI is a rapidly emerging field that is making inroads into healthcare [54], sports [55] and rehabilitation [56] too. X-AI can help to answer many interesting questions related to cardiac and pulmonary health also. X-AI is a newly emerging field, and it is argued in [57] by Ghassemi et al. that the current explainability models and frameworks do not fulfill the needs of the healthcare domain in a reliable manner. To this aim, better models need to be developed that represent a window of opportunity in this rapidly growing field.

Ghassemi et al. have particularly criticized the current inherent as well as post-hoc explainability techniques. These are the two widespread categories of achieving X-AI. Inherent explainability refers to a model's quality of being inherently explainable if it is a simple model and the relationships between inputs and outputs can be figured out easily by visual explanation. Examples of such models are those achieved by linear regression or such simple techniques. However, the model and the data of the current real-world problems are normally too complex to be explained with inherent X-AI. Textual, image, video, and speech data does not render itself for inherent explainability. To address the limitations of inherent X-AI, the research community has formed certain post-hoc explainability techniques. These include heatmap analysis, Locally Interpretable Model-Agnostic Explanations (LIME) and Shapley Values (SHAP). LIME, for instance, tries to learn the importance of decisions at the individual level by tweaking the values of various input values slightly. It tries to estimate which perturbations change the decision of the model. They have reported some shortcomings of the post-hoc explainability techniques. Not only the model itself can be right or wrong, but so can the explanation be as well.

There is nonetheless an ever-growing urge in the healthcare community to transition from developing black-box models to explainable solutions as highlighted by Abadi et al. [58]. An interesting application of X-AI in healthcare is to develop online symptom checkers as proposed by Tsai et al. [59]. Another interesting theme proposed by Nazar et al. is to weave a synergy between X-AI and Human-Computer Interaction (HCI) [60]. X-AI has also been recently deployed for the diagnosis of coronary artery disease by Otaki et al. [61]. Similarly, X-AI has been developed recently for pulmonary nodule classification by Jiang et al. [62]. An interesting application of X-AI in recent literature has been to predict the probability of hospital re-admission of frail patients after discharge by Mohanty et al. [63]. This is expected to have huge monetary benefits for the healthcare system. A similar approach can be applied to estimate the risk of injury or illness after cardiac and pulmonary rehabilitation. X-AI is also being employed in elite sports to answer questions related to the risk of injury to athletes [55]. Moreover, X-AI has also been employed to answer questions related to the effectiveness of stroke-related rehabilitative exercises by Lee et al. [56]. In a recent article by McCoy et al. [64], the authors have argued that ML in healthcare does not need explainability to be evidence-based. In particular, they mention that explainability is often achieved at the cost of accuracy. To this end, they propose that explainability should be sought where it is required. Other than that, black box models are good to suffice for the prescribed job.

4.2. Adaptive AI in cardiorespiratory rehabilitation

AI-based medical device software is mostly static nowadays. This means that once developed the software, no matter how good, smart, and intelligent, remains fixed throughout the lifetime of the application. In order to change the behavior of the software, continuous updates and upgrades are required. A desire for developing self-adaptive, self-improving, self-repairing AI systems is on the horizon of the medical device software innovation community. According to Gilbert et al. new regulations are underway for software that will be adapted in real-time during its lifetime [65]. At the same time, the AI/ML community has taken great strides in terms of developing the ability to automatically repair software according to Yuan et al. [66]. Genetic improvement of software is also a promising enterprise that could be used for improving medical device software in use [67], allowing automated software repair, bug fixing, and updating.

Summary of Transparency and Regulation
In this section, we discussed: • The role of X-AI in systems for cardiorespiratory rehabilitation. • Adaptive AI in cardiorespiratory rehabilitation. • ML algorithms cited by different studies have been reported in Table 1.

5. The case of AI -based rehabilitation in post-covid world

COVID-19 has changed many aspects of healthcare, and of life, across the world. Work cultures and personal lifestyles for many people are drastically different now in the post-Covid world. We consider here how AI and ML tools have bee used to address the cardiorespiratory rehabilitation challenges posed by this worldwide pandemic. One of the auspicious aspects of our present era is that while there are unique challenges in almost any sphere of life, including healthcare, the speed of innovation is also staggering [68]. Advances in telemedicine, remote patient monitoring, and emerging wearable technologies have been unprecedented during the COVID-19 pandemic. The role of modern technologies in post-COVID-19 cardiorespiratory rehabilitation has been recently thoroughly studied by Doru et al. [69]. To this end, the study focuses on post-COVID-19 patients who are in need of cardiorespiratory rehabilitation. The authors have cited the role of video guides, hybrid approaches in which the patient is initially treated in a hospital facility and eventually encouraged to participate in a rehabilitation program at home using various medical technologies. They also cited literature related to telemedicine-based rehabilitation and noted its importance. Moreover, the use of VR and video games for remote rehabilitation are also considered as preferable tools. Results show an increased resistance to fatigue as well as an improved quality of life using these tools.

It is a well-known fact that post-COVID-19 infection, cardiorespiratory fitness is impaired [70]. The level of impairment is a function of the severity of the illness. In [70] Gomes-Neto et al. the authors recommend the adoption of rehabilitation and therapeutic strategies to address this issue. Similarly, apart from cardiorespiratory health decline, skeletal muscle damage is also a serious matter [71], calling for the need of urgent intervention.

A requirement in treating COVID-19 is for the patient to be quarantined. In the case of long COVID-19, it was impossible for hospitals to host the patient for too long due to monetary and space constraints. Ideally, there should be a way to continue to rehabilitate the patient at home. In [72], Swarnakar et al. have reflected on this and related issues. They conclude that it is most important to identify the rehabilitation needs of patients. They also highlight the need for further studies on various rehabilitation interventions. They also highlight the need to utilize AI-based systems for remote rehabilitation.

The crux of the above discussion is that the onset of COVID-19 could affect the cardiorespiratory health and brain function of patients. Although post-COVID-19 recovery and rehabilitation are positively correlated [73], according to Besnier et al. more studies are required to assess the effectiveness of rehabilitation programs for the patients [74].

According to the World Health Organization (WHO) the COVID-19 pandemic is over, but its prolonged presence and long-lasting effects across the world demand a readiness on our part to be able to tackle the next pandemic of such proportions. Fortunately, mankind has learned to catch up with such calamities with alacrity in technological terms as discussed earlier [68]. While the capability and willingness to tackle such problems when they arrive is necessary, it is also important to contemplate systems and solutions for future global health crises before they reach pandemic proportions.

6. Conclusions

In this paper, we have reviewed the applications of AI and ML in cardiorespiratory rehabilitation as reported in high-quality peer-reviewed literature. Table 1 shows the distribution of studies across various problem domains and the AI/ML algorithms used to devise solutions. We began with a review of different approaches that are used in the diagnosis and monitoring of cardiorespiratory health issues. After that, we reviewed some RSs that have been employed in cardiorespiratory rehabilitation and offered a review of applications of VR systems for exercise rehabilitation. X-AI is a newly emerging niche in AI/ML and we have considered its applications in healthcare. We have also reviewed techniques and technologies that are used in monitoring a subject's adherence and compliance with suggested exercise therapy procedures and prescriptions. We also touched on the topic of nutrition therapy and reviewed some state-of-the-art RSs for advice on nutrition. The COVID-19 pandemic has had a significant impact on healthcare across the world. We considered how AI and ML tools have been used to address cardiorespiratory healthcare for COVID-19 and long COVID patients. As the challenges arising from the COVID-19 pandemic continue to pose issues for healthcare around the world, we anticipate that AI and ML modules and tools could play a large part in addressing these issues and be used to develop new approaches and solutions to this ongoing global problem.

Combining data from various types of sensors such as an IMU, a heart rate monitor, an oximeter, and/or any type of motion sensor, as suggested by Nicolo et al. [16], can have the added benefit that cardiac and pulmonary health could be measured in different contexts, such as health, well-being or even elite sports. The role of AI/ML could be crucial from multiple vantage points in this regard. Firstly, AI could help analyze, annotate and understand the combined data more accurately. Choosing which sensor's data to trust in a particular scenario is a challenge that could be addressed with applied AI. Similarly, analyzing the data on different time scales and in different settings spread over space could help to answer many important questions. For instance, consider the heart health of a patient over a two-week period when they alternate between high-intensity exercise and rest. What data could be collected and analyzed every day, hour or even second? Similar questions could be addressed such as: What is the effect of a sunny day's outdoor workout on the heart rate? Or, how has a particular set of aerobic exercises combined with a resistance training workout helped the blood oxidation level? X-AI can help to quantify explanations of various phenomena that may help to address questions such as these.

Until now, much of the focus of the research community has been on developing narrow-AI (n-AI). This means that specialized applications for classified problems have been proposed using n-AI. Recently, there has been an increasing interest in various research communities working with AI tools to develop generalized AI which, in theory, should be more human-competitive. More powerful, generalized AI could have a much higher impact on many real-world problems. This paper gave a review of AI and ML as applied to approaches to address and assist cardiorespiratory rehabilitation in recent years. With ongoing global challenges such as the impact of the COVID-19 pandemic and an aging population, our future work will build on this body of work to apply new AI methods, especially those deemed X-AI, to further address and alleviate the challenges identified here.

In [75] late Professor Marvin Minsky provided a practicable theory of mind. He proposed that a mind could be thought of as composed of a society of smart agents, each of which is ascribed to perform a certain specialized task. Together, the whole society of agents could function as a general intelligent agency. A whole academic discipline of cognitive architectures exists in this regard that is dedicated to developing machines capable of Artificial General Intelligence (AGI) more or less on these lines [76]. The discipline has been moribund for the past few decades mainly for the reason that computing hardware of past times had limited capabilities. Advent of modern High Performance

Table 1
Distributions of citations across different disciplines and ML algorithms.

Learning	Cardiac	Pulmonary	Exercise RS	Adherence	Compliance	Nutrition RSs
SVM	[5]	[9,10,12]		[30]	[35,36,40]	[52]
ANN	[4]	[10]		[30,32]		
DTs	[5]			[30]		
K-NN	[5]	[10,12]			[35]	[50]
CNN	[8]	[9,11]			[37,40,41]	
RNN	[8]		[23,27]			
LSTM			[25]		[37,40,42]	
GMMs		[10]			[41]	
NB					[35]	
HMM					[39]	

Computing (HPC) tools as well as advances in AI and ML now allow for the adoption of the development of cognitive architectures for AGI. Thus, it will be one of our future ambitions at Regulated Software Research Centre (RSRC) to adopt cognitive architectures for AGI related to medical devices.

Acronyms

Abbr.	Meaning
AI	Artificial Intelligence
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
COPD	Chronic Obstructive Pulmonary Disease
CT	Computed Tomography
CVD	cardiovascular disease
DT	Decision Tree
ECG	Electroencephelogram
GMM	Gaussian Mixture Model
HCI	Human-Computer Interaction
HMM	Hidden Markov Model
IMU	inertial measurement unit
K-NN	k-Nearest Neighbor
LIME	Locally Interpretable Model-Agnostic Explanations
LSTM	Long Short Term Memory
MFCC	Mel Frequency Cepstral Coefficient
ML	Machine Learning
NB	Naive Bayes
PA	physical activity
RNN	Recurrent Neural Network
RS	Recommender System
SHAP	Shapley Values
STFT	short time Fourier transform
SVM	Support Vector Machine
VR	virtual reality
WHO	World Health Organization
X-AI	Explainable AI

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Muhammad Adil Raja reports financial support was provided by the Technological University Transformation Fund (TUTF) of the Higher Education Authority (HEA) of Ireland.

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