Lecture Notes in Bioengineering

Mario Bochicchio · Pietro Siciliano ·
Andrea Monteriù · Alice Bettelli ·
Domenico De Fano *Editors*

Ambient Assisted Living

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Lecture Notes in Bioengineering

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Preface

The domain of Active and Assisted Living (AAL) has increasingly been recognized as a crucial element in shaping the future quality of life in our society. Endorsed by institutions like the European Commission, AAL is viewed as a foundational block essential for addressing the pressing challenges brought on by demographic changes. These include sustaining people in productive and healthy work, maintaining independence and integration at home, and enhancing the delivery of care precisely where and when it is needed.

The 2023 Ambient Assisted Living Italian Forum, held in Bari, Italy, continues to uphold its significant role as a fundamental gathering for an extensive network of stakeholders. This forum serves as a platform for researchers, professionals, policymakers, developers, and end-user organizations engaged in the evolving fields of AAL. They come together to share their results, expertise, prototypes, and innovative solutions, thereby fostering a collaborative environment to drive forward the integration of AAL technologies into daily living.

This volume captures the discussions and explorations undertaken during the conference. It reviews current research, technological advancements, and the integration of these technologies into practical applications, emphasizing their potential to transform everyday life. The range of topics covered here is extensive—from human monitoring systems to smart living services and robotic solutions—each contributing to the overarching goal of AAL: to enhance the autonomy and well-being of individuals across all life phases.

The interdisciplinary approach adopted in this forum brings together diverse perspectives that merge technology with social needs, ensuring that the developed solutions are not only innovative but also empathetic and user centric. This approach is crucial in ensuring that AAL technologies are adaptable and responsive to the needs of individuals, thereby enhancing their quality of life without demanding significant adjustments on their part.

The Ambient Assisted Living Italian Forum remains dedicated to advancing these technologies, promoting a future where they are integral to addressing the challenges of an evolving demographic landscape. This volume is an indispensable resource for all those involved or interested in the field of AAL, inspiring ongoing innovation and commitment to enhancing lives through technology.

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Contents

Towards the Development of Human Action Recognition and Monitoring System for Rehabilitation Purposes: A Feasibility Study

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Abstract. According to the World Health Organization, the growing number of individuals affected by neurocognitive diseases (e.g. Alzheimer, Dementia, Parkinson) is expected to rise and there will be an increased risk of hospitalization and an increase necessity to do rehabilitation at home as well as to stay active. The primary aim of this paper is to develop a Human Action Recognition (HAR) system that can be used at home by the patient as both a portable fitness tool and personal coach. The system's primary function is to suggest personalized exercises and supervise the proper execution of movements. Additionally, clinicians can monitor patients' progress on a daily basis through a set of biomechanical key performance indicators (Bio-KPIs). The ultimate goal of the system is to empower patients to improve their physical health and allow clinicians to track their progress over an extended period of time. We conducted a test of the network using 10 participants who performed 4 rehabilitation exercises, resulting in a test accuracy of 78.45%, a precision of 87.75%, a recall of 84.7%, and f1-score of 82.5%. The performance is quite encouraging since we tested the system in real environments under different light conditions and we obtained performance values that are comparable with the literature. Moreover, the Bio-KPIs extraction let us characterize the rehabilitation exercises.

Keywords: human action recognition · vision sensor · deep learning

1 Introduction

In the last decade, addressing major neurocognitive disorders (NCDs) has become a critical concern for public health, and according to the World Health Organization, the growing number of individuals affected by major NCDs is expected to rise significantly by 2050 (Akkaladevi and Heindl 2016; Loizzo et al. 2022). This increases the risk of hospitalization, and nursing home placement, and places a burden on both professional and informal caregivers. As a result, the cost of care is expected to rise, and this situation brings the necessity to do some part of the rehabilitation process at home.

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Moreover, people feel more comfortable doing rehabilitation in their private houses with respect to hospitals or external environments (Nocentini et al. 2019). Human Action Recognition (HAR) involving the automatic analysis of human actions using data from different sensors, such as vision sensors, can play a vital role as a technology for support in doing rehabilitation at home. HAR has different potential areas of application, including human-robot interaction (HRI), and its focus is on recognizing different activities depending on the specific context. One important application of HAR is in monitoring the rehabilitation of older individuals in an Ambient Assisted Living (AAL) environment (Moschetti A. et al. 2017). By tracking their rehabilitation activities, the system can help them maintain a healthy lifestyle and live longer (Fleury et al. 2010).Various sensors are used in HAR, including RGB-D cameras, inertial wearable sensors, lightweight systems, and mobile phones. Among these, RGB-D cameras are widely available, cost-effective, and provide detailed information on the scene, making them the best choice for HAR. Several classifiers from the classical machine and deep learning are used to recognize and classify the activities an older person is performing at their private home, while a geometric approach is usually used to extrapolate Biomechanical Key Performance Indicators (Bio-KPIs) (i.e. max height of the wrists, angle of the shoulders) that are useful for clinicians for the evaluation of the patient's activities.

In this context, this paper focuses on the development of a portable Human Action Recognition (HAR) system that can function as a physical coach. The system is designed to suggest personalized exercises and monitor the execution of the movements through the computation of Bio-KPIs. Indeed, the final purpose of this system is to provide patients with an effective tool to improve their physical fitness and allow clinicians to track their progress over time. Particularly, the proposed work is intended to evaluate the performances of the recognition system in classifying four physical exercises, using the metrics of accuracy, precision, recall, F1-Score and extract the Bio- KPIs of the patient. Bio-KPIs were also extracted to monitor the exercises executions.

The structure of the paper is the following: in Sect. 2 a general overview of the related works is provided, while in Sect. 3 the architecture of the system and the approach followed in this work are explained. Finally, in Sect. 4 and Sect. 5 the results of the previously performed data analysis are respectively presented and discussed.

2 Materials and Methods

In this section, the system description, the experimental protocol and the pre-processing of the data are presented.

2.1 System Description

The proposed system architecture was designed to develop a not intrusive technology that can be adopted in real AAL scenarios as a solution for monitoring the rehabilitation activity of older people (Fig. 1a). The main idea beyond our system architecture is described in Fig. 1b. The system is composed of the following key elements:

- **Exercise recognition** This module is based on deep learning classifier (e.g. LSTM). It will analyze the pre-processed keypoints data *(pre-processing module)* acquired from the camera giving feedback on the accuracy of the performed exercise.

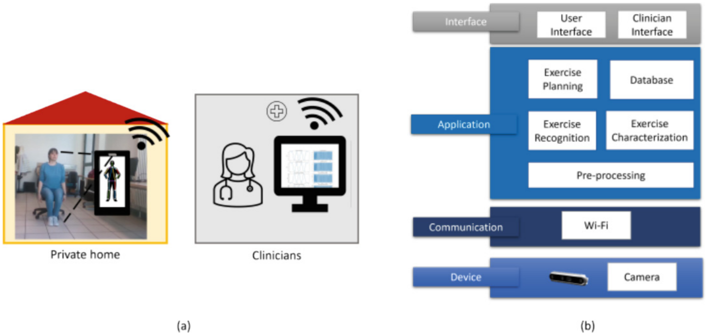

Fig. 1: (a) Proposed services; (b) System architecture: device, communication, application, and interface layers.

– **Exercise characterization** Within this module, the customized algorithm will analyze the data extracted from the camera to measure selected Bio-KPIs that give clinicians feedback on the quality of the performed movements. Some examples are number of exercise repetitions, maximum excursion of the shoulder joint.
– **Exercise planner**: the purpose of this module is to propose a personalized physical rehabilitation plan. Through the *clinician interface* the clinician will select some exercises for the older adults according to his/her residual physical abilities or specific necessities. This module processes the information, organizes the plan, and provides a detailed explanation to the older person on how to replicate the rehabilitation exercises (i.e. how many repetitions, at which velocity, and angular excursion) through the *user interface* module.
– **User interface** the user interface can be installed on the user's personal device that has an embedded camera (e.g. smartphone). Through the interface, the user can access the exercises proposed by the clinician and monitors his/her improvement (output of *exercise characterization* module). Additionally, the user interface can give visual information in real-time (e.g. the number of repetitions, the name of the exercise the person is performing).
– **Clinician interface** the user interface will be installed on clinician's personal device. Through this interface, the clinician can basically perform two actions: i) select and personalize the set of exercises to be executed by the older adults verifying if the user performs the exercise (*exercise recognition* module output; ii) monitor the performance and the progression of users' exercises by checking the values or graphs of the Bio-KPIs *(exercise characterization* module output).

In addition, the proposed architecture includes also i) the device capable of acquiring video data; ii) the *pre-processing* module that will extract and normalize body key points; iii) the *database* that can storage the anonymous data collected. In this paper, we focused on three modules of the system namely *Pre-processing, Exercise Recognition,* and *Exercise Characterization.*

2.2 Experimental Protocol

A significant constraint observed in the current body of research lies in the inclination to exclusively train human activity recognition systems within controlled laboratory settings that offer ideal lighting conditions. Conversely, our objective was to evaluate our system's performance in a broad spectrum of real-world scenarios featuring diverse lighting conditions. In order to maintain uniformity in video recording conditions across various environments and ensure consistent video quality, we opted to employ a single device. For this work, the user personal device is implemented using a RGB-D camera (Intel-RealSense D435i). While we could have chosen any webcam for data collection, we made the decision to utilize an Intel Realsense camera primarily because it was readily available in our laboratory, even though we did not utilize the depth data it can provide. For real running also smartphones or tablets can be used.

In this protocol, each participant is placed 3 m away from a vision sensor and they perform 4 rehabilitation exercises that are: Hands Up (HU), Clenched fists (CF), Steps (S), and Leg bending (LB).

In the exercise HU, the user is seated and raises his/her arms at the sides of the body at the same time. In CF, the participant is seated and alternately raises his arms with clenched fists, while in S, the user is standing with his/her hands anchored to the arm of the chair they take alternating steps backward. Finally, in LB, the participant is standing and, with his/her hands anchored to the arm of the chair, they bend their legs. In exercises HU and CF, the person is seated in front of the camera, while in LB and S, the user is lateral to the camera.

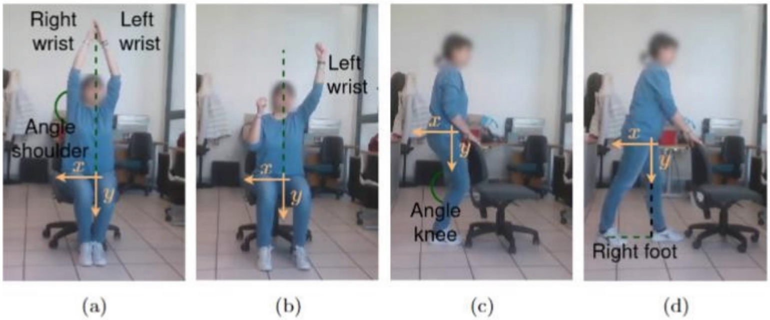

Fig. 2. Experimental setup and indication for Bio-KPIs extraction: in (a) and (b) the exercises HU and CF are presented, while in (c) and (d) the LB and S are shown respectively.

At the beginning of the data acquisition, the participant was asked to perform the selected exercise three times with the request to perform it as best as they can. This phase is called *calibration* and it was used as the reference value for intra-subject analysis (see Sect. 2.6). After, the participants were requested to perform the exercise for 2 min in front of the camera without any constriction. All the data were stored in a GDPR compliance database and off-line analyzed.

Table 1. KPI values for the four exercises

Exercise	Bio-KPIs	Computation
HU	Left wrist	Value along y of the left wrist of the user
HU	Right wrist	Value along y of the right wrist of the user
HU	Angle shoulder right	Angle between hip, shoulder and elbow of the user
HU	Angle shoulder left	Angle between hip, shoulder and elbow of the user
CF	Left wrist	Value along y of the left wrist of the user
CF	Right wrist	Value along y of the right wrist of the user
LB	Right knee angle	Angle between hip, knee and feet of the user
S	Right feet	Distance that the right feet does

2.3 Participants

The experimentation was conducted with 10 young subjects (8 females and 2 males), whose ages ranged from 24 to 30 and height from 1.50 to 1.95 m. Regarding educational level, all the participants graduated. About attitude towards the current technology, all participants were very familiar with PC, Smartphones, and Tablets.

All the participants signed the informed consent form before entering the study.

2.4 Pre-processing

The Mediapipe software (Lugaresi et al. 2019) was utilized to analyze RGB videos and to obtain skeleton features. Specifically, 33 keypoints were estimated for the body, each representing the joint's (x, y) pixel coordinates. Each keypoint has a visibility value that describes the visibility of a landmark and we decided to discard the keypoints that have less visibility than a certain threshold (0.8). These features were normalized by shifting the original reference frame from the camera to the torso joint. This normalization process produces data that is not dependent on the individual's size or the camera's relative position.

The normalization obtained by shifting the original reference frame from the camera to the torso joint is described by the following formula:

$$k_{normalized} = k_i - k_{torso}$$

where $k_{normalized}$ is the keypoint normalized with respect to the torso keypoint, k_i is every keypoint of the skeleton, and k_{torso} is the torso keypoint. The torso keypoint is obtained considering the mean along x axis of the two shoulder keypoints.

2.5 Exercise Classification

According to the state of the art, Long Short-Term Memory Network (LSTM) was the most used deep learning classifier, therefore, to facilitate the comparison with previous work, we select this same classifier. For this work we decide to rely on LSTM because it can be found in literature that this classifier has a better performance than other deep learning classifiers (Zhu 2021; Mohamed et al. 2021; Deb et al. 2022). In the future, other classifiers will be tested. Additionally, we also chose this network since it has feedback connections as opposed to standard feedforward neural networks. The normalized key-points were used to feed the LSTM and we used a batch size = 128, a learning rate = 0.0005, the Stochastic Gradient Descend as the optimizer, and the Cross Entropy as the loss. As for the evaluation, we perform the Leave-one-Subject-Out methods, thus, to mimic the operative conditions where the classifier must evaluate the performance of an unknown subject. The accuracy, precision, recall, and F1-score parameters were used to evaluate the performance. The final values were computed as the mean values of the 10 trials.

2.6 Exercise Characterization: Extraction of BIO-KPIs

To provide the clinician with objective measurements of the exercise performances, some Bio-KPIs were extracted as detailed in Table 1 and as can be seen in Fig. 2. These parameters were used individually (i.e. left and right wrist height) or can be combined to extract other clinical indications (i.e. ϵ). For each parameter, the average values as well as the standard deviations were computed (absolute values).

Data from the calibration phase was also analyzed and the extracted features were used for intra-subject comparison. In this work, we evaluated the discrepancies (ϵ) with respect to the calibration data using the following formula:

$$\epsilon = \left| \frac{value_{calibration} - value_{exercise}}{value_{calibration}} \right|$$

In this section, the results of this work are presented and divided into the classification part and the characterization part for the extraction of the Bio-KPIs.

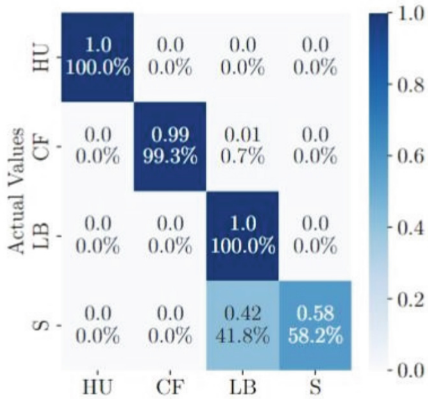

Fig. 3. Confusion matrix of dataset for participant ID003.

2.7 Exercise Classification

The customized dataset used is composed of 10 people doing 4 different rehabilitation exercises. During the training of the LSTM, we used 9 people for train, and we left one subject out for test, and we evaluated the system using the following performance indicators: accuracy, precision, recall, and F1-Score.

The test accuracy of the system is 78.45%, the precision 87.75 %, the recall 84.7%, and f1-score 82.5%.

In Table 2 the precision, recall, and F1-Score for each exercise is shown. From the table, it can be seen that the higher performance is obtained by HU exercise, while the worst performance is obtained by the exercise LB. Figure 3 shows the participant ID003. From the matrix, it can be seen that exercises HU, CF, and LB are well recognized while exercise S is confused with exercise LB, these results confirmed the average results obtained for the entire group.

2.8 Exercise Characterization: Extraction of BIO-KPIs

The parameters for each exercise are summarized in Table 3, 4, 5, 6. In Fig. 4, the raw data related to the left, right wrists and left and right shoulder angles for calibration and the exercise are presented respectively.

For what concerns the Bio-KPIs related to the four exercises, we can see that in 2 min the maximum value of repetitions is performed in the exercise LB with 57 repetitions, while the minimum number of repetitions is performed in exercise CF.

Moreover, for what concerns HU exercise it can be seen that the right arm opens more than left shoulder, since the excursion of the angle for the left is 173° and the right angle is 178°.

Table 2. Precision, recall, F1-Score of each exercise

Exercise	Precision (%)	Recall (%)	FI-Score (%)	Accuracy (%)
HU	94	99	96	99,8
CF	99	92	95	87
LB	72	74	67	55
S	86	74	72	72

3 Discussions

The main objective of this research paper is to create a portable HAR system that doubles as a personal coach. The primary function of the system is to propose customized exercises and oversee the proper execution of movements by classifying the action the person is doing. Furthermore, clinicians receive a set of biomechanical key performance indicators (i.e. Bio-KPIs) to monitor the patient's progress on a daily basis.

As concerns the classification part, the exercise which is confused the most is S since it is most of the time exchanged for LB exercise (Fig. 3). This result could be due to the fact that the standing position of the subject is the same for both exercises. As for the classification accuracy, the most recognized exercise is HU followed by CF and LB. The lower accuracy of LB and S is due to the lateral view that occludes part of the body affecting the Google MediaPipe skeletal model reconstruction. Indeed, the accuracy obtained (78.45%) compared to the state of art is quite aligned with the performances of (Phommahavong et al. 2015; Matos et al. 2019; Wang and Wang 2021; Mohamed et al. 2021). The most important point to be remarked is the fact that the data are acquired in a real environment, under different light conditions, backgrounds and without giving any constriction to the participant in performing the exercises.

Table 3. Bio- KPIs for HU exercise

Exercise HU	Mean(SD) Calibration	Mean (SD) Exercise	ϵ	# Exercise Repetition
Left wrist [m]	0.42(0.04)	0.41(0.04)	0.03	46
Right wrist [m]	0.42(0.04)	0.42(0.04)	0.03	46
Left angle shoulder [deg]	173(3.9803))	172(4.98)	0.007	46
Right angle shoulder [deg]	178(2.03)	173(2.81)	0.007	46

Table 4. Bio-KPIs for CF exercise

Exercise CF	Mean(SD) Calibration	Mean(SD) Exercise	ϵ	# Exercise Repetition
Left wrist [m]	0.4(0.02)	0.4(0.03)	0.03	36
Right wrist [m]	0.4(0.03)	0.4(0.04)	0.1	36

Table 5. Bio-KPIs for LB exercise

Exercise LB	Mean(SD) Calibration	Mean(SD) Exercise	ϵ	# Exercise Repetition
Kneangle [deg]	138(10.37)	137(9.98)	0.02	57

For what regards the Bio-KPIs, by looking at the data we can observe symmetry for the left and right height of the wrists for the CF exercise. Moreover, we can see that for the LB exercise the excursion of knee angle mean is quite similar between the exercise and calibration parts. Furthermore, the S exercise has the same mean right foot

Table 6. Bio-KPIs for S exercise

Exercise S	Mean(SD) Calibration	Mean(SD) Exercise	ϵ	# Exercise Repetition
Right foot [m]	0.02(0.008)	0.02(0.008)	0.04	44

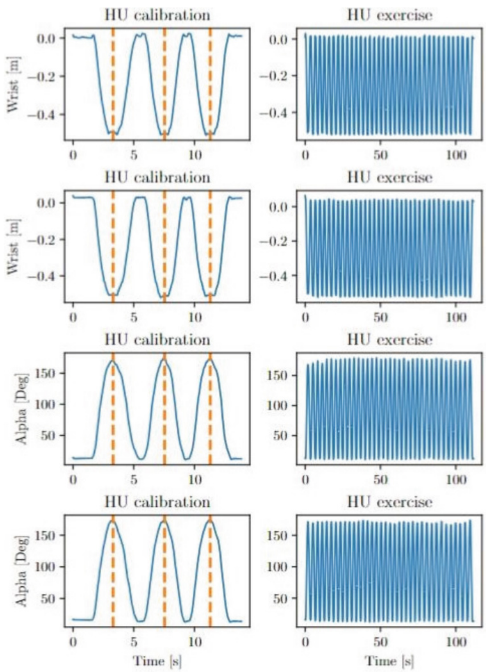

Fig. 4. Wrist position and shoulder angle trajectories during calibration and exercise of HU. The vertical dashed line represents a repetition.

distance for calibration and exercise execution. This finding is aligned also with the ϵ values that are quite small for all the exercises; this suggests that there is consistency between calibration and the exercise execution. In the future, we would like to consider more Bio-KPIs variables, such as trunk inclination, to monitor the patient and how their pathology progress is going.

There are some issues that remain opened and should be addressed in further studies. Firstly, the dataset that should be enlarged adding new rehabilitation exercises or other participants to the experiments. Moreover, comparing the performance of different classifiers could be an issue to analyze in the future and the analysis of both right and left part of the body in the performance of the exercises should be done. Finally, adding new Bio-KPIs and combining the classification part with the characterization parts should be something to study in deep.

In this work, the analysis of the data has been conducted offline. However, this application aims to achieve a system that is able to recognize the rehabilitation exercise in real-time. The main idea is to use the classification part to understand if the user is doing an exercise selected and, if it is doing it properly, to extract the Bio-KPIs. In conclusions, we would like to integrate the classification and the characterization module to produce a complete system that can support the patient as a personal coach.

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SAFE GYMS: IoT Systems for Safe and Healthy Sport and Working Environments

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Abstract. The Pandemic has highlighted the need for a novel conceptualization of public and private living spaces to increase safety and salubrity. The aim of the conceptualization is to improve the well-being and quality of living of people who work, inhabit, or frequent these indoor spaces. Cutting-edge technologies that leverage the Internet of Things (IoT) paradigm can be exploited for sanitization or monitoring compliance with anti-Covid-19 safety norms. The present paper describes a trial organized in a gym equipped with an IoT-integrated system for air quality monitoring, ventilation, filtration, ionization, and surfaces and objects sanitizing. Athletes and professionals in biomedical sciences participated in assessing the IoT system. Self-reported instruments were administered. The comparison between pre and post-tests showed that knowing the features and functioning of these advanced and innovative systems increase the degree of their acceptance and the perception of healthiness and safety in an indoor environment, also considering a post-pandemic situation.

Keywords: Safety · Healthiness · IoT · Smart Environments · Covid-19

1 Introduction

The Covid-19 pandemic has brought to evidence the need to make indoor environments safe and healthy to reduce the spread of the virus Sars-CoV-2 and the contagion risks. The easiest way to allow an air change in interior spaces is opening the windows, but it is not always the most appropriate choice considering, for example, different seasons and relative countries (e.g., winter) or specific environments with ill individuals (e.g., hospitals) or people with poor health (e.g., old adults), the environmental sustainability in terms of heating costs and energy waste, and the pollution.

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Several studies have focused on air quality, pollution, and their relationship with the spread of the SARS-CoV-2 virus [1, 2]. Air pollutants have been demonstrated to have a facilitatory effect on the transmission of the virus by resulting in an inadequate response of the immune system [3, 4]. Chronic exposure to air pollution can result in more severe/lethal SARS-CoV-2 infection [5]. In addition, regarding indoor air quality (IAQ), the scientific literature has analyzed the impact of temperature, humidity, and various chemical pollutants (e.g., carbon dioxide, volatile organic compounds, VOCs) to assess potential health risks to the occupants of internal spaces, even not considering a pandemic situation [6]. Air pollution, especially in indoor sport environments, can badly influence athletes' performance [7, 8] and put them at health risk (e.g., respiratory issues [9]).

Several gyms or sports centers have a reduced number of windows. When these last are present in every room, it is necessary to consider the specific season (e.g., winter) and the outdoor conditions (i.e., pollution such as carbon monoxide, CO, or VOCs) before opening them to change the indoor air. Indeed, this action could decrease indoor air quality instead of ameliorating it, and pollutants are proven detrimental to sports performance [7] and increase the contagion risk [1, 2]. A healthy environment may positively impact the athletes' health and sports performance while training in indoor spaces. A recent study [8] reported that high levels of carbon dioxide and particulate matter (PM_{10}, $PM_{2.5}$) could result in issues in fitness centers and gyms, especially when the air ventilation in these facilities is insufficient.

Scientific studies, focused on air treatment in the context of the Covid-19 Pandemic, have mentioned the relevance of mechanical air ventilation/air forced recirculation, air filtration/purification, monitoring and maintaining of low levels of the chemicals present in the air (e.g., particulate matters, CO_2, Ozone, and VOCs [2, 5, 10]). A critical review analyzed different systems for heating, conditioning, and air ventilation (HVAC) during the recent global health crisis, the importance of the filters used to fight the spread of the virus, and the ventilation process aimed at reducing the risk of infection through the air [11]. A set of 22 recommendations were provided concerning, for instance, the type of filters, circulating the air before the arrival of individuals in the environment, maintaining the indoor temperature around 25–27° and the humidity around 50–70% [11].

Furthermore, regarding internal spaces, to fight the spread of SARS-CoV-2, sanitizing surfaces and objects in indoor places is necessary to reduce the likelihood that individuals could unwittingly touch an infected area and then their nose, mouth, and eyes, increasing the contagion risks. To this purpose, disinfectant sprays and instructing individuals to sanitize their hands with gel are often relevant measures to implement. Considering the technological tools, the most exploited were UV direct lighting [12–14], which mimics the solar UV radiation demonstrated to be highly effective for the inactivation of SARS-CoV-2. Artificial UV lighting can kill the virus in seconds or a few minutes. In addition, ionizers have been utilized in interior spaces [15] to generate ions to inactivate airborne pathogens to improve IAQ [13].

Besides, several cutting-edge technologies based on the Internet of Things paradigm have been considered in the context of the recent Pandemic for different purposes, such as to check compliance with safety norms (i.e., social distancing/gathering avoidance; [16–18], presence and correct usage of personal protective equipment (PPE), checking body temperature, etc. [19–21]) and sanitizing interior environments utilizing UV lighting [22]. These specific systems can be included in the Non-Pharmaceutical Interventions (NPIs; [19, 23, 24]) as the lockdowns, insofar as they are considered a set of preventive measures, not a type of medical treatment. These advanced technological solutions can be paired with artificial intelligence algorithms to automatically adapt their functioning to the actual environmental conditions and the presence/absence of individuals to avoid harming them (e.g., the direct UV lighting in the presence of people) or wasting energy resources. Besides, they can alert and implement autonomous actions in dangerous or risky situations (e.g., intelligent doors connected to smart cameras that emit an acoustic signal and remain closed if the people outside are not wearing protective masks [25]).

Given the opportunity to exploit IoT-based systems, equipping indoor ambients with such technologies could be a suitable solution to automatically monitor IAQ, increase the sanitization of indoor surfaces and objects, reduce the viral load, and, consequently, the risks for their inhabitants.

In the following sections, we will describe the assessment of an IoT-based system, involving a group of final users, that was designed and developed to ensure the automated: monitoring of IAQ; air recirculation and filtration; and the activation of an ionizer to sanitize surfaces and objects in a sport environment (i.e., a gym of the Department of Biomedical Sciences of the University of [blank for review purposes]). For instance, the integrated intelligent system automatically activates the air recirculation and filtration based on specific thresholds (comply with air-quality standards) concerning the elements monitored (e.g., CO_2, PM_{10}, VOCs). We will detail the participants involved, materials and equipment used, experimental procedure, analyses performed and their results, and finally, we will discuss the outcomes of the study, its limitations, and future directions.

2 The Study

The experiment aimed to assess the perception of athletes and researchers in biomedical sciences regarding some dimensions of acceptance and user experience of an IoT system and safety perception related to its presence in the environment. The ethical committee of [blank for review purposes] approved the study (protocol n° [blank for review purposes]).

2.1 Method

Participants. A total of eleven individuals ($M_{age} = 26.45$; $SD_{age} = 7.22$; Women = 3), recruited by [blank for review purposes] and [blank for review purposes] authors voluntarily participated in the trial. Six participants were researchers in biomedical sciences, while five were gym users. They reported not owning or using IoT systems in their living environments (i.e., home, workplace) to increase their safety or healthiness.

Materials and Equipment. The following materials and tools were considered in the assessment:

- (Pre-test) a demographical questionnaire to collect participants' background information (e.g., gender, usage of IoT devices for safety and salubrity of living spaces);
- (Pre and Post-test) an ad hoc questionnaire, this tool comprises fifteen items (7-point Likert scale; from 1 = "completely in disagreement" to 7 = "completely in agreement"; items, e.g., "*The SAFE PLACE devices could enhance the safety of the library*" and "*I believe that the use of SAFE PLACE systems within the library could be an effective method for contagion prevention.*") to assess the acceptance of the installed IoT devices (based on the TAM model; [24]) and the actual (items, e.g., "*I would feel secure in environments where SAFE PLACE devices are present*") and during-the-pandemic safety perception (items, e.g., "*During the most severe phases of the pandemic, I would have felt safer if the premises were equipped with SAFE PLACE technology*") linked to the presence of the considered IoT advanced tools in the environment;
- an iPad Air (10.5"; screen resolution 2224 × 1668 pixels) allowed the administration of pre and post-test questionnaires;
- a Huawei MateBook X Pro (display 13,9"; resolution: 3000 × 2000 pixels) was used to present a set of slides on the IoT devices and their function.

Besides, the subsequent IoT-based devices were installed in the experimental setting:

- a multi-sensor device for air quality monitoring that assesses in almost real-time the level of different parameters of the indoor air (i.e., CO_2; particulate matter, PM 2.5-10; Ozone, O3; Volatile Organic Compounds, VOCs; temperature, humidity; Fig. 1);
- a tablet (i.e., Smart Control Display) that shows all the information on air quality and IoT devices' state (Fig. 1). When the monitored air-quality parameters exceed specific thresholds, automated rules are implemented. IoT devices are activated to improve indoor air quality and sanitize air and surfaces.

Fig. 1. Sensor for air-quality monitoring (up-left) and Smart Control Display to check air parameters and IoT systems operating (down-right).

– an ionizer with advanced cold-plasma technology (Cube IOT; Jonix©; Fig. 2) for air/surfaces sanitizing to help in the prevention of airborne diseases such as Covid-19 through the emission of ions and the reduction of air pollution;

Fig. 2. Cube IOT Ionizer.

– a heat recovery unit (VMCS700SH; Brofer©; Fig. 3) with very high energy efficiency for air filtration and recirculation to exchange outdoor-indoor air for increasing the quality of the air (Fig. 3).

Fig. 3. Air recirculation unit (VMCS700SH).

The integrated IoT system encompassing all the devices mentioned above enables real-time communication among them. Data collected through the multi-sensor, which