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Survey paper

Application of Internet of Things and artificial intelligence for smart fitness: A survey

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ABSTRACT

The revolution of Internet of Things (IoT) is pervading many facets of our everyday life. Among the multiple IoT application domains, well-being is becoming one of the popular scenarios in IoT which aims to offer new services including smart fitness. This paper focuses on smart fitness covering IoT-based solutions for this domain as well as the impacts of artificial intelligence and social-IoT. IoT-based smart fitness is divided into three categories: Fitness trackers (including wearable and non-wearable sensors), movement analysis and fitness applications. Data collected from IoT-based smart fitness and users could be used for enhancing training performance by Artificial Intelligence (AI)-based algorithms. Sensor to sensor relationship is another notable topic which can be implemented by social-IoT that can share data, information and experiences of users' training from different places and times. In this his study a comprehensive review on different types of fitness trackers and fitness applications in provided and followed by a review of AI algorithms used in smart fitness scenarios. Lastly detail discussions on the benefits and the potential problems of smart fitness are presented and a shortlist of existing gaps and potential future work have been identified and proposed.

1. Introduction

The Internet of Things (IoT), and related technology such as wireless sensor networks (WSN) [1] are progressing rapidly and their new developments and applications are shaping our daily life. According to [2] there are about 30 billion devices and over 7.7 people connected to IoT networks in early months of 2020 and it is estimated that this number will be raised up to 75.44 billion connected devices [3]. There are several definitions for the IoT, but a universal definition describes it as a global network of sensors, devices and objects that can connect to each other automatically and sense data, thereby allowing to measure, control and process an environment and make it perform in an intelligent manner [4–7]. All these recent advancements made it possible to offer a large number of applications in many different domains including e-healthcare, environment monitoring, transportation systems, and other commercial areas [8,9].

Among the IoT's different application domains, health is a very relevant sector that is gaining increasing interest. The advancement of IoT may have a tremendous impact on the transformation of healthcare to the fully extended capabilities of e-healthcare [10–13]. Fig. 1 shows some IoT subcategories with a focus on the health domain.

Smart healthcare is a broader domain that comprises different fields, from the care of patients under strict medical supervision to well-being practices. As shown by previous studies, a healthy lifestyle is based on five important interrelated factors: 1 — Physical activity (PA) 2 — Food and drink consumption 3 — Sleep quality 4 — Stress; and 5 — Social interaction[1] [14–16]. To meet the mentioned needs, a mechanism to measure and monitor the above mentioned items is needed, with the capacity to automatically monitor sleep duration, diet and physical activity.

In fitness, when people want to exercise and work out, they usually face some challenges. They have some needs such as workout plan and diet regime in line with their goal, also a monitoring mechanism to supervise the meal and workout plan and decision making mechanism that can determine and suggest the next workouts level and the composition of an appropriate meal plan. Smart fitness and specially IoT based fitness trackers are already playing an important role in smart fitness and well-being [17]. Some simple features and functionalities such as

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[1] http://qsinstitute.com/about/our-focus/.

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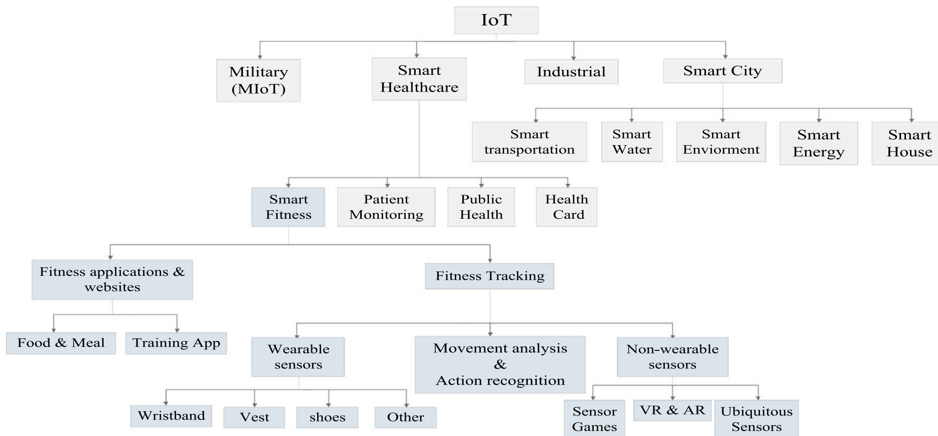

Fig. 1. Main areas of IoT (white color) and smart fitness as a subset of the health domain in IoT (blue color). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

personal data recording, action history, body state and heart rate can be acquired and monitored easily by recent technologies [17,18]. This advance will allow to provide services for more supporting the fitness practitioners.

In social interaction phase we have social features of fitness applications which can influence on changing health and fitness behavior and receiving support by other people in these social networks [19]. Currently physical activity is a good way in order to improve resistance against psycho social stress [20] and recently Garmin has introduced a mechanism to measure stress level of smart watch's users by determining the interval between each heart beat.[2] One of the technologies which can hep smart fitness to be more effective for user is "Social-IoT" which actually is "device to device" interconnection that provides information sharing between non-human devices such as smart phones [21]. This can help system to use experiences of all connected systems and devices and collect beneficial data and information for making better decisions and prediction for athletes and participants.

On the other hand, sensing capabilities, together with advanced AI algorithms are capable of measuring many actions and behaviors of people during their daily activities. General purpose sensing is the attempt to equip devices with general sensing capabilities and to use them for specialized tasks such as Fitness. In fact trackers in fitness domain are essentially based on this approach. In addition, sports related applications (e.g., tennis ones) could be supported by this kind of devices (e.g., smartwatches)[3] [22].

Artificial intelligence (AI) is the ability of a system that can explicate data correctly and learn from them to make decisions and achieve particular goals [23] and trying for automation of activities which need human intelligence and are performed by human-thinking such as decision making and problem solving [24]. AI can help in action recognition and, movement analysis as well as provide services such as recommending foods and portions [25] to act as a trainer [26]. Because of the number of produced data by existing sensors and applications, AI algorithms can be performed for different usages in sports such as training session monitoring, injury recovery, training plan prediction and other professional supporting [27]

This study provides a comprehensive overview of the state of the art in the sector of smart fitness with a particular attention to the available technologies in the wearable devices. This paper does not consider professional athletes and their associated technology due to their complexity and their need for supervision by of medical staff. Smart fitness comprises tracking one person's activity, the steps taken, the eating habits [28], monitors their sleep [29] and controls and monitors factors on that influence well-being. IoT sensors and portable devices (from smart phones to wearable devices) can help in collecting the appropriate data and enable applications to analyze that data to determine the most appropriate actions and evaluate an individual's progress [18,30,31].

Considering the existing similar surveys on smart fitness methods [32–35], we can summarize our contributions in this study are as below:

I. We investigate the current market for smart fitness and identify existing gaps in this research domain and provide a summary of the existing solutions, technologies and architectures.

II. We illustrate a comprehensive study of the impact of the IoT on Smart Fitness application with details on different existing categories of smart fitness and existing protocols.

III. with a focus on AI, machine learning and social-IoT and also their subsets we study their impacts on smart fitness and their potential for providing advanced personalize services based on fitness data, collected from wearable and non-wearable sensors.

IV. Finally, we identify the challenges and provide a list of the potential future directions.

The next sections of this survey are as follow: in Section 2 we overview challenges in fitness and impacts of IoT on smart fitness and other areas of sport. In Section 3 we review current academia and commercial, solutions and types, in smart fitness. Next we talk about social-IoT and its services and describe how S-IoT can help smart fitness to be more efficient. In Section 5, we also describe current AI solutions in smart fitness and some other helpful ideas in other areas of IoT and opportunities for using them in smart fitness. In Section 6, we discuss about negative and positive side effects and also future directions and gaps in smart fitness. Finally, in 7 we discuss the conclusions of the presented taxonomy and describe findings.

2. Fitness — existing gaps and proposed solutions

This section includes a general overview on the existing challenges and solutions for fitness domain as well as an overview of the impacts of IoT on healthcare and fitness is presented. We also study very briefly the market of smart fitness.

2.1. Existing challenges in fitness domain

Sports and fitness play an important role in people's lives. However, in various sports most of the time the "do it yourself" approach can be unsafe. This is particularly problematic when practitioners decide not to follow best practices and perform fitness exercises on their

[2] https://bit.ly/382nLjH (accessible in 8 June 2020).

[3] https://ioshacker.com/apps/best-tennis-apps-for-iphone-apple-watchFigure.

own. Under these conditions, it is not rare for injuries to happen or for training performance to decline [30,36]. Most people have limited knowledge about safe and efficient fitness training, and maintaining a medium/long term training plan requires both motivation and monitoring [37]. As sports injuries is a common problem, several medical studies are trying to find solutions for predicting, preventing and/or decreasing their occurrences. Some tools have been available and utilized for years, such as leg supports and wrist protectors, and even various types of glue muscles and many other physical items to prevent or reduce the severity of injuries. Several studies have tried to improve fitness problems by preventing the most common injuries and the consequent waste of money and time [38] but still this is the main challenge to tackle in this direction.

2.2. Smart fitness based on IoT

IoT concepts and services have a considerable impact on most of the sports including fitness. There are various applications of smart fitness such as soccer [39], ski [40,41], ballet [41], and etc. Several sports like soccer [42], taekwondo [43], cyclist [44] and all other sports that have pre-season period are engaged with smart fitness which is the best time for improving aerobic and performance [44] and most of the sports that need pre-season preparation course are using smart fitness for better monitoring. There are so many similarities between smart fitness and other smart sports. In smart sport training some external factors (such as kinetic energy, metabolic power, acceleration, body loads and etc.) and also some internal factors (e.g. oxygen uptake, heart rate, joint load, muscle load, etc.) have potential to be monitored [42]. Monitoring training load and effects of training plan on athlete's body for providing program and preventing under or over training in sports like cycling [45] is another issue that exactly exist in smart fitness. However, there are some differences between smart fitness and other smart sports such as volleyball, soccer or basketball. These differences are due to the nature of the sports for example in volleyball some features such as reaction time, precision in ball, situation awareness and etc. are considered [46] and jump power is considered in soccer [47] or shooting angle and velocity is important factor in basketball [48] but these are less important factors in smart fitness and some of them are not exist in fitness. In smart fitness loaded weights, duration for each set, time for performing training plan and feature extraction for performing an action (like moving a dumbbell or barbell) and monitoring on the angle of movement of the hands and feet are important.

The major difference between smart fitness and smart sports is that in smart fitness we are dealing with ordinary and non-professional people who do not want to have coaches more than professional ones but in smart sport training the aim of clubs, coaches and athletes is to enhance their performance and physical preparation.[4] For example A.C.Milan lab leverage this possibility for optimizing personal well-being of athletes and toward that optimizing the team results by making decisions according to the previous data of athletes[5] As described above, a lack of mechanisms to measure and monitor practitioner activities will cause lower training performance and increase dissatisfaction [31]. Smart fitness is taking advantages from improvements in many sectors: increasing precision in sensing capabilities, new algorithms associated with Inertial Measurement Units (IMU), progress in the medical monitoring of vital functions (heartbeat, blood pressure, etc.). The rapid technological progress in this area has made the smart fitness domain a very attractive area indeed. While AI and machine learning mechanisms based on advanced technologies such as deep learning and neural networks (NNs) can be used to identify patterns and improve the training. This combination of technologies has taken a step toward improving quality of training programs [49].

Smart fitness helps practitioners to monitor their activity [50] by automatically and remotely measuring and checking their training sessions. We are confident that there are many practitioners who are capable of doing good exercise sessions that are suitable for their physical needs and level. People generally determine a training plan on their own, and they usually make poor choices because of unrealistic knowledge of their own status and capabilities [38]. On the other hand, smart fitness aims to track and monitor a practitioner's movements automatically and remotely [30,31,51], as well as being able to track other factors affecting well-being and health such as sleep [29] and even eating [28] by using existing sensors in the IoT. Feedback for better practitioner self-awareness [50] and performance analysis will help individuals to select the training sessions that are best for them [52]. IoT devices already offer the possibility of measuring some of the medical values that are desirable during physical training. By wearing IoT devices, they can assists coaches to evaluate athlete's situation and make better decisions. Today's wearable sensors like Gym watch [50] and Virtual reality (VR) and Augmented reality (AR) [53] make it possible to implement smart fitness in indoor workouts.

Fig. 2 shows a general view of smart fitness ecosystem, broken into three main subcategories: *fitness trackers*, *movement analysis* and *fitness applications*. Fitness trackers are further divided in two sub-categories: *Non-wearable Trackers* and *wearable Trackers*. Among the current solutions for smart fitness, measurement accuracy is not good enough to evaluate the correctness of the activities undertaken by a practitioner, as the collected data are not sufficient to precisely detect good or bad activities. There is not yet a reliable system that can monitor fitness workouts and detect fitness actions, analyze the different parts of body movements made during a training session, and compare them with the current defined plans or standards in order to assess if the actions are correct. However, based on earlier studies in smart fitness, enhancing AI in smart fitness scenarios allows data to be processed in order to understand a subject's strengths and weaknesses [25,54,55], and thereby to assess the effectiveness of a training program [26]. Improved models could even provide a new workout plan for better results. We explore more this direction in Section 5.

2.3. Smart fitness market analysis

Sales of fitness trackers devices are increasing each year. According to the Consumer Technology Association,[6] shipments of smart watches, one of the most popular fitness trackers, increased steadily from 2014 to 2018, not showing any letdown and thus indicating that the market is still growing. According to statista (https://bit.ly/38eDxGs) based on IDC (www.IDC.com) research, Apple had the major market share in wearable sensors in 2018, with 46.2%. However, in 2014, Apple did not have any share in the wearable sensor market, as shown in Fig. 3. These statistics show that mega companies like Apple and Samsung have understood that there is an expansive and expandable space in the smart fitness area to be exploited.

As shown in Fig. 3, Apple is very hard working in marketing, but their sales strategies remain to be consolidated. Studies have shown that brand, display size, price, form and standalone communication are the five most important factors for motivating consumers to consider a product [56]. Another feature to motivate consumers to choose a fitness product is accuracy. According to [57], Apple provides the best values with 99.06% accuracy for step counting. Another important factor for consumers is the ecosystem associated with a device, including the number and quality of compatible applications. Here again Apple plays a major role, as it has a huge share of the application market with around 10k applications, about half of them offered for free [58]. Fig. 3

[4] https://www.catapultsports.com/about.
[5] https://www.acmilan.com/en/club/venues/vismara/milan-lab.
[6] https://bit.ly/2I64mCc.

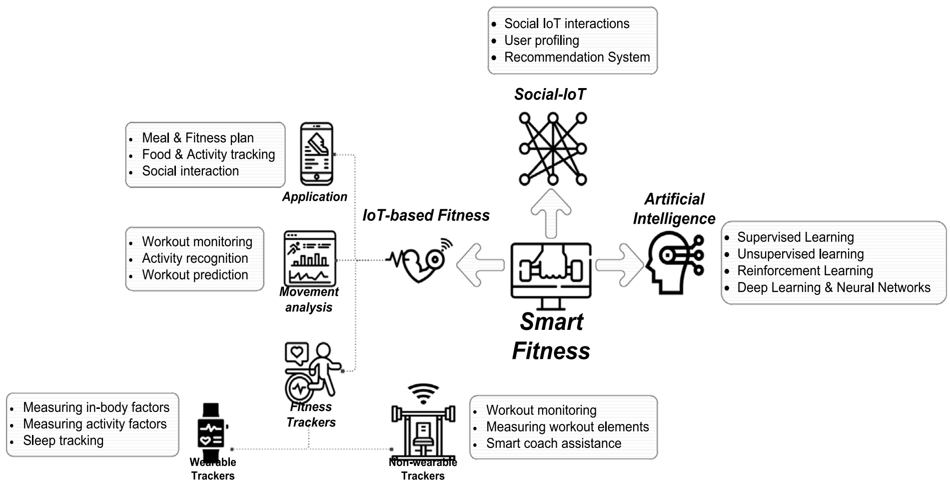

Fig. 2. Smart fitness ecosystem in three subcategories and their features.

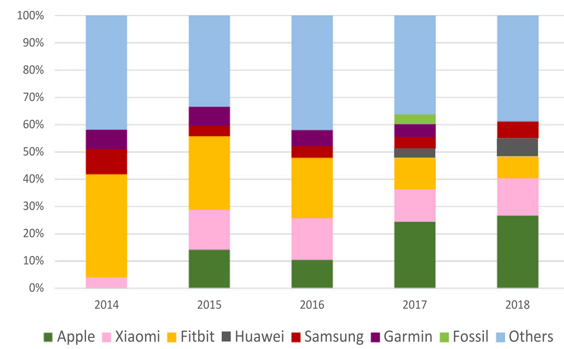

Fig. 3. Market share for vendors in wearable trackers (https://bit.ly/38eDxGs).

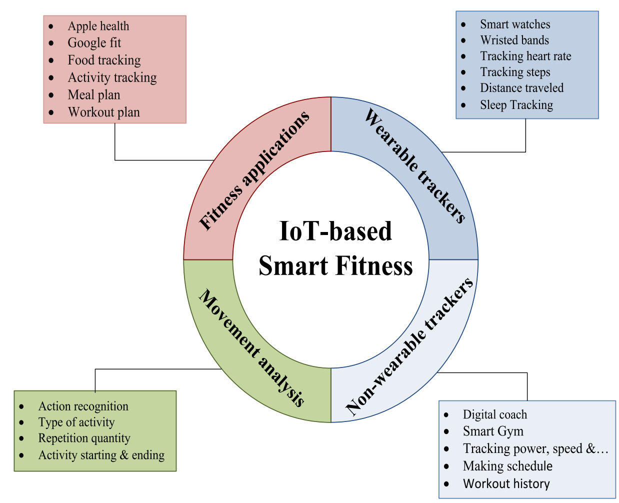

Fig. 4. IoT-based solutions in domain of smart fitness.

shows that vendors are certainly motivated in smart fitness, as this area is still in its early stage; more products are expected soon. In Section 3.4.1 we go in details of existing commercial solutions and trackers.

2.4. Authors insights and summary

Smart fitness is a new topic in IoT domain where statistics show that the market value of the fitness trackers has been raised in recent years and mega companies are investing in this field. There are so many sports engaging with fitness such as sports which have preparation season or need high body performance and for these sports smart fitness can play a coach assistance role. Ordinary people may need smart fitness more because their lack of knowledge about fitness movements, workout and meal plans. Smart fitness can prevent injuries and over training and also can increase effectiveness of exercises.

3. IoT-based solutions for fitness

Smart fitness is relatively a new subtopic in e-healthcare. A growing number of solutions have recently been provided from both academia and industry. IoT has various architecture descriptions such as five layer [59,60], SOA [59], middle ware [59] and the most popular architecture of them that is three layer architecture [61,62]. Three layer architecture consists of Perception layer, Network layer and Application layer. Perception layer is like the skin of IoT which performs data collecting tasks using IoT devices such as GPS, bar code label and readers, sensor, sensor networks, camera and terminals. Network layer provides network services which are based on current mobile telecommunication and internet for performing data forwarding connection in short and long range, information center intelligent processing and etc. At last application layer is the layer that discovers and provides services for user, share information for communities and making information secure. Application layer has extreme impact on economic and national development. In general, IoT-based fitness is divided into three major categories: fitness trackers that get and analyze information from users and are categorized into wearable and non-wearable sensors, fitness applications that provide various features like planning food intake and training sessions or social network capabilities such as connecting practitioners who have similar and movement analysis that extract patterns from actions and performs action recognition on body activities preferences or similar physical capabilities. As shown in 4 these topics are covered in detail in this section. In [63] a four tier architecture has been introduced which consists of observe (collecting data and signals from environment), contextualize (computational facilities, filtering and analyzing data), decide (classifying condition and identifying proper action), act (informing users about the condition and feedback generating).

3.1. Smart fitness enabling technologies

In IoT domain, there is an interaction between the user and physical entity with some intermediaries. In this domain IoT service plays the role of mediator and is associated with a virtual entity that represents the physical entity. The IoT service interacts with the thing with a IoT device which extracts the actual capabilities of physical object [64]. For measuring exercise intensity and exercise values there is two different methods: wearable and non-wearable sensors. In wearable sensors the user's body plays as the thing's role. In this part wearable sensor extracts capabilities and features of the body and sends it to IoT service (e.g mobile application, web site or some times local process in fitness trackers) and user can be informed about exercise information by referring to the services. Wearable trackers are devices attached to the practitioner's body (e.g., in a shirt or vest, or as a wrist band) [65].

In non-wearable sensors fitness device (such as barbell, dumbbell, leg press device and etc.) plays as the thing role. The sensors are placed on them and extracts their features and capabilities and send them to IoT service (mobile application or web site). User can interact with fitness machine and be informed of the exercise features through the services. Non-wearable trackers are devices with specialized sensors that are embedded on fitness machines. On the other hand, fitness applications have the task to collect data from fitness trackers, make a good user interface for users and implement AI algorithms on these data for better categorizing and decision making. In [66] the application is connected to wearable sensor and collects data such as heart rate and then it uses Artificial Neural Network (ANN) for data classification. Current and future fitness applications and services could use cloud computing resources and available sensors in order to collect and process useful data [67,68]

3.2. Fitness trackers

As we mentioned in Section 2 and illustrated in Fig. 1, fitness trackers can be divided in two main categories:

(1) Non-wearable devices that measures the activity of the user through sensors embedded in objects. For example sensors in specialized fitness machines capable of accurately monitoring user activities. Information like speed, power, and weight loads are usually measured during the course of a session and associated to the specific (registered) user.

(2) The second category is wearable devices, with sensors attached to a user's body, e.g., a sensor vest or gloves, as well as wrist bands or smart-watches. This type of tracker measures some practitioner's in-body values and monitors changes in these values, such as the heart rate, blood pressure and breathing rate.

(3) The third category is movement analysis and that is an important part of pattern recognition. Movement analysis generally is based on collected data by body worn sensors and the focus in this field is on gesture, gait and posture [69]. The goal in movement analysis is to inform users and help them for performing tasks in the best way [70].

These three categories are evaluated below, along with an assessment of the current solutions and features being offered to customers.

3.2.1. Non-wearable trackers

This sub-section covers studies that use specialized sensors and IMUs that are generally embedded in fitness machines. We focus on five different aspects: architecture, implementation, service, management, and evaluation.

Architecture. Several studies proposed solutions in this domain, such as an architecture designed to collect and verify information about users in terms of power, speed and skill (for example [31]). That work had two goals: (1) increasing the efficiency and effectiveness of the collected information; and (2) analyzing the collected data and offering suggestions for improving the training session results. Our analysis of this type of infrastructure shows they usually have four functional elements containing: (1) servers associated with experts, utilized to provide advice; (2) practitioners' devices that sense and send data; (3) a web server that manages the data collection process; and (4) a data warehouse that archives history of the processed data. For individualized and tailored results, there are personalized solutions in which each practitioner has a unique profile in the prototype application, in the system. Their activities are captured, processed and registered, creating an archive with the historical data of each practitioner. As a sample implementation, this architecture [31] is based on the Nintendo Wii Remote controller, instead of expensive sensors and even more expensive motion capture devices like Gypsy 7, IGS 190-M, Shapewarp III or Xbus, or video game consoles like Move and Kinect. The solution was implemented using C#.

Fig. 5. A sensor embedded squat machine [72].

Implementation. From a software perspective, this type of solution requires an application for the trainer and the administrator, and another for the practitioner. While the trainer can only monitor the information sent from the practitioners, the trainer has several options to create, assign, edit, add or delete some part of the training schedule for the practitioner. The administrator can manage the data and any other information to monitor the user's activities. When a trainer logs in, he/she has several options for choosing the training mode (such as stretching or maintenance, or others). The trainer can change a predefined schedule, for example he/she can change one specific activity or the intensity of an activity. The individual practitioner can only see the daily schedule. Related to this topic, [38] proposed the Digital Personal Coach (DPC) based on mathematical models for studying the practitioners' activities. This approach could be considered as a new step in the smart fitness field, providing a prototype and making use of mathematical models such as the Markov Decision Process (MDP) and the Partially Observable Markov Decision Process (POMDP) [71]. Fig. 5 shows a sensor equipped on a sample fitness device.

Another interesting research trend is related to the use of IMU-based architectures. The authors in [50] discuss how to use IMU within fitness devices and training machines. Generally in this type of approach, the system analyzes physical activities in terms of differences (in space and time) between the various movements, seeking to detect the actions performed. The beginning and the end of an action is determined by a device that contains an IMU. This information is passed along by means of a communication function based on BLE on the same device. This implementation uses a prototype processor on the dumbbell or device, with a detector implemented on it to determinate vertical movement and the beginning and end of the action. An accelerometer and a gyroscope are used to extract acceleration and angular velocity. Position and orientation of the sensors which are acquired from row signals are two important factors in better understanding action. By transmitting acquired accelerometer sensor data to global frame and integrating acceleration data (corrected by gravity) with position data, errors are determined. The movement is assumed to be around the X, Y, Z axes, and by using these incoming data from accelerometer and gyroscope systems, it is possible to identify what type of workout a user is engaged in.

To determine the various actions and movements, as well as their repetition pattern(s), in order to analyze them and determine the sequence of movements, usually a classification method can be considered. One of the most important and basic classifications is the multivariate of time series (MTS), which is divided into three categories of classifications, Distance [73], Model [74] or Feature-based [75].

Service. One of the relevant objectives of smart fitness and (at least partially) healthcare in general, is exercise and training activities for elderly people. Some studies have tried to develop suitable solutions for older people in order to foster well-being and inclusion. Paper [76], proposes some solutions for the elderly in the context of smart fitness. The case study was a gym in which each practitioner registers with his/her name and personal data. These data are written and stored in a card after each registration. The cards are not personalized and registration is needed for each entry. Each device in the gym has a touch pad with a slot in which to insert the card. After reading the written data (such as age, height and weight) in the card, the fitness machine shows user's settings and tasks such as repetition and weight for particular fitness machine on the screen. The resistance and power of the machine will match those of the user's training plan, and the user will be guided to use the device and to repeat the exercise as many times as indicated in their plan. The device counts the sequences and monitors the activities of the user. The problem with this solution is that some physical characteristics of the device cannot be automatically changed, e.g. the seat height, the foot position and others. Elderly users may need someone's help to make changes to a fitness machine's setup and status. On the other hand, personnel could be limited or occupied with other users and on a crowed day, some users would have to wait some time before being served. Another problem is elderly people's unfamiliarity with new technology and lack of knowledge of the new terms and icons, which could limit their self-confidence with such devices and increase their diffidence to the technology, thereby limiting the usage of the proper devices. To prevent this problem, simple icons that require no specific knowledge have been designed. The user interface may be a fundamental way to create a useful confidence between the elderly and the system. Other strategies have been designed for those who have numb fingers or issues with their eyesight. For the problem of numb fingers, specific glows have been designed for easy touch, while eye problems can be addressed by using larger icons that have been designed to make the interface more appealing.

The system described in [77] called IoT-based Intelligent Fitness, consists of a fitness device, i.e., a sensor placed on the exercise machine to measure the work load, a fitness band to measure the heart rate; a development board; and a server to collect and analyze the data sent from the sensing devices. This system is based on a computing cluster, performing high-level computational tasks in order to determine calories burnt, make recommendations and perform other action-recognition tasks The application is designed to show the workout results. Action recognition can also be used to monitor exercises' correctness. Other similar studies have provided solutions for smart fitness with embedded sensors continuously emitting data. The researchers in [72] paid particular attention to different sides. Their study presents a system that shows the current practitioner's status and information in addition to his/her history.

Management. Several management solutions are still required. Smart gym equipment is a set of smart devices that equip a gym; their task is to record everything, e.g. the number of sequences, duration of actions and the intensity of an activity. All the other modules would need to refer to this module in order to have access to the information. Some sort of history data management is needed. This type of database stores the data at the end of any equipment usage. Identity management is a part of the system that deals with the identification and association of devices to the users' IDs. Level management is that part of the system devoted to determining and specifying the levels of exercise to be applied in the system and in a specific machine. Workout management determines a dynamic workout pattern according to the information received from each user. Information such as age, height, weight, BMI, body fat and other data related to physical status will be saved in the database. This data allows the system to determine and tune the system according to each practitioner's initial capabilities and abilities, as well as eventually tuning the exercise program to match their growing ability. Level management. determines a practitioner's current level and tells him/her what workouts to do. In this system the gym equipment acts as a user interface, with Identity management allowing users to be identified precisely so that the system can retrieve the user's complete training history, Level management then determines the user's basic level according to the information received from the user (basic information such as age, weight, workout history and gender). Finally, Workout management determines the actual training sequences.

Evaluation. There are already existing technologies that could be applied to smart fitness in order to evaluate fitness training sessions to define and provide more efficient fitness schemes. One of the most interesting technologies in this field is thermography. Authors in [53] introduced thermography as a means to evaluate the efficiently and prevent injuries during users' activities. Thermography is a non-radiating and contact-free technology: the skin temperature is measured by means of a thermographic camera at the beginning and end of an activity. Where muscles are under stress, the skin temperature rises, while the skin temperature does not change in areas that are at rest or that are less involved in the exercise sequences. The system takes several pictures of each skin area (and hence body parts) during the exercise period and measures the minimum, maximum and average temperature values before and after actions. For example, lifting exercises can be quantified and compared to each other in order to determine their efficiency. It is noteworthy that values may vary significantly for different people, and so the measured and computed values are tailored to each user. By using this technology and other methods for this purpose, we can evaluate the efficiency of training on the target muscle and also be aware about injuries, incorrect and inappropriate actions.

A high level comparison of the seven studies presented here in non-wearable sensors domain and their proposed solutions for smart fitness is presented in Table 1. This table shows that the most complete architecture among the seven studies is IoT-Based Intelligent Fitness [77] which has most of the characteristics of a smart fitness system but is still lacking a recommendation system (which could be a future research direction).

There are other methods for detecting and analyzing movement during physical exercise. For instance, [78] presents an image processing system that detects human actions in sports by detecting key body parts in terms of their salient regions and skin tone. In human movement detection we have salient regions that are more obvious than other regions in images due to their contrast. For segmentation by skin tone, a color-space transformation approach [79] can be applied. That study developed a prototype and applied it to soccer training; by using sport images from the University of Central Florida Sports Athletics (UCF) this approach could identify seven key body parts in images. Lastly, it is treadmill devices, as they are very popular in gyms. Smart treadmills obtain a user's general data and some specific exercise values to determine the ideal level of activity, slope and speed for each user [80]. One study introduced a ubiquitous monitoring system in smart space (UMONS) that used Smart treadmills to determine the time spent on exercising in order to determine how much a user had achieved toward their goals with respect to exercise time, heart rate and well-being (e.g. Exercise index or Health index) [81].

3.2.2. Wearable trackers

This sub-section covers studies and technologies that use specialized sensors and IMUs that are generally embedded in wearable objects such as shirt, shoes or other gadgets. Tracking activities by using sensors embedded in fitness machines is an effective way for monitoring user's activity. However, those mechanisms are limited to the capabilities implemented in fitness machines. Wearable devices offer a complementary solution. These trackers can evaluate other values and measures related to users' activities, e.g., heart rate variations, breathing rate, skin temperature, etc. The popularity of these devices is increasing

Table 1
Existing solutions for non-wearable fitness trackers designs.

Method	Ref.	Attribute	Disadvantages
Ubiquitous low-cost sports training system for athletes	[31]	Training history on web server Training information accessible from web Get personal information (e.g height, age) Monitoring on correctness of action with gaming consoles Wii Presenting advices by trainers	No identifying mechanism Only presenting advices by trainers and no automatic plan generator
Digital personal coach	[38]	Recording the previous and current exercise information Training information recording Limited movement analyzer only monitors current advised workouts Workout plan proposed by the Markov Chain	No identifying mechanism No attention to basic information
IMU-based smart fitness devices for weight training	[50]	Recording training information on external host Monitoring on fitness workouts by accelerometer and gyroscope and determining correctness by classification algorithms	No identifying mechanism No attention to basic information No training history No workout plan providing
Smart gym for elderly	[76]	Writing training information on a card Getting basic information Identifying mechanism Monitoring on fitness action by human Providing fitness plan daily	No training history No systematic and automatic monitoring mechanism
A smart gym framework: Theoretical approach	[72]	History management system for recording history Providing workout plan according to level of users	No monitoring mechanism on correctness of action
Thermography	[53]	Scanning skin after exercise for determining effectiveness	No identifying No plan generator No training history and training information and no basic information
IoT-based intelligent fitness	[77]	Recording burnt calories Running distance and weight lost Training history on web database Getting basic information Identifying mechanism Action recognition and neural networks for monitoring on fitness actions by web-cam and neural networks	No mechanism for workout plan Only recommendations for similar users

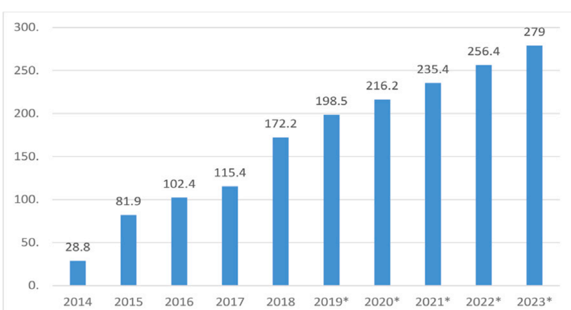

Fig. 6. Rise of wearable Fitness trackers based on their shipments data (in million) (https://bit.ly/38cOhFt).

Fig. 7. Three types of wristed band fitness trackers: (a) AppleWatch 4 (b) SamsungGear 3 (c) Fitbitflex 2.

rapidly. According to statista 2019 report on wearable trackers (https://bit.ly/3aj6D9f), their shipments in 2014 were around 28.8 million units, while in 2017 they reached to 115.4 million and forecasts predict 279 million units in 2023 (see Fig. 6).

By using these wearable devices, multiple physical activities can be measured, and over a long time range, e.g., heart rate during the exercise period and at rest, body temperature, number of steps taken, distance covered, and sleep duration [82–84]. In addition, even more services can be offered, such as the calculation of calories burnt, by these devices by embedding accelerometers, altimeters and other sensors [83]. Wearable trackers are even able to monitor sleep phases [57] These devices are offered in a variety of forms such as wristlets, smartwatches, or embedded in clothes or sports devices, available in a variety of brands and models like Xiaomi, Nike+, Fitbit, Samsung Gear, Apple watch, LG Smartwatch and many others [57]. Fig. 7 shows few popular wristbands in 2019.

To visualize the information they collect, most tracking devices usually use a particular web site or mobile application. While they offer many beneficial features, one of the issues with wristlet trackers is their lack of accuracy [57,82,84]. As discussed in [33], brands have different levels of accuracy according to their various technologies. However, the real problem is the difference between the actual and the measured values [82]. Researchers in [57] compared various brands of wristbands in 2015 in terms of their performance. We constructed a general comparison among seven popular trackers (Table 2) with a focus on their characteristics and abilities.

Wristbands are only one type of wearable devices. A new wearable sensor is the Oura tracker. The Oura tracker is a ring with embedded sensory capability. It fits on a finger and can be made of different materials; it can even be decorated with diamonds. It utilizes infrared optical pulse measurement and contains a 3D accelerometer, gyroscope and body temperature sensor. Designed to measure body activity and conduct sleep monitoring, the Oura tracker is compatible with the iOS and Android.[7]

[7] https://bit.ly/2NDFDJz.

Table 2
High level comparison between seven wearable fitness trackers (based on market in 2019).

Attribute	Apple watch	Samsung Gear S	Fit bit	Mi band	Nike+ fuel band	Moto 360	Oura ring
Type	Smart watch	Smart watch	Smart watch	Fitness tracker	Fitness tracker	Smart watch	Ring
OS	watchOS 5.0	Tizen	Fitbit OS	Proprietary OS	–	Android Wear	–
Mobile OS compatibility	iOS	Android–iOS	IOS–Android-windows	Android–iOS	Android–iOS	Android	Android–iOS
Web interface	No	No	Yes	No	NO	No	No
Sleep tracker–feedback	Yes-On 3rd part App	Yes-On 3rd part App	Yes-On 3rd part App	Yes-On mobile App	Yes-On mobile App	No	Yes-on mobile app
Heart rate & calories burnt	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Accuracy [57]	99.06	82.28	80.43	96.56	95.64	88.96	–
Water proof — Depth	Until 50 m	1.5 m for 30 min	Until 50 m	Until 50 m	1 m for 30 min	Yes	100 m

Vests (or very high-tech t-shirts) are another type of wearable tracker. One of the most popular and commercial vest trackers is the *GPSport* tracking model. These are used by some famous football clubs like Real Madrid and Valencia, as well as over 150 clients across 10 sports. *GPSports* vests provide information that is specialized for different sports and for different levels (from amateur to professional athletes).[8] They provide heart rate measurement before and during matches and training, sessions, total distance run, body load, maximal aerobic power and maximal aerobic velocity [85]. The data collected by the vest can be presented as graphs that provide an analysis of chronic loads (the amount of workouts done during four weeks [86]) and acute loads (the amount of workouts done during one week [86]). Access to this data allows coaches and players to better understand how their body functions and its current situation (https://gpsports.com) and as well as to be aware of their injury risk by calculating their acute:chronic ratio [86].

Smart shoes are another example of wearable devices. They come with embedded sensors that can monitor and analyze people's steps and their walking patterns. They have long-lasting monitoring capabilities and offer the possibility to proactively prevent diseases and help in early medical diagnosis. Sportswear manufacturers will produce even more smart shoes in the future [87]. Human activity recognition using smart shoes can be investigated as a means to better understand specific movements like running or walking, as well as to create useful feedback regarding user's behavior. This feedback and analysis will be especially useful for physical therapy [88] and could also be applied to health monitoring and sports sciences [89]. There are other developments in this field, such as smart gloves that can track users activity. By measuring the pressure exerted on a specific point, the system can recognize which activity is being carried out by users, and by tracking these movements, the system can count the number of repetitions, determine the calories burnt and recommend subsequent sequences [90].

3.3. Movement analysis

The major motivation for the development of wearable devices is the ability to determining a person's movements. There is a wealth of research focused on movement analysis for fitness objectives, for example activity recognition in daily activities using WSN sensors to detect activities like lying down, walking, running, sitting, cycling, rowing and playing a sport, conducted by utilizing the data collected by sensors and analyzing acceleration and GPS changes [91]. One investigation has placed gyroscopes and accelerometers on an athlete's body to identify the movements in Wing Tsun (a form of KungFu), implementing them on the right and left, right and left ankle right and left knee (directly above the knee cap), on the neck (at shoulder height), and at the lower back (on the backbone origin) [92].

In this field of research, the analysis of each athlete's activity can help coaches to design better training plans [93]. Action recognition can detect any muscle movement that requires an energy level higher than the resting energy level [94]. One study has focused on movement analysis by detecting negative and positive peaks [30], objective detecting positive and negative peaks (PNP) in an individual's movements. That system also analyzes positive peak average (PPA) and negative peak average (NPA) in order to measure the extension of the movement. Their system calculates and analyzes the average time in positive peaks (BPPAT) and negative peaks (BNPAT) and the times between positive to negative peaks (BPNPAT) and negative to positive peaks (BNPPAT). The analysis was conducted for three exercises: arm curl, squat and triceps. The Descending Slope Tracing (DST) method was used to detect positive peaks, and the Ascending Slope Tracing (AST) technique was used to detect negative peaks [95]. This work required a 9 DoF Inertial Module for its implementation [30]. It consists of accelerometer, magnetometer and gyroscope. It has been attached to the person's body. This design can help users to evaluate their fitness activities. Another study implemented a movement detection system by using Graphene-coated composite fiber on soccer and basketball athletes' joints to monitor and detect movements. These sensors are very lightweight and placed on the wrist, shoulder, ankle, elbow and knees of the athlete [96]. A prototype of a smart shirt has been created to measure physiological data by means of electrocardiogram (ECG) signals, and physical activity by using accelerometer signals. They equipped a smart shirt with wireless sensor nodes, an ECG board and an accelerometer, and used a communication module for data transmission. The data was collected and forwarded to a PC server capable of processing and analyzing the received data [97]. In [98] an analysis of movements has been implemented using two wearable sensors: heart rate and motion sensor (placed on hip). Random forest (RF) [99] and k-nearest neighbors (KNN) [100] has been performed for classification and labeling data in data set in order to recognize human activities and calculate the workload for each person. A mechanism for gym workout recognition based on couple voltage variation has presented in [101] which considers the human body as a plate and gym environmental as another plate and there is no need for placing wearable sensor on moving body part (which is specific to the workout). An electrode with BLE and battery and processing unit as hardware unit are placed on user's body and signals are analyzed and classified by deep convolutional neural networks. Fig. 8 shows two wearable tracker prototypes that are currently implemented: (a) shows gloves for tracking fitness workouts and (b) shows a smart shirt workout recognition implementation.

3.4. Fitness applications

Applications play a key role in smart fitness, and can be seen as a category in themselves. They can provide several functionalities to the final users and connect to fitness sensors and devices; they can provide additional functionalities such as the scheduling of food intake and workout plans, provide examples of training sequences and connect people; and can even serve as alternatives to wearable devices. Several applications available in the mobile marketplace provide fitness workout schedules and meal plans for different types of targets (e.g., fat burning or muscle building). Fitness applications commonly are based on measuring body activity in a period of time (usually a day). They measure steps taken, distance traveled, calorie burnt and also if they have capability for monitoring meal and food they also will have

[8] https://gpsports.com.

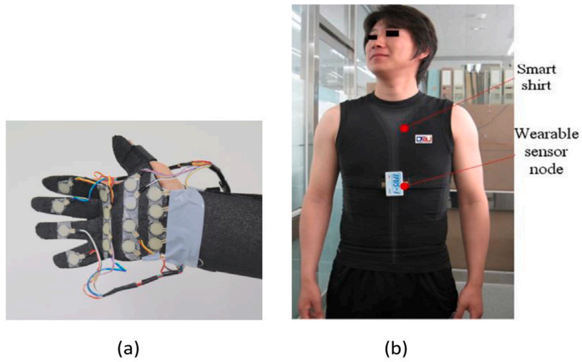

Fig. 8. Two types of wearable tracker prototypes: (a) glove tracker [90] (b) smart shirt [97].

recommendations for participant's meal and also count gained calorie. Fitness application usually have four main strategies to motivate users for being more active; first strategy is self-reflection which user will be aware of their body activity [102,103]. Second is competition that encourages the user to compete with others [104,105], third is a combination of self-reflection and competition [104,106] and forth is gamification that have some game components such as score board or achievements to motivate users to reach personal goals [107]. On the other hand, social aspect of fitness application is an important subject that must be attended. People who are performing fitness exercises have requirements for social support in fitness applications [19]. These requirements are divided in to four major categories: 1-Informational 2-emotional 3-tangible/instrumental and 4-appraisal [108].

3.4.1. *Existing commercial fitness applications*

One of the most popular applications is 8fit (available on iTunes[9] and google play[10]). This application receives your information about sex, height, weight, current body condition and desired targets. It then provides a schedule for you comprising meal and workout plans (https://www.8fit.com). One of the better known applications in this field is Google fit. Designed in order to be aligned with the world health organization indications (WHO),[11] Google fit follows two major parameters for health: minutes of activity (movement), and "heart points". These parameters are defined according to WHO and AHA (American Heart Association) instructions. Google fit tracks your activity by sensors on a user's android phone or smart watch with android OS.[12]

One of the most popular apps on iTunes[13] and google play[14] is Lose It!. It sets a goal for subscriber and tracks food consumed and activities undertaken, Lose It! can be synchronized with Google fit and Apple health or Nike+ run club and other applications. It is also compatible with other activity trackers like Fitbit. Based on statistics presented on its web site, over 75,000,000 pounds have been "lost" using this application as of October 2018 (https://www.loseit.com). Apple has also introduced a health application one with a complete set of useful abilities. Apple health is based on four fundamental health factors: (1) Activity, presenting how much activity a user has done collecting data from other applications on user's phone; (2) Sleep, tracking how long a user has slept through the night; (3) Mindfulness, suggesting the best moment for a deep breath session and free up the mind; and (4) Nutrition, [showing how much a user] has eaten, including how many calories, how much protein and carbs have been consumed.[15]

Fig. 9 presents four popular fitness applications with their main focuses and targets as well as their unique characteristics: (a) Lose it! meal plan for a 26 years old person with 188 cm height and 81 kg weight (https://www.loseit.com); (b) the four fundamental parts of the Apple health application[16]; (c) the home page of Google fit and the calories burnt[17]; and (d) the 8fit workout plan for a 'normal' young man.[18]

BodySpace is one of the most important fitness applications today with about 15 million subscribes which specially is dedicated to fitness workouts and body building information [109] and in [110] is described as "Facebook of fitness apps". In BodySpace users can interact and follow each other use other training plans, express personal information and also post photos relating to their workout progress. There are many more applications available on google play (play.google.com), itunes (itunes.apple.com) and other Internet marketplaces, such as my fitness pal, cardio: Heart rate monitor, Fitbit, Nike Fitness Club, Workout for woman, etc. Table 3 presents a comparison between seven popular health and fitness application summarizing their characteristics. As shown in Table 3, some applications focus on diet and others are focused on physical activities.

3.4.2. *Existing academic fitness applications*

In this era, [104] presented the *Healthy Together* application to motivate subscribers to do more exercise. *Healthy Together* is a social network application that people can use in order to compete with other, or to send messages to people they are in touch with.

Another application was developed for assessing and tracking physical activity and cardio activities [66]. This application has three major tasks, activity recognition, estimation of the calories burnt and quantifying the fitness scores. Their activity recognition feature utilized an Artificial Neural Network approach for the engineering and classification.

Another study, [37], has presented a prototype fitness application that, using sensors in smart phones can assesses physical activity and give user feedback. It uses a quality assessment algorithm that does not need any database, server or even internet connection. All computations are locally executed and the application is "self-contained". In this domain authors in [111] described a tracking system. It is based on a web server that collects data about students activities during the day. This system gets data from students' fitness trackers. These data (after the identification and authorization of students) are collected into a university website, the system can recognize user activity, steps, heart rate, calories burnt. On the other side, the user can observe his/her exercise performance and the teacher can monitor all students activities. Posting fitness data on social networks can help people to achieve a better self awareness and better analysis of their status and can have more collaboration and better understanding for communities and social networks [112]. Individual can compare their behavior or health status with the average "champions" of the same age or conditions, this can help to make more accurate self health evaluation of individual status and requesting medical help.

3.5. *Smart fitness communication protocols*

In all mentioned topics in smart fitness, one of the notable subjects is communication protocols. There are various methods for transmitting sensed data by trackers to server or processing unit in each smart fitness design. Wearable trackers such as smart watches and wrist bands commonly have touch screen and support communication technologies such as wi-fi, Bluetooth and GPS [56]. Famous fitness trackers like Xiaomi band 3 or Nike+ fuel band use Bluetooth for transmitting data to the mobile application. In [113] showed that different wristbands

[9] https://apple.co/2mQQh3D.
[10] https://bit.ly/2HX390U.
[11] https://www.google.com/fit/.
[12] https://bit.ly/2Z7hv4j.
[13] https://apple.co/2j1wkmm.
[14] https://bit.ly/2IiO5tk.
[15] https://www.apple.com/lae/ios/health/.
[16] https://www.apple.com/lae/ios/health/.
[17] https://www.google.com/fit/.
[18] https://www.8fit.com/.

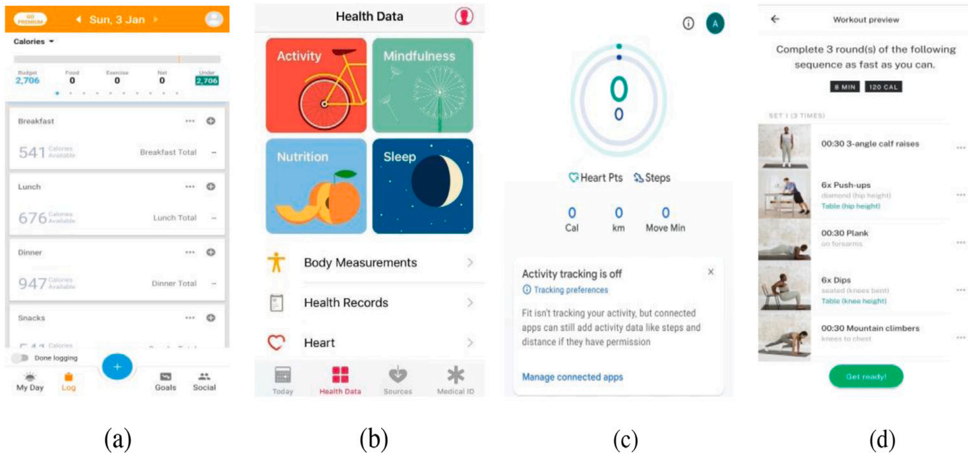

Fig. 9. Four popular fitness applications (a) Lose it! meal plans (https://www.loseit.com) (b) four essential parts of Apple Health (https://apple.co/2TbVtx9) (c) Google fit focuses on activity (https://www.google.com/fit/) (d) Training plans on 8fit (https://www.8fit.com/).

Table 3
Compression between seven popular fitness applications in the market (2019).

Functionality/APP	Google fit	Apple health	8fit	Lose It!	Nike+Run club	Samsung health	Mi fit
OS compatibility	Android	iOS	iOS–Android	iOS–Android	iOS–Android	iOS–Android	iOS–Android
Sleep monitoring	No	Yes	No	No	No	Yes	Using tracker
Workout plan	Yes	No	Yes	No	Yes	No	Only monitoring
Meal plan	No	Yes	Yes	Yes	No	Manually, counts calories	No
Sync with other devises	Android	Apple	Yes	Yes	Yes	Yes	Limited #brands
Heart rate monitoring	Yes	Yes	No	No	Yes	Yes	Using tracker
Activity monitoring	Yes	Yes	No	With 3rd party Apps	Yes	Yes	Using tracker

use HTTPS protocol to transmit fitness data to their servers. For data protection they use different methods like FIT protocol (Flexible and Inter-operable data Transfer protocol), Protocol buffer[19] and JSON files [114]. For protecting data they used HMAC [115] and encryption methods.

ANT+ is another protocol with energy optimization using for monitoring body parameter, smart fitness and collecting medical data by optimizing battery life up to 3 years in comparison with Bluetooth Low Energy (BLE) and Zigbee. Zigbee is a low power, low cost, secure, long lasting battery life and easy to deploy protocol.[20] The capacity of Zigbee network is up to 653 356 devices and each node can have 50 m distance with other ones. Zigbee is suitable for applications with low data rate such as body area networks, healthcare, smart fitness and gym [115]. SensCrypt is a secure data storing and communication protocol introduced in [116] using for lightweight wearable trackers. It also reduces data overhead in the network and increases capacity for communicating with more devices. In [50] BLE is also used for collecting data from dumbbell and transmit data by Bluetooth to the laptop for processing. A combination of Bluetooth inertial measurement and Zigbee networks has been used in [117] for gait assessment to evaluate rehabilitation process by measuring acceleration, ground reaction force and direction of feet. ESP8266 is a Wi-Fi module which sends sensed data through the internet to the server by connecting to Wi-Fi network [116]. In [57] for transmitting fitness data sensed by non-wearable sensors to database and server ESP8266 has been used.

3.6. Authors insights and summary

In this section IoT-based solutions for smart fitness is discussed and categorized into three main parts: 1. fitness trackers (divided into wearable (measuring in-body values such as heart rate oxygen uptake and etc.) and non-wearable trackers (measuring training values such as power, speed and etc.)), 2. fitness applications (providing feedback and services such as meal plan) and 3. movement analysis (activity and exercise recognition). IoT-based solutions are most focusing on sensing, determining activity and feedback generating for users. In this section some of the IoT architectures were mentioned and three layered IoT architecture was explained and showed that how an IoT-based solution can be fit into this architecture. At last in this section communication protocols which are currently used in smart fitness domain were disclosed.

4. Social-IoT and smart fitness

With the increasing deployment and usage of sensors, it is important to share and exchange data between different systems in order to have a full understanding of the user status and context and to enable better decision making processes that mediate between the user needs and the actual context in which he/she is operating. In smart fitness, different systems related to users (e.g., a tracking device and a smart fitness machine) could share data and identify what is the status of the user and suggest a combined schedule for exercises. On a larger extend, public well-being applications could benefit from interoperability and data exchange with personal trackers and smart fitness devices in order to identify patterns of behavior within a large population sample and propose or exert policies beneficial for a large part of the population.

One of the emergent concepts that can support the “sensor to sensor” interaction is Social-IoT which is deriving of current human social networks but it is not exactly the same [118]. There are several definitions for social-IoT Social-IoT is establishing relationship between IoT objects to share resources and some services with friend objects and interact with each other to achieve common goals [118,119]. In [120] SIoT has been categorized into some kinds of objects relationships: 1 — Parental object relationship (POR): established among objects depending to the same production category 2 — Co-location object relationship (C-LOR): established between objects in a same

[19] Available in: https://developers.google.com/protocol-buffers.
[20] www.zigbee.org.

place whether homogeneous or heterogeneous objects 3 — Co-work object relationship (C-WOR): established between objects for providing particular IoT application 4 — Ownership object relationship (OOR): established between heterogeneous objects depending to a particular user 5 — Social object relationship (SOR): established between objects that are in touch with others because their owners are in contact with each other in a place. These establishments are and management of such relationships should occur without human intervention. In this section the social-IoT, its benefits and possible services are presented and discussed in the context of Smart Fitness applications.

4.1. Social-IoT in smart fitness

Today social networks are very popular. By using social networks, people can be connected around the world and reach information and groups that fit the specific interests and tastes of individuals. Social network are capable of satisfy the human to human communications and interaction as well as to provide a wealth of personalized services. The concept and underlying mechanisms of the social networks are also interesting from the perspective of interoperability of smart fitness systems and, more in general, of IoT systems. According to the definition proposed by [12], the IoT is "a dynamic global network of things, devices with self configuration. IoT comprises heterogeneous devices, sensors and systems. They usually are siled solutions, i.e., IoT systems can interact and communicate if they use compatible Operation Systems, hardware, software and protocols [119]. There is a requirement for interoperability of IoT systems and sensors' data to create the possibilities for collaboration and socialization of IoT data and machinery [119]. This can allow to achieve bigger social goals and make real global IoT solutions. Social-IoT (SIoT) is a paradigm by which IoT smart objects, applications and devices can establish connections to each other in a trustworthy, secure fashion for exchanging data and functionalities [121–123]. These possibilities promise to improve the global quality of services and functionalities offered to the final users. The application of the SIoT definition to smart fitness is very promising because it can support different kind of relationships: between humans in a way very similar to the social network interactions, as well as between "things" that socialize information and functionalities [122]. These relationships is not necessarily available to all the objects, it is driven by commonalities of goals and constrained by data ownership and privacy of the users. Related things and objects can then create favorable interactions between allowed objects [123]. By using SIoT concept and mechanisms, a robust and rich in functionalities system can be developed. It is capable of coordinating and orchestrating members and objects of the "social Thing network" [121].

One of the simplest examples of a SIoT application is QR code usage. For instance, by scanning the code of a specific book with a smart phone, additional references and links related to the object can be retrieved and associated to the user and its applications (e.g., YouTube videos, other users interested in that book, and the like). This is a relationship between physical and digital world [123]. In SIoT there are areas like user profiling and recommendation system that can improve capabilities of system and enhance quality of provided services.

4.2. Social concepts in smart fitness

As mentioned before, there are various SIoT concepts that can be used in smart fitness. The two most important concepts are user profiling and recommendation system. In this section these two phenomena are discussed.

4.2.1. User profiling

User profiling is defined as the process of collecting data generated by a clearly identified individual that is using networked services and continuously elaborate them in order to scope down user's behavior, and finding his/her interests. The profiling could be instrumental for customization of services or for improving services and increasing customer's satisfaction [124]. User profiling actually is derived of machine learning [124]. In fact User profiling detects behavior of a device, based on analysis derived of machine learning algorithms [125]. User's information domain consists of several characteristics such as behavior, characteristics, user's background, his/her priorities, goals, and desires [126]. User profiling is not only for representing and continuously refining individual behavior and activities; it is also used for studying and clustering similar user's behaviors into groups or for determining patterns of usage of services and functionalities. Different techniques and processes can be applied. For instance, the study [127] has utilized clustering mechanisms and fuzzy C-means algorithm [128] on users data with user's behavior and their activities. This algorithm can also extract similar users for clustering according to their behavior. For final clustering users demographic data (sex, age and employment) and preference was considered.

In order to create user profiles, various methods, algorithms and procedures can be applied. one of the simplest methods is asking users to filling forms. A more dynamic and complete one is monitoring user's actions during a period of time for collecting and analyzing his/her actions and inferring preferences and patterns of usage. A hybrid approach to user profiling is to combine the previous options [124]. Actually, user profiling is a field that is receiving a lot of attention from academy and big Internet companies. There are several other methods based on statistics or numerical analysis like Bayesian Networks, Association Rules and Case-Based Reasoning [126]. Also, other techniques based on AI and machine learning are applied, data mining, data aggregation, data cleansing, clustering [125]. Bayesian Networks is a graphical model of probabilistic relationships and communications between variables. Bayesian Networks is one of the easy ways to present qualitative and quantitative relationships between user's interest elements, making prediction and decision making [129,130]. Case-Based Reasoning is a problem-solving method which makes decisions for each problem according of previous experiences of older problems. A nice example for Case-Based Reasoning is requirements of a professor in a university in university data set that could be met by a personalized profile which have expected characteristics for a professor [129]. Association Rules is one of the most important methods which discovers a set of events that occur in a while and the most usage of them is in supermarket baskets [131]. Association Rules discovers and extracts that people who have chosen product A also chose product B.

As a comparison between these three techniques, Bayesian Networks are the most focusing on the relationship between attributes and characteristics to reflect dependence between them; this can help for better filtering data in a data set. Case-Based Reasoning is focused on similar situations and results; here filtering is according to the problem and situation and previous experiences and at last Association Rules only focuses on the event that mostly happen at a specific time. Filtering in Association Rules is mostly on number of simultaneous selections.

In IoT systems, it is possible to associate specific users to sensors or measured contexts. Monitoring the sensor data, may be useful for collecting users related data. Monitoring and collecting behavior and data of nodes and objects can be useful to reconstruct the user behavior and profiling him/her [125]. User profiling in smart fitness could be a means to offer relevant data to interoperable applications that can offer integrated suggestions on training exercises levels and schedule as well as meal plans. As shown in Table 1, user profiling is implemented in current smart fitness solutions. For example in [72], user's information like Age, sex, ID, mass, experience, height and other basic information is collected. In addition, more dynamic data are also retrieved

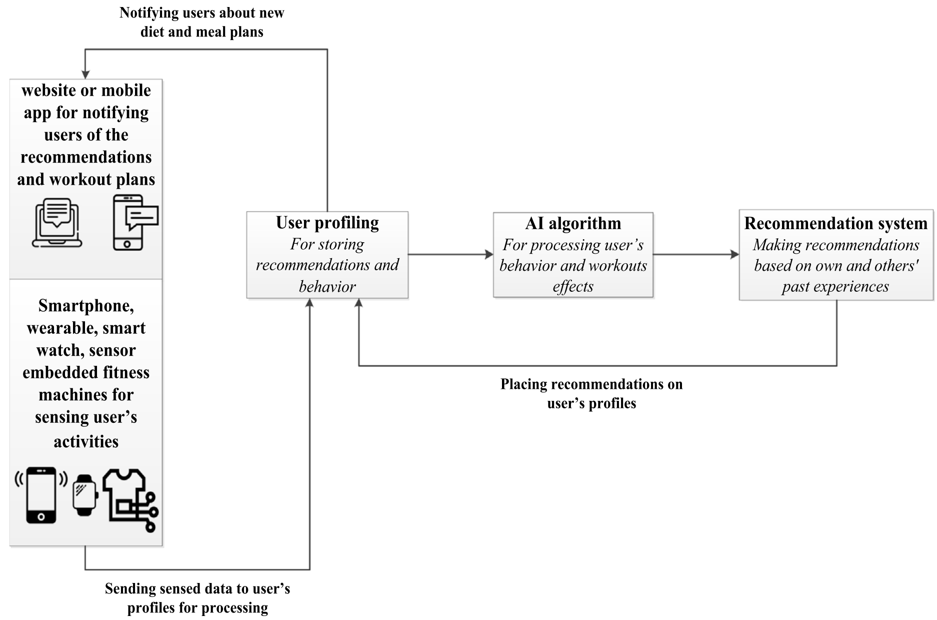

Fig. 10. General schema of enhancing AI an Social IoT in smart fitness for designing user-based services.

and stored such as type of exercises and results. Many smart fitness architectures use basic data [31,77]. User profiling is used in about all fitness scenarios. When a fitness tracker. e.g., miband 3, is chosen, the user must download an application from an application store and enter personal and basic information. These data are a basic requirement for all the smart fitness applications. As noted in 3.4 applications like 8fit (https://www.8fit.com/) and Lose it! (https://www.loseit.com) collect and store basic information and then elaborate workout or meal plans with graphs and graphical representations of users' progress or regression. All these information are based on capture of basic and dynamic data and they are part of the user profile.

4.2.2. Recommendation system

Recommendation systems can improve the way users are exploiting the resources and demand services. Recommendations are tailored on user interests, and attributes [132] and in this research, they are quite relevant in different smart fitness scenarios. It can be used for recommending more efficient training depending on individual body types. They also can collect and determine the most appropriated experiences depending on different typologies of body characteristics, or age, sex and other individual factors. Recommendation systems are based on user profiling and a deep analysis of data, patterns and behaviors inferred by means of AI and machine learning algorithms. A recommendation system for university physical education has used static students' data and has complemented those with habits, behavior, and experience of each student. This system is also able to get as input the teacher's observations about student's activities and endurance exercises. It uses all these data to build a personal training plan [133].

A recommendations system also can be useful for preventing injuries. For example, if, in a S-IoT organized interoperable system serving different smart gyms locations, a particular action has caused injury to a specific type of user (for example of a certain age of physical shape), then the recommendation system can determine that this action is not suitable for this type of users or it can be risky. Another good example of a valuable recommendation system is in [38]. When this system warns users to *select heavier* or *select lighter* exercises, it is actually recommending and suggesting a personalized training session. Food prediction and recommendation for meal plan is another topic that is performed by analyzing user's situation and feedback [134].

In summary, Fig. 10 represents a simple scenario of a smart fitness system using some SIoT concepts. In this proposed model, users do fitness exercises and their workout data are recorded in the personal profile. These data are processed by means of AI algorithms and results are provided to a recommendation system. Depending on the profile and the achieved results, the recommendation system provides personalized suggestions and stores them in the user's profile.

4.3. Authors insights and summary

In this section social aspects of the IoT sensors, their role and opportunity in the domain of smart fitness was discussed. Social-IoT commonly focuses on sharing data of sensed data of different people around the IoT network to use the experience of all current smart fitness methods and solutions. In social-IoT interaction between sensors is based on their common letter, goal or even location and these interaction is without human intervention. In S-IoT two main topic are raised: user profiling and recommendation system. User profiling is detecting user's interests, habits, goals and background acquired by machine learning analysis. In this section three user profiling methods (Bayesian Networks, Association Rules and Case-Based Reasoning) were introduced and compared. Recommendation system is another topic in the domain of smart fitness which recommends to users according to their habits, interests and strengths and weaknesses. Recommendation system can make an easy way for users to achieve resources, services and also their goals in fitness.

5. Artificial intelligence and smart fitness

Today, AI and machine learning (ML) are impacting substantially the IoT paradigm. Different studies have exploited AI techniques in various IoT use cases [143]. This evolution is impacting all aspects including fitness as the topic of our research. Currently there are some solutions for enhancing smart fitness applications by introducing AI algorithms. In addition, the relationship between IoT and AI is so deep that many solutions stemming from this twinning of technologies will have an impact also in the smart fitness field. There are three types of computational intelligence family algorithms first one which derived from human brain operation (Artificial neural networks (ANN) [144]), the second that are derived from Darwinian struggle for survival (Evolutionary Computation (EC) [145]) and at last algorithms derived from behavior of social animals, colonies and insects (Swarm Intelligence (SI) [146]) [147].

Table 4
Existing AI algorithms and their application in sports and fitness actions.

Learning strategy	Algorithm	Ref	Input data	Output data	Application
Supervised	Decision Tree	[134]	Wearable sensor data	Food recommendations	Meal plan
	Apriori algorithm	[54]	Wearable sensor data Answered questions	Table of processed attributes	Preventing over training
	Convolutional Neural Network (CNN)	[135]	Axes received from accelerometer personal data	Feature extraction and classification	Predicting physical activity and fitness level
	Iterative polynomial regression	[101]	Wearable sensor voltage variation	Detected peaks	Counting number of repetitions and steps
	k-nearest neighbors (KNN)	[136]	Records of important marathons	Runners analysis	Recommending pacing plans Runners training
	Linear Regression (LR)	[136]	Records of important marathons	Runners analysis	Recommending pacing plans Runners training
	Elastic Nets (EN)	[136]	Records of important marathons	Runners analysis	Recommending pacing plans Runners training
	Random forest (RF)	[98]	Wearable sensor on hip labeled features Manually labeled data	Label data Classified data	Calculating workload Action recognition
	Linear Discriminant Analysis (LDA)	[36,137]	Reduce the input data dimension	Classified data	Detecting fitness actions Detecting beginning, ending and repetition
UnSupervised	Principal Component Analysis (PCA)	[36,137]	Wearable sensor and IMU data	Reducing dimension Simplifying data	Important parts of data in low-dimension
	Bat algorithm	[26]	Smart watches data (XML format)	Analyzed fitness data Training effort value	Intelligent plan generator
	K-means	[138] [139]	Mobile data worn by athletes Championships race videos	Extracted features, clustering Extracted parameters PCR, Position, speed	Planing a sport training session Cyclists position prediction
	Convolutional Auto encoder (CAE)	[135]	Axes received from accelerometer personal data	Lower-dimensional feature extraction	Predicting physical activity Efficient fitness level Regression and classification
Deep learning and Neural N.	Kohonen Feature Map (KFM)	[55]	Video camera	Feature based High-dimensional patterns	Sports and games analyzing
	Artificial neural networks (ANN)	[140]	Heart rate and oxygen uptake	Approximating oxygen uptake	Controlling and approximating aerobic actions
	1D and 2D Convolutional Neural Networks	[141]	Wearable sensor data	Sliding window segmentation feature extraction Classifying fitness actions	Predicting Fitness actions
	Genetic Algorithm and Artificial Neural Network (GAN)	[142]	Athletes' questionnaire	Performance diagrams for users	Predicting sports performance
	Deep Convolutional Neural Network	[101]	Wearable sensor voltage variation	Labeled and classified workouts Labeled sliding windows	Workout recognition
	3D-Convolutional Neural Network (3DCNN)	[77]	Video frames	Action and image recognition Feature extraction and classification	Monitoring fitness actions
Reinforcement	Markov Decision Process	[38]	Collected data by activity tracker	Modeled training plans recommendations based on trial and error	Presenting digital coach recommendations for sport training

In this section, we first overview some of the existing AI solutions in IoT and fitness domain and later on we focus more on smart fitness and describe the previous efforts on leveraging AI on defining scenarios. Considering the huge amount of existing AI algorithms, in this section we only focus to few of them which are more famous and mostly used in smart fitness and sports and overview some of the efforts by using those algorithms. For evaluating performance of a workout there is four main learning scenarios, Supervised learning, Unsupervised learning, Reinforcement learning and, deep learning and neural networks. As a general approach, AI algorithms can be applied on fitness data and extract information and analyzes training for providing meal plans for endurance training [134], provides fitness plans [142] and preventing injuries [148].There is some popular algorithms for data mining in fitness data base such as apriori [148], Eclat [149] and Frequent Pattern-Growth FP-Growth [150]. FP-Growth has been used in badminton videos data set in Final Asia Man Badminton Team Championship to provide a pattern and post-match analysis of badminton matches In [54] there is an approach for applying data mining Apriori algorithm on fitness data for preventing over-training. In [151] bat algorithm for association rule mining (BatMiner) [152] was used for mining realized sport training and extracting features and attributes existing in the database. For predicting functional fitness level and physical activity level in [135] two machine learning and classification methods has been presented. In this study Convolutional neural networks (CNN) and Convolutional Auto-encoder (CAE) [153] has been used for extracting features of acceleration data coming from smart phone. In Table 4 there is an overview of current AI solutions which are classified by their learning strategy.

5.1. Supervised learning techniques in smart fitness

In supervised learning labeled data are used to infer a machine learning algorithm using a classified data set and predicting classification for other unlabeled data [154]. In supervised learning the machine tries to produce correct outputs from input data according to desired outputs defined for the machine [155]. One of the notable concepts in AI that is very useful in IoT is data classification. In this field, Random Forest (RF) has received significant attention over last two decades. This attention is due to the capability of the algorithm to provide an accurate classification [99]. In [98] it proved that RF had the better result in comparison with KNN algorithm. In smart fitness we can use the idea of using RF algorithm in choosing alternative routes for choosing alternative movements and actions for users when an action is not effective any more on user's body or when the gym has not specific fitness machine for performing an individual fitness action it can be replaced by another action that has same effects. Decision Tree algorithm (DT) is an appropriate technique for complex multi-step decisions. The algorithm divides the complex and large decisions into simpler decisions and attempt to draw conclusions from them [156]. DT can be applied on remote sensing [156], drug development, health care and medical [156,157] and many other services. For presenting meal plans for athletes in [134] decision tree has been used to choose the most suitable meal plan.

Another research, [136], presented an AI-based application for marathon runners by providing a pacing plans for runners according to their fitness level, condition and goal time. By processing previous reference levels and records, the system recommends a *personal best* target and a pacing plan for different segments of racing. During the race, all runner's pacing measures are monitored and compared with the recommended plan. The application gives the runner additional suggestions. For goal time prediction three algorithms ((KNN) [100], Linear Regression (LR) [158], and Elastic Nets (EN) [159]) has been used. Results showed that the accuracy of prediction usually increases by adding more land marks but it always does not happen.

In [36], the basic plans are defined by coaches and the system analyzes data coming from wearable trackers (e.g., smartwatches). The analysis is based on some features like heart rate, time duration of the session, calorie burnt and etc. For detecting, analyzing and clustering the fitness actions tracked by wearable sensors, a combination of unsupervised machine learning algorithm (Principal Component Analysis (PCA)) [160] with supervised algorithm (Linear Discriminant Analysis (LDA)) [161] is performed. Using a combination of PCA for feature reduction of data coming from wearable sensors and LDA for classification also is performed in [137] because LDA is very simpler than Support Vector Machines (SVM). The results determine upper and lower peaks, maximum values, first peak after zero crossing. This study could evaluate fitness activities and count them. By implementing mentioned algorithms computational tasks and overloads are reduced in this approach.

5.2. Unsupervised learning techniques in smart fitness

Unsupervised learning gets input data without any desired output patterns or any reward. Actually unsupervised learning does not get any feedback from environment and produces useful inputs for decision making or other machine learning inputs [155]. Unsupervised learning is processing unlabeled data and making outputs that is useful for predictive models [162]. AI and machine learning techniques have already focused on sports and well-being and some solutions have already been implemented [163] aiming at acquiring more knowledge on athletes or practitioners body and behaviors in order to improve performance or providing better satisfaction in practicing a sport. Today using machine learning algorithms [35,164,165], systems are able to monitor human activities, track practitioners and calculate useful measurements that will create new metrics. These will be used in order to provide beneficial insights to athletes, coaches, and practitioners [52]. In [166], a combination of AI with heart rate (HR) has been done to understand the type of activity (sitting, running, swimming and etc.). The system provides training methods for practitioners, aiming at improving the performance and preventing injuries (e.g., heart problems), maximizing the efficiency of the training by tuning up the power output. An investigation [138] has applied the k-means algorithm to data retrieved by means of user's wearable trackers. It has clustered activities existing in data sets based on heart rate and time duration. In this approach, an online data generator has been implemented so users can access the generator from any where and the computational process is faster. Analyzing peloton cyclists (a group of cyclist that ride together during a race so they benefit from energy savings because of drafting) [139,167]. In [139] K-means clustering has been performed on British Columbia Provincial track championships videos to analyze cyclists positions in each second. By simulation and analysis presented in [139,167] power output, peloton–convergence-ratio (PCR), time, best position for each cyclist and etc. can be predicted. Another work, [26], has applied bat algorithm [168] for planning fitness sessions because of its low complexity and the reduced number of monitoring points. As mentioned above in [36] and [137], PCA algorithm also has been used to make clusters of actions and reduce data coming from wearable sensor.

5.3. Reinforcement learning techniques in smart fitness

Reinforcement learning is a machine learning method that interacts with environment by producing some actions. These actions are effecting the environment and the feedback of these actions are returned to the machine by scalar rewards and the machine's goal is to maximize rewards [155]. Reinforcement learning enables learning by trial and error function and can be modeled by MDP [169]. By using reinforcement algorithms system can model training plans and transitioning to the next action and also monitoring and approximating right training plan for each person according to his/her behavior [38] as these algorithms have been successfully used to help people with dementia problem for decision making [170]. In [38] it has introduced mathematical models for studying the activities of the practitioners. In particular MDP and POMDP algorithms have been considered because of their performance [71]. This investigation has exactly used MDP and also POMD where POMD consists of (S, A, T, I, O, μ) where S is the limited state, A is set of limited activities, T (s, a, s′) is the transformation moods. C is the cost of activity, I is initial state, O is the limited state of observations, μ (O|S) is a distribution over observation. A defines the kind of activity (CL, K, CH). CL means that the current workout is heavy for the current status of the practitioner and he/she must choose a lighter workout. K means the current train is suitable for the practitioner (he/she must keep this training) and CH means that the practitioner must choose heavier workout. I represents the first workout scheduled. It is based on the information that the practitioner has provided before the first training session. O represents the system observations and an evaluation about the suitability of the current training session respect to the practitioner. μ represent a score of the executed workout (the training session) in the context of the workout plan. For the other algorithm, MDP is defined as (S_{MDP}, A_{MDP}, P_{MDP}, R_{MDP}, υ). The procedure has defined S_{MDP} as the possible world states.

5.4. Deep learning and neural networks in smart fitness

Deep learning [171,172] and neural networks [173] are AI techniques that are going to be widely adopted in more complex IoT applications. As an example [55], used neural network to extract information of a match or a training session and make patterns of these information for reducing amount of information without losing any important data. This is useful for understanding weaknesses and strength of your own and analysis of your opponents. In [77], deep learning has been used for action recognition and correction for preventing injuries. Artificial neural network (ANN) can potentially help for approximating, controlling and defining aerobic fitness exercises by measuring oxygen uptake and heart rate and using demographic variables [140]. For controlling heart rate deviations, [174] has proposed a system that contains a heart rate sensor that is placed on user's chest and sends data to heart rate receiver. By applying recurrent fuzzy neural network heart rate controller (RFNNHRC) that is a combination of fuzzy logic and neural networks system can have online learning and also can controls speed and slope of treadmill for each person. Deep learning is useful for monitoring and recognition of fitness movements. In [141] it has used 1D and 2D convolutional neural networks for recognition and prediction of some types of fitness movements (e.g. bench press, dead lift, overhead press and etc.). For performing this, this study has implemented a gyroscope on user's shoulder for tracking user's shoulder and another gyroscope and one accelerometer for tracking acceleration and rotation of user's arm. Beside these there is a Bluetooth low power for sending data to a mobile application. In [142], genetic algorithm and artificial neural networks has been used on sports for predicting performance. First some features like fatigue, weather, experience, training time, weigh, height and nutrition facts are evaluated and assigned to different levels (ranked A, B or C). Then an initial solution (a training plan) is determined by considering the available features and their ranking. After each session or training period, a new solution is determined considering the previous set of features and the results of training. This process continues until: (1) a fixed number of iterations is achieved; or (2) the desired target is reached, or (3) the best fitness solution is determined and it is not possible to reach better results; or (4) a human examination takes place in order to understand if there are problems; or (5) All of items. In Table 4 existing AI algorithms used in the sports and fitness are illustrated.

As mentioned in 3.3, in [101] deep convolutional neural network used for voltage variation signals coming from wearable sensors to perform classification and deep analyzing and sliding window [175] for generating instances from the workout. In this workout recognition and labeling and also repetition counting is performed using iterative polynomial regression algorithm [176]. This is done analyzing number of peaks and difference between them. In [177] a combination of neural networks and PCA algorithm has been used for detection of fatigue. In this approach data coming from XSens MTw acceleration sensor (placed on participant's right hand for upper body movements and left ankle for leg exercises) and a linear potentiometer placed on weights to determine movement velocities. features extracted such as time, duration for each set and range of movement are processed with linear regression to get scalar values then by processing data with PCA system can understands does fatigue happens or not and if the density of exercise is suitable or not. In [178] for detecting and improving athlete physical training fuzzy algorithm has been used for analyzing High-Density Surface Electromyography Maps (sEMG). The inputs in this approach are the muscle activation area and the mean intensity of muscle activity and the results are shown as graphical interface where difference between reference image (sent by user to server) colors and processed image are explained as percentage. In [48] Using neural networks and genetic algorithm could to improve shooting hit ratio by guidance of results concluded from algorithms.

According to the definition of the various AI algorithms and their usages in previous works mentioned in this section, Reinforcement algorithms is more suitable for applications that are focusing on motivating users because they give users awards according to their and the aim of machine and user will be maximizing awards. Unsupervised learning has less usage in smart fitness domain and making final decisions about exercises. They try to make suitable input by reducing unnecessary data and clustering data for other AI methods. Supervised learning, deep learning and neural networks can be more useful in smart fitness domain because the output and the goal of the system is defined for the system and these algorithms make decisions to achieve the goals in the best way as soon as possible.

5.5. Dataset resources in fitness domain

In this part, we aim to study the available datasets in the community related to fitness topic. Starting from sport activity datasets [147], the first one was acquired activity data form connected Garmin and Strava profiles for seven cyclists [138]. The second one was activity data of nine cyclists in two different formats (GPS Exchange Format (GPX) and Training Center XML (TCX)) [179]. Third one is about sport activity data of cycling supplemented and power meter data [180] and at last there is a data set of triathletes (swimming, cycling, running) sport activity data in GPX and TCX formats [181]. In [182] 11 publicly data sets is provided in three main categories: acquired data from ambient sensors, wearable sensors and combination of both. These 11 publicly data sets are: Gravity, DMPSBFD, MobiFall, MobiAct, RealWorld (HAR), Shoaib PA, Shoaib SA, tFall, UCI HAR, UCI HAPT, UCI UIWADS, UMA Fall, WISDM and UniMiB SHAR. In [183] a data set of Sports Videos in the Wild (SVW) has been introduced. Videos in this data set consist of videos captured by user while watching a game or performing an exercise. Accessing to the data sets of fitness trackers mostly is limited because of privacy policy of users and only vendors have permission to access their subscriber's data. So in the most cases for achieving the fitness trackers data, owner's permission is needed.

Using fitness applications, data reflecting social, life style, psychological, level of physical activity and economic factor of a community can be extracted and analyzed [184]. This can help for enhancing public policy and city planning [184], using for public health data and policies, analysis of fitness trends, urban planning and building infrastructure in accordance with people's habits and needs [112]. Analysis of behavior of large shares of population with respect to physical activities can be quite important for prevention or for stimulating a better approach to well-being.

5.6. Authors insights and summary

A trending topic in smart fitness is artificial intelligence solutions which are most focusing on feature extraction, classification or regression data according to the type of algorithm (supervised, unsupervised, reinforcement or neural networks and deep learning) and prediction for fitness exercised in the future. Each type of AI algorithms has an attribute that provide individual functions and could be used for different usages. In this domain fitness datasets are very important because there are a limited number of these datasets and many of them are not public and accessible.

6. Discussion and future directions

This section aims to provide a short summary of what is presented in this article and discuss about side effects of smart fitness trackers then we provide few potential ideas as future directions of this research domain.

6.1. Discussion

In this article, we have evaluated the impacts of IoT and related technologies on various aspects of fitness. We categorized smart fitness into three major groups: 1 — IoT-based smart fitness, 2 — Social-IoT and 3 — Artificial intelligence. We reviewed each group considering their features and abilities. The IoT-based category was further divided into three subset: fitness trackers, movement analysis and fitness applications. In this section, a discussion of future characteristics or features of smart fitness devices and applications is presented organized according to some major needed enhancements: As noted earlier, fitness trackers, smart watches and other wearable trackers help users to gain self-awareness. Also health insurances companies can motivate their consumers to share their fitness data (captured by fitness trackers, smart watches or even smart phones) by offering discounts. This helps insurance companies to make better policies and also present offers life and health insurance products according to consumer's activities [33, 185]. Sharing fitness data can help to prevent frauds in insurance information and in better tailoring insurance programs to the real life style of people [33,113].

Apart from the positive aspects, authors in [186] show fitness trackers have some negative sides effects. For example smart watches and fitness bands like Fitbit may become addictive. It means that if a practitioner forgets to wear her/his tracker he/she may feel disappointed and feel their activity is not counted. A subject to be considered is motivating people for using fitness applications. As discussed in [187] 45.7% of people finally stop using fitness apps after starting using them. Abandonment of using fitness trackers is caused by several reasons relating to user's characteristics and also features, abilities and weaknesses of the trackers [188].

On the other side, some studies also showed positive sides like motivating recreational runners to achieve better goals while making them feeling better during training [189]. A study, [190], explored the effective factors on motivating someone to choose and adopt a fitness tracker. These factors are: interpersonal influence, attitudes toward a wearable healthcare device, self-efficacy, personal attention toward innovation, health interest, and perceived expensiveness. On the other hand, some of the fitness tracker users think some additional functions like movement monitoring during sleep or calorie burnt are unnecessary [191].

6.2. Potential future directions

In this section, a discussion of future characteristics or features of smart fitness devices and applications is presented organized according to some major needed enhancements:

1. Advanced Smart Fitness by enhancing AI based coaching. Non-wearable sensors could track some features of training. Architectures and solutions in previous studies had not provided a system capable of fully substituting a coach. For moving toward this direction, AI approaches can help for processing data collected from practitioners and provide a complete feedback, monitor and advisor system. AI based solution can better exploit user profiling for extracting patterns and identifying individual behavior. In such a way, AI based coaching can give recommendations for workouts exercises still trying to prevent injuries.

2. Accuracy Improvement. Accuracy is an open issue in tracking sensors [192,193]. The accuracy of collected data and measured values by wearable sensors should reach a quality level comparable with the data collected by other IoT sensors in the field of professional sports and healthcare. In addition, due to sensing technology improvement and need of people, features and possibilities in wearable sensors must be updated. On the other hand, in non-wearable sensors because of needing to be more accurate in processing data, more monitoring factors is needed. In designing this system attention must be paid to have *More accurate recognition of correctness* of fitness actions, more attention to age, gender, and workout history to suggest exercises, more *monitoring parameters* like action duration, angle, distance from fitness machine, time and etc should be present in monitoring the correctness of movement.

3. Adopting an SIoT approach for better decision making. In the smart fitness domain, there are plenty of fitness applications that collect data sensed by trackers. They provide workout plans, meal plans, and define next targets for user activity, as well as the suggest objectives about user weight or even user's target body. Using social-IoT can help tocollect more precise data from all the relevant smart fitness devices used by the individual as well as accessing to clustered information related to people and practitioners similar to the specific one. This "social" capabilities allow to take better decisions with respect to the suggested activities and plans.

4. Integration of sensed data per User in a place. The integration and presentation of all the possible data collected by several wearable and non-wearable sensors is another step to take. The ideal case is integration of all these data (generated by non-wearable and wearable sensors) in a unique user profile that can be accessed by several applications. In more practical terms, interoperability of some applications (e.g., according to the SIoT approach) can provide more insights about exercise schedules and possible injuries.

5. Improving security and privacy. Privacy and security are two important topics in any ICT technology. While IoT and its services have an increasing success, cyber-security and privacy is becoming a major issue. In this era, IoT devices, due to their limits in processing power and storage and the need to devote these resources to achieve their purposes, are usually easier to attack. Other reasons that makes IoT vulnerable are heterogeneous infrastructure, dynamic and complex environment [194]. Fitness trackers are sensor based devices which are not primarily designed for reducing security and privacy risks as in these sensors more attention is on accuracy [195]. Therefore there is a high potential risk on leveraging the personalized data in different way. Securing fitness data is important, but fitness trackers are not providing strong security and privacy functionalities. In 2017 a research, [113], showed that only four of seventeen evaluated fitness devices has data protecting mechanism. This research recommended utilizing end to end encryption using device-specific key.

Another problem is related to the communication protocols used between tracking devices and other systems components (e.g., a smartphone), if the tracker connection to a smartphone is via Bluetooth, for example, it is a good target for attackers. In addition, if connection is based on MAC address then its a good target for unwanted tracking [196]. In addition, trackers and smart fitness applications do not generally provide the raw data to users. They just offer graphical representation of activities or a smaller set of data. The data collected are not owned by the user, they are properties of the producers of the device.

IoT devices and specially fitness trackers use automatic data collection mechanisms, this is a good area for mis-usage. For example, cheating by sending wrong data to the servers could be used in order to introduce disruption and wrong analysis in the training activities [197]. The most dangerous risk is attack to firmware. It costs more, but when an attacker can access to the software of microprocessor, he/she can control all aspects of the device [198]. There are many security and privacy issues, they exceed the purpose and extend of this study. However, security deserves more attention in IoT especially in e-healthcare and smart fitness.

Considering that fitness trackers and applications is directly related to collecting basic people information, the security must be taken into consideration and higher level of privacy protection should be pursued. On the other hand, because of importance of fitness data and their potential usage in public health, healthcare providers and also insurances may be granted an access to a part of these data. As already said, in these cases, the quality of sensors used in trackers must be appropriate and algorithms should be enhanced.

6. Reducing cost. One of the most important challenges is the cost and price of smart fitness devices. Implementing a smart fitness system has relevant costs comprising costs for appropriated sensors to embed in trackers, costs for developing, deploying and maintaining a system for storing and processing data sent from sensors, costs for implementing functionalities and function a based on distributed communications, SIoT functions and applications of AI/ML techniques. For processing data coming from practitioners, the development of an entire systems (and even more if they are local systems) is expensive; the adoption of cloud based solutions can limit the complexity and the expenses (as health system are doing) [199]. If a large distributed system has to be developed, fog computing capabilities and architecture can help [200].

7. Data management and big data collected via smart fitness applications. There is a need for a data management for fitness trackers and applications. Current trackers and applications save measured data in their own format (for example TCX or GPX) [138]. There should be a standard format for storing data and a data architecture for organizing and orchestrating the usage of tracked data. In the domain of fitness data, regarding to previous studies on fitness big data usages, there is a good opportunity for more studies and reusing these data for analyzing and decision making for other fitness and health applications.

Table 5
Current usage of AI based services and technologies in IoT and the opportunity for using them in smart fitness.

Services/Tech.	Current solutions in IoT domain	Potential application for smart fitness domain
Lightweight AI algorithms	Securing IoT devices for preventing attacks and preventing over load [194]	Securing low power modules in smart fitness without heavy processing load
Electronic records	Recording demographic data, health data, care and medical data [12,201,202]	Electronic records of exercise information accessible from authorized applications and specialists
Big data analytics	Predicting diseases, epidemics, insurance policies, road safety and traffic handling [185], consumer behavior [203]	Analyzing people according to situation and demographic data Providing added value services or beneficial advices
5G	Real time monitoring factory automation process [204] Less delay and more stability [205]	Real time fitness monitoring less packet lost and delay packet transmission

8. Establishing other IoT solutions. There are some solutions for improving quality of services and results. One of the recent hot topics in the IoT is 5G. 5G implementation has some benefits for network such as more connected devices, connection availability in any time and any where, longer battery life, high bandwidth and etc. [206]. In 5G reducing delay and providing stability for 99.999% is achieved [205]. Electronic health record is collection of the all care information of patient such as drugs, demographic data, medical care data and etc. from birth to death which can be integrated with other data (such as genetic data) for more analysis [202,207]. IoT sensors are producing a huge number of data. This huge data is a good opportunity for new research trend, analytics of impact of a decision on an event, Predicting diseases, epidemics, helping insurance for making better policies [185] or analysis of behavior change and market analysis [203]. By data sets presented in Section 5.5 there is a good potential for big data analytics, feature extraction and behavior analysis in smart fitness. Due to the power and computing limitation in IoT sensors there should be a security mechanism adapted to the IoT network capacity [208]. AI algorithms can be implemented on IoT devices and simplifying security management and achieving protection by adapting to complex dynamic environment in a wide network [194]. Using solution already established in IoT, smart fitness could improve its results and effectiveness providing more accurate and complete services to the users and practitioners. Table 5 shows big potential and good opportunities that can be achieved by adapting them with smart fitness.

7. Conclusions

This paper provides a comprehensive overview on the existing studies and solutions related to smart fitness. Toward that end, three domains of smart fitness have been considered; IoT-based solutions (including: fitness trackers, fitness applications and movement analysis), artificial intelligence and social IoT. Considering the existing solutions and architectures related to IoT-based solutions, an AI based approach with complete monitoring mechanism is still demanding. AI in smart fitness has some task such as exercise feature extraction, workout and diet prediction and over training and injury prevention. Also in smart fitness domain social IoT is a major requirement which can help for improving knowledge of the smart fitness by sharing the experience of various solutions, sensors types, methods and also various people with difference in culture, economic situation or even habits. Smart fitness has the potential of being like team of assistants for a coach to help for better decision making. To have a complete and ideal smart fitness solution, it should perform some tasks such as authorizing and identifying users, workout and diet prediction and monitoring training information history management and fitness big data analysis. Smart fitness has still good potential to be improved in all aspects and there is still a lot of research opportunities in this field. Current studies, researches, prototypes and market value in smart fitness domain shows that there can be a good opportunity for companies which are working in technology and sport domain, to invest in this field in the future. Some of the mentioned studies and prototypes in this study can be improved and transferred from academic research and prototype to industrial or commercial product and make smart fitness solutions more effective. Finally, this study identified a set of challenges in smart fitness domain that can be considered as potential future research directions in this field of research.

CRediT authorship contribution statement

Alireza Farrokhi: Conceptualization, Methodology, Writing - original draft. **Reza Farahbakhsh:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing, Supervision. **Javad Rezazadeh:** Conceptualization, Resources, Writing - review & editing, Supervision. **Roberto Minerva:** Conceptualization, Writing - review & editing, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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