Advances in Human-Computer Interaction

Personal Assistance and Monitoring Devices Applications

Lead Guest Editor: Renato Ferrero
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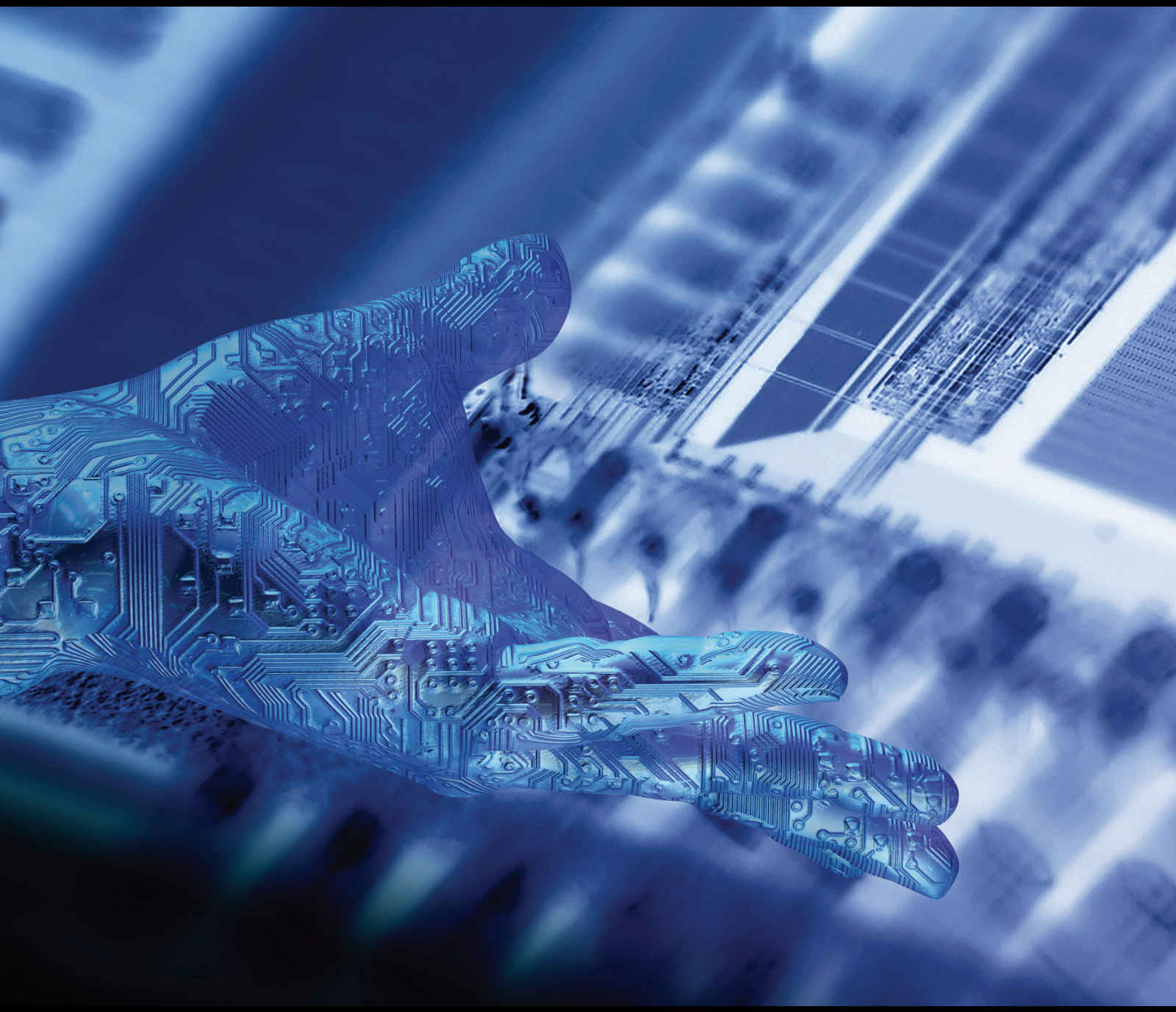

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Editorial Board

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Editorial

Personal Assistance and Monitoring Devices Applications

Renato Ferrero,[1] **Maurizio Rebaudengo**,[1] **and Francisca Rosique**[2]

[1]*Dipartimento di Automatica e Informatica, Politecnico di Torino, 10129 Torino, Italy*
[2]*Universidad Politécnica de Cartagena, Cartagena, Spain*

Correspondence should be addressed to Renato Ferrero; renato.ferrero@polito.it

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During almost the whole day, people are carrying or wearing one or more personal devices, such as smartphone, smartwatch, smartband, activity tracker, or smart ring. From one side, these devices provide an extraordinary source of information. They can collect health parameters, such as heart rate and blood pressure, and measure the activity of the user, for example, by counting the number of steps, track position, and speed of the user. From the other side, the personal devices offer an intuitive and implicit interaction with the user. Their interface is designed to recognize the user's actions and respond to them. A natural communication, based on touch, gestures, voice, and sounds, is established with the user in order to recognize his/her actions and respond to them. Furthermore, the personal devices can be aware of the usage context, for example, by automatically recognizing the activity performed by the user. Their behaviour can be proactive: by recording previous routine and needs of the user, they can propose specific suggestions related to the current context, so anticipating the explicit user input. New applications of the personal devices are arising in many fields, such as health, wellness, and entertainment. At the same time, the service can be personalized and adaptive, because the continuous flow of collected data simplifies the knowledge of the user and the understanding of routine changes.

This special issue contains excellent contributions about emerging applications of personal devices with intuitive user interaction. In addition, a comprehensive review paper gives an insight into a healthcare application of personal devices. In this way, we think that the special issue may attract a broad section of readership, from beginners to advanced researchers.

A common application in mobile healthcare is fall avoidance, due to the high social cost caused by unintentional falls. Personal devices have been exploited in many fall detection systems, which are able to recognize falls and notify user's acquaintances in order to provide quick assistance to the user after the fall. However, if the goal is the fall avoidance, more promising approaches require the evaluation of the fall risk. The prediction of the fall in real time is used to alert the user before the fall occurrence or to activate some external aid, such as a walking assist robot, whereas proper exercise for improving gait and mobility can be assigned to the user according to the assessment of his/her probability of future falls. The paper of M. Hemmatpour et al. provides a detailed review on fall prediction and prevention systems based on wearable devices. The posture and gait of the user are commonly studied by means of accelerometer, gyroscope, motion sensor, and piezoelectric sensor. The main features extracted from the collected data are gait speed and acceleration, trunk tilt, foot posture, and duration of the transitions between postures. Different machine learning algorithms can be applied to process these features: threshold-based algorithm, decision tree, support vector machine, and fuzzy logic. In the paper of M. Hemmatpour et al., a dataset of walk patterns was populated by recording data when a group of users is asked to walk in a flat area, where different types of obstacles cause irregular gaits. The level of fall risk predicted by the different machine learning algorithms was compared by using the speed, acceleration, and tilt extracted from the collected data. The evaluation criteria for the outcome of the machine learning algorithms include specificity, sensitivity, accuracy, error rate, precision, and recall. According to the analysis, normal and abnormal walk patterns can be

distinguished at best by evaluating the tilt feature with a decision tree.

Another healthcare application of wearable devices is the monitoring and controlling of heart problems, as shown in the paper of A. J. A. Majumder et al. The authors have developed a smart IoT system composed of embedded temperature and pulse sensors for data collection, an Arduino board for analog-to-digital converter, a Bluetooth chip for data transmission, and a smartphone for data analysis and visualization. Temperature and electrocardiogram (ECG) data are read from the sensors at 5 Hz and 160 Hz, respectively. First, a filtering technique is applied to the ECG data to reduce the noise, with removal of baseline wander and high-frequency component. Then, three features are extracted from the ECG signal: heart rate, that is, number of beats per minute; R-R interval, that is, interval between successive heartbeats; and ST segment, that is, length of the flat section between the waves in a heartbeat. A novel algorithm based on the decision tree model with a standard deviation statistical analysis has been implemented in order to evaluate the three ECG features and the temperature. Input data are analysed every second; the algorithm evaluates the analysis results in the last five seconds to determine the degree of heart rate abnormality, according to five warning levels. The developed IoT system has been evaluated with healthy test subjects, without triggering any warnings and with data from an online database of patients who suffered from sudden cardiac deaths. In the latter case, the algorithm is able to distinguish the abnormal ECG pattern and raise the proper warning level.

Wearable technology can be a reliable and objective support for humans' senses. An example is provided in the paper of V. Ferraro et al. about a plurisensorial device aiming at preventing occupational disease. In particular, a prototype was designed for coating plants, where the concentration of Volatile Organic Compounds (VOC) is high during material lacquering. VOC-prolonged inhalation may cause asthma, lung cancer, pulmonary and respiratory diseases, and so forth, so environmental monitoring and personal protective equipment are mandatory by law. However, according to the authors' initial observation, the lacquering tasks were performed in cabins equipped with an aspiration system to reduce the inner air pollution, but the workers did not wear the protective mask. In fact, despite the strong smell of VOC, the workers' perception about them was low: this is an adaptation due to the long-term exposure. Without feeling bad odours, the workers do not perceive the dangerousness of VOC. V. Ferraro et al. have designed and prototyped a wearable system able to provide objective data to the users in order to enhance their perception of risk. The system is composed of an electronic nose device, a smart protective mask, a chest band, and a mobile application for smartphone. The electronic nose device is equipped with a VOC sensor and gives feedback about the air quality thanks to coloured LEDs. The mask monitors the user's breath by means of temperature and humidity sensors. The chest band measures the respiration frequency. Data collected by the three devices are sent via Bluetooth to the mobile application, which provides real time and historical statistics. The testing of the prototype reveals that, during the tasks performed in the cabin, the level of contaminants was high during most of the time. According to the final interview, the workers changed their consciousness about their health conditions and were interested in wearing the protective mask.

T. Khan et al. present a study of the impact of an Augmented Reality (AR) mobile application on learning motivation of a group of undergraduate health science students. They present a very complete literature review, emphasizing the advantages and challenges of the current state of augmented reality technology in education. Preusage and postusage questionnaires were used as instruments for data collection. To measure motivation, authors use the Attention, Relevance, Confidence, and Satisfaction (ARCS) model. Based on the ARCS factors, the authors developed a questionnaire in the form of a five-point Likert scale. The results showed that using an augmented reality mobile application can increase the learning motivation of students. The attention, satisfaction, and confidence factors of motivation were significantly enhanced.

Another interesting mHealth application along with a computational model is presented in D. Baretta et al.'s paper. They present an experimental system formed by a mobile application, a wearable device, and a computational model that is conceptually framed in self-efficacy theory with a particular emphasis on self-efficacy beliefs and goal setting constructs. The computational model represents a mathematical description of a behaviour change model based on self-efficacy theory that needs to be tuned according to real case studies. The proposal of the authors turns out to be an innovative approach to promote physical activity behaviour change among inactive adults.

Conflicts of Interest

The guest editors declare that the work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Authors' Contributions

All the guest editors wrote and contributed to and approved the final editorial.

Renato Ferrero
Maurizio Rebaudengo
Francisca Rosique

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Review Article

A Review on Fall Prediction and Prevention System for Personal Devices: Evaluation and Experimental Results

Masoud Hemmatpour, Renato Ferrero, Bartolomeo Montrucchio, and Maurizio Rebaudengo

Dipartimento di Automatica e Informatica, Politecnico di Torino, Italy

Correspondence should be addressed to Masoud Hemmatpour; masoud.hemmatpour@polito.it

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Injuries due to unintentional falls cause high social cost in which several systems have been developed to reduce them. Recently, two trends can be recognized. Firstly, the market is dominated by fall detection systems, which activate an alarm after a fall occurrence, but the focus is moving towards predicting and preventing a fall, as it is the most promising approach to avoid a fall injury. Secondly, personal devices, such as smartphones, are being exploited for implementing fall systems, because they are commonly carried by the user most of the day. This paper reviews various fall prediction and prevention systems, with a particular interest to the ones that can rely on the sensors embedded in a smartphone, i.e., accelerometer and gyroscope. Kinematic features obtained from the data collected from accelerometer and gyroscope have been evaluated in combination with different machine learning algorithms. An experimental analysis compares the evaluated approaches by evaluating their accuracy and ability to predict and prevent a fall. Results show that tilt features in combination with a decision tree algorithm present the best performance.

1. Introduction

Health centers have to deal with a large number of patients due to unintentional falls, resulting in huge cost on the society. For example, the average hospital cost for fall injury is over $ 30,000 [1]. Thus, there is a critical need for the development of cost-effective systems to reduce the injuries of a fall and to give faster assistance when a fall occurs. Several risk factors for falling can be identified, and specific interventions can be designed in order to reduce injuries. To this end, several systems were developed and are now available. Most of these systems concern fall detection [2–8], and they only notify user's acquaintances after a fall occurrence. However, there are systems with the goal of predicting and preventing a fall, called fall prediction and prevention systems (FPPSs) [9–13]. Such systems track and report data from wearable sensors without engaging the users in the monitoring process. FPPSs include sensors to collect data and software applications to process them: first, data are collected from sensors, then, the collected data are analyzed to extract an appropriate feature set. Afterwards, a machine learning algorithm is applied on the obtained data. Since smartphones nowadays are broadly used as personal digital assistance and they are equipped with precise sensors and communication component, they are used commonly in FPPSs as a monitoring device to collect data.

Fall prediction systems typically estimate real-time or future fall risk. These systems are helpful in reducing the financial and health consequences of a fall. Since both prediction and prevention systems evaluate a fall risk sometimes prediction and prevention terms are interleaved. These systems are essential to check the feasibility of performing recovery mechanisms before a fall occurrence.

Real-time fall prediction system aims to identify an abnormal gait pattern in order to estimate the probability of a real-time fall occurrence [14–16]. In real-time fall risk prediction, data are collected from sensors, and are analyzed to compute the appropriate feature set. Then, the risk of a possible fall is evaluated through classification algorithms. Real-time systems continuously assess the fall risk while the user is doing his/her daily activity. When an abnormal gait is

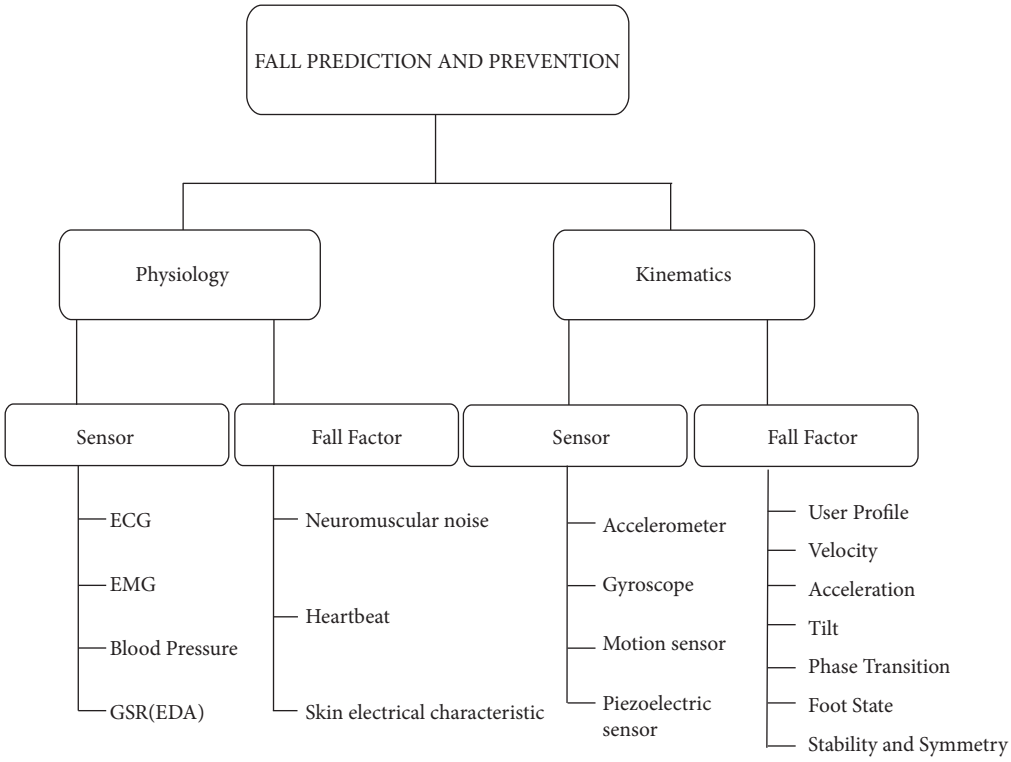

Figure 1: Fall prediction and prevention taxonomy.

detected then the user is alerted [14–16], or an external aid, such as a walker or robot, is exploited to prevent a probable fall [17, 18].

Future fall prediction is estimated through some clinical assessment tests. Probable future falls are prevented through improving gait and mobility by some exercises [17, 18]. These tests often involve questionnaires or functional assessments of posture, gait, cognition, and other risk factors. These clinical tests are subjective and qualitative and typically use threshold assessment scores to categorize people as fallers and nonfallers. Typically, these tests are timed up and go (TUG) [19], Berg Balance Scale (BBS) [20], sit to stand (STS) [21], and one leg stand (OLS) [22] to evaluate balance and lower limb strength.

The design of a fall prediction and prevention system faces several significant challenges. They need to be accurate, reliable, robust, and cost-effective [1]. In this paper, a fall prediction and prevention system is described in three parts: fall factors (i.e., fall symptoms), their features, and machine learning algorithms. This paper investigates every mentioned stage and experimentally evaluates the various approaches. This paper does not present systems using sensors such as camera and sound since they are prone to violate individual's privacy comparing to kinematic wearable sensors. In this paper, accelerometer (for measuring the acceleration) and gyroscope (for measuring the angular rate around one or more axes of the space) are considered for evaluation. These sensors are chosen since they are easily accessible and do not disturb the privacy of the user. The main contributions of this paper are the following:

(i) A comprehensive discussion on fall prediction and prevention systems

(ii) Preparing a dataset with realistic parameters to simulate abnormal gait

(iii) Finding the most representative fall factors

(iv) Evaluation of the fall factors based on the extracted feature on commonly used machine learning algorithms

This paper is organized as follows. In Section 2, existing FPPSs are classified according to the fall factors. Then, in Sections 3 and 4, feature extraction techniques and machine learning algorithms are described. Evaluation criteria are illustrated in Section 5. Afterwards, experimental results are shown in Section 6. Finally, conclusions are presented in Section 7.

2. Classification of Fall Factors

Fall prediction and prevention is a multifaceted problem that can be broadly categorized into two different domains: physiology and kinematics, as can be seen in Figure 1.

Physiological solutions consider intrinsic fall factors, i.e., parameters which mostly originate from the body. These solutions entail an in-depth medical evaluation of the risk factors and exploit sensors related to body monitoring:

(i) Electrocardiogram (ECG) sensor

Typically, ECG is used to assess the electrical and muscular operations of the heart but ECG sensing can

also determine abnormalities that might lead to a fall [23, 24].

(ii) Electromyography (EMG) sensor

EMG is a technique for evaluating the electrical potential produced by muscle cells. EMG in combination with other medical sensors is used in FPPSs [23].

(iii) Blood pressure sensor

Blood pressure sensing is a physiological sign that can be investigated to determine abnormalities that may lead to a fall [23].

(iv) Galvanic Skin Response (GSR) sensor

GSR is a method for measuring the electrical characteristics of the skin. GSR in combination with ECG and EMG are used to predict and prevent falls [23].

Fall factors in physiological analysis are as follows:

(i) Neuromuscular noise

The increased neuronal noise associated with aging increases gait variability and consequently fall risk [25].

(ii) Heartbeat

An irregular heartbeat increases the risk of a fall [23, 26].

(iii) Skin electrical characteristic

Since the sweat glands are controlled by the sympathetic nervous system, which controls also emotions, a variation of the skin electrical characteristic could demonstrate a state of stress, which indicates the risk of a fall [23].

Unlike physiological solutions, kinematics-based FPPSs consider user's posture or gait variables. These solutions usually exploit movement sensors to investigate the extrinsic parameters of fall, i.e., characteristics of the movement of the body:

(i) Accelerometer

An accelerometer is a device that measures acceleration, i.e, the rate of change of the velocity of an object.

(ii) Gyroscope

A gyroscope gives the angular rate around one or more axes of the space. Angular measurement around lateral, longitudinal and vertical plane are referred to as pitch, roll and yaw, respectively. Typically, in FPPSs, the gyroscope is used in combination with an accelerometer.

(iii) Motion sensor

A motion sensor detects the movement of an object in the environment.

(iv) Piezoelectric sensor

A piezoelectric sensor measures the variations in pressure and force using the piezoelectric effect and converts them into an electrical charge.

Kinematic-based FPPSs focus on future or real-time fall occurrence. Future fall solutions evaluate a user to estimate his/her fall risk: if the fall risk is high, a probable future fall can be prevented through some exercises [27]. In contrast, real-time fall solutions avoid a fall while the user is doing his/her daily activity by alerting the user [14–16] or using an external aid such as a walker or robot [17, 18].

As extrinsic fall factors are among the most common causes of fall, this study surveys kinematic-based FPPSs, considering in particular data acquired with gyroscope and accelerometer sensors. The main kinds of factors in kinematic analysis which can increase the risk of fall in FPPSs are explained in the following.

2.1. User Profile. User profile can affect the fall risk. For example, the risk of a fall for elderly people is higher than young people, and the risk of a fall is higher in people who experienced a previous fall. Fall risk can be assessed through a weighted generic formula that combines all these factors [28].

2.2. Velocity. People with increased fall risk tend to walk slowly. As such, the actual fall risk can be quantified according to gait speed [29]. Gait speed is estimated by measuring duration and length of user's steps. The step duration is calculated as the time between two consecutive foot contacts. The step length is calculated as the sum of the displacement during the swing phase and the stance phase.

2.3. Acceleration. Changing of body movement in a prefall state causes alternation in the acceleration, so by processing the Acceleration Time Series (ATS), a fall event can be predicted. As Figure 2 illustrates, human motion during the time period S can be presented with n smaller periods T_s [30]. Period T_s itself consists of m short periods T with m acceleration samples. Basically, ATS is characterized by a series of elements c_i over time, where each element describes the feature of the movement during period T_s.

2.4. Tilt. Tilt is inclination from horizontal or vertical line. When a user significantly tilts in a direction, it shows an abnormal posture, which can lead to a fall. So, the user tilt can be a factor to assess the risk of a fall. Table 1 illustrates the notations to measure user's tilt [14–16].

Some traditional standard balance tests, such as sit to stand (STS), uses trunk tilt to evaluate the risk of a fall. The trunk tilt is calculated based on the angles between the sensor and the horizontal line of the ground [31].

2.5. Postural Transition Duration. Posture specifies the position of the body. Any activity begins with a posture and ends with another posture. Postural transition duration specifies the duration of a transition from a posture to another one. Balance control and stability of the body during postural transitions are key factors for avoiding falls. Postural transition duration can be an indicator of fall because it is significantly correlated with the fall risk [31]. Higher transition duration means lower muscle strength, and consequently higher fall risk. The duration of the postural transition can be computed by means of the accelerometer and gyroscope by measuring

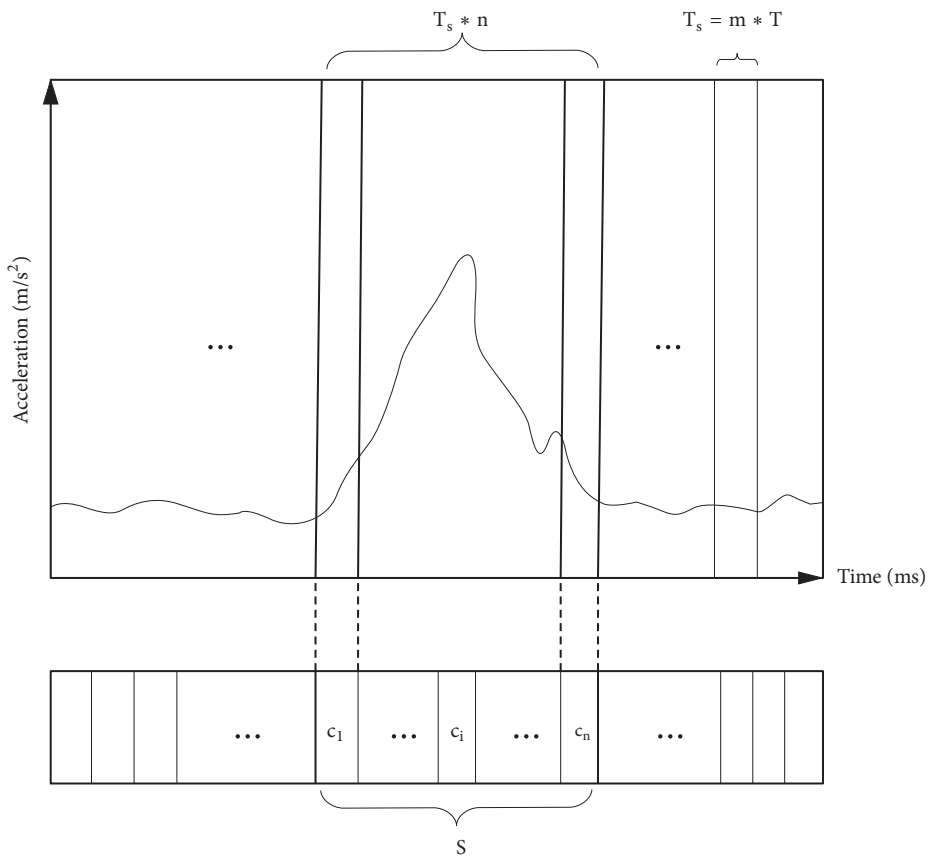

Figure 2: ATS accelerometer.

Table 1: Results of different approaches with decision tree and support vector machine classifications.

Measures	Tilt		Speed		Acceleration	
	DT	SVM	DT	SVM	DT	SVM
Accuracy	*83.88*	65.7	72.11	61.53	*81.42*	56.66
Error Rate	16.11	34.2	27.88	38.46	18.57	43.33
Sensitivity	0.88	0.74	0.87	0.66	0.78	0.26
Generality	0.21	0.42	0.43	0.43	0.15	0.12
Precision	0.81	0.63	0.67	0.60	0.83	0.68
Recall	0.88	0.74	0.87	0.66	0.78	0.26
ROC Area	0.86	0.65	0.69	0.61	0.82	0.57

the depression on the vertical axis acceleration signal, and the positive and negative angular rotations of the horizontal axis. The depression of the acceleration signal comes from the movement of the body, and the angular rotation is due to the forward and backward leans of the trunk during transition.

2.6. Foot State. The foot state indicates the posture of the foot during the gait cycle. Since foot state can specify the balance of the user, investigating the foot state can help to define the prefall state and estimate the fall risk. Some FPPSs focus on features related to foot state such as foot clearance (i.e., the distance of the foot and ground during walking) and foot age (i.e., relation of the age with the foot pressure) [32, 33].

2.7. Stability and Symmetry. Stability means the resistance of standing against a position change. Symmetry is the balance of the pressure on two feet. Stability and symmetry affect the functionality of the user gait: a gait with weak stability and symmetry has a higher fall risk. According to the stability and symmetry of gait, an assessment model can be used to predict the fall risk [34].

3. Feature Extraction

After acquiring signals from sensors, a feature extraction technique should be applied to extract appropriate information. Since data collected from sensors contain undesired information, filtering techniques are essential. A filtering

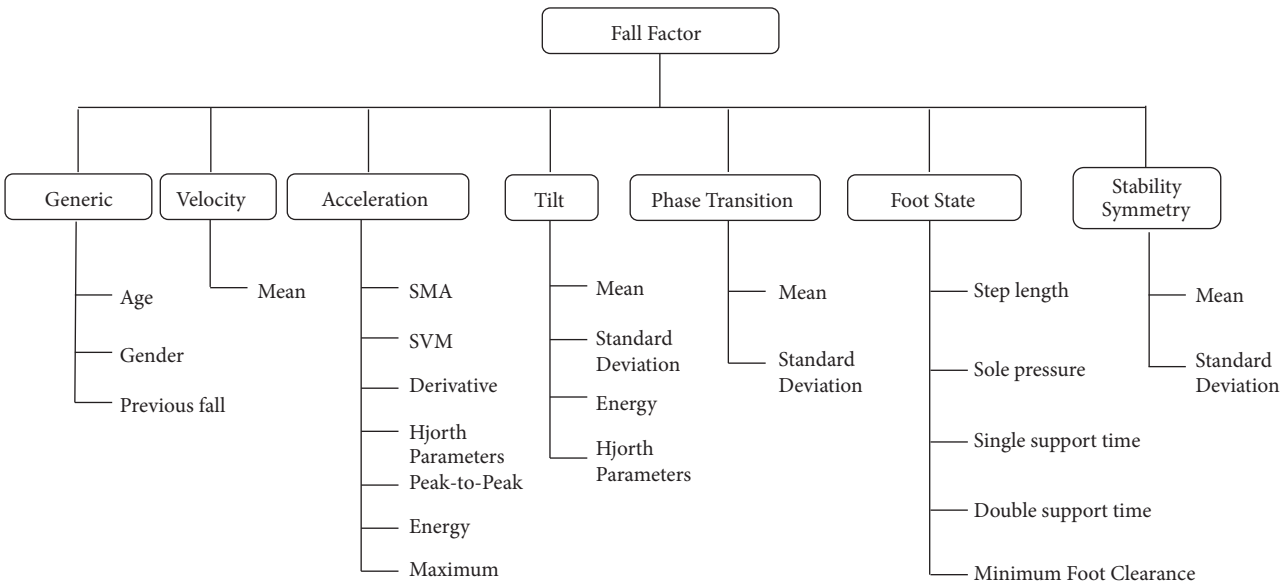

Figure 3: Fall factors approaches.

technique eliminates some frequencies from the original signal to attenuate the background noise and to remove undesired frequencies [29, 35]. Frequently used filters in FPPSs are high-pass filters, which eliminate frequencies lower than the cutoff frequency, and low-pass filters, which pass only frequencies lower than a certain threshold frequency. After filtering the collected data, appropriate features should be selected. Since analyzing a high number of features requires a large amount of memory, finding the optimal feature set can improve the performance of the system. The main features extracted from each fall factor are listed in Figure 3 and described in the following.

3.1. User Profile. Falls are the result of a combination of factors involving age, sex, mobility, daily activity, cognition, and previous fall. Thus, fall risk can be expressed as a simple function of user profile features with appropriate weights [28]:

$$\begin{aligned} Fall\ Risk = {} & 0.13\left(I_a\right) + 0.15\left(I_s\right) + 0.14\left(I_m\right) \\ & + 0.1\left(I_{adl}\right) + 0.18\left(I_c\right) + 0.33\left(I_f\right) \end{aligned} \tag{1}$$

where

(i) I_a is the age index: the risk of falls in the elderly is assumed increasing with age [36];

(ii) I_s is the sex index: female gender is associated with greater risks of fall [37];

(iii) I_m is the mobility index: mobility implies the ability to move from place to place which can be indicator of a fall [38, 39];

(iv) I_{adl} is the index derived from the activities of daily living (ADL): fall risk and a person's perception of capabilities within a particular domain of activities have strong independent correlation with ADL [40];

(v) I_c is the cognition index: impaired cognition and dementia independently predict falls [41];

(vi) I_f is the previous fall index: a history of previous falls has been recognized as being a significant risk factor for future falls [41].

The weights in the above formula and the choice of indices are made by statistical result of the earlier study [28]. The weights differ for male and female; in the above formula weights are calculated for female gender.

3.2. Velocity. As mentioned in Section 2.2, low gait speed increases the risk of a fall. The average speed of the gait can be measured to estimate the fall risk [29].

3.3. Acceleration. Frequently used features of the acceleration are described in the following. In the formulas, $A(t)$ refers to the acceleration and $A_x(t)$, $A_y(t)$, and $A_z(t)$ indicate the components of the acceleration in the 3 axes. Moreover, A_{xi}, A_{yi}, and A_{zi} are the i-th acceleration samples in the 3 axes.

The Signal Magnitude Area (SMA) can be used as a feature of the acceleration signal to classify the activities of the user [35]. SMA is computed as follows:

$$\begin{aligned} SMA = {} & \frac{1}{T}\left(\int_0^T \left|A_x(t)\right| dt + \int_0^T \left|A_y(t)\right| dt \right. \\ & \left. + \int_0^T \left|A_z(t)\right| dt\right) \end{aligned} \tag{2}$$

where T is the length of measurement time.

The Signal Magnitude Vector (SMV) is one of the common measures to calculate the resultant of the signal:

$$SMV = \frac{1}{n}\sum_{i=1}^{n}\sqrt{A_{xi}^2 + A_{yi}^2 + A_{zi}^2} \tag{3}$$

SMV demonstrates the degree of the movement intensity and it is an essential metric in FPPSs [15, 16, 30, 35].

Moreover, the derivative ($A'(t)$) of the acceleration indicates the vibration of the movement and can be used as an acceleration feature [35].

Hjorth parameters are statistical features of the signal in time domain [42]. They are based on the variance of the signal $var(A(t))$:

(i) $Hjorth\ activity = var(A(t))$; it can indicate the signal power.

(ii) $Hjorth\ mobility = \sqrt{var(A'(t))/var(A(t))}$; it can be an indicator of the smoothness of the signal curve.

(iii) $Hjorth\ complexity = mobility(A'(t))/mobility(A(t))$; it can effectively measure irregularities in the frequency domain.

The Hjorth parameters are mostly used to analyze the electroencephalography signals but they are also utilized to analyze accelerometer and gyroscope signals in FPPSs [15].

Peak is the absolute maximum value of the signal over the period of time, and peak-to-peak is the difference between the minimum and the maximum value of the signal over the period of time. The peak-to-peak acceleration amplitude and the peak-to-peak acceleration derivative are two features used in FPPSs [29].

The energy of the acceleration signal describes the amount of physical activity in the vertical and horizontal directions. It can determine the strength of the contact with the floor, so it can be used to recognize abnormal walking pattern such as stumbling [14, 16]. The energy of the signal can be computed as

$$E_x = \int_{-\infty}^{\infty} |A(t)|^2 \, dt, \tag{4}$$

As described in Section 2.3, ATS can be characterized by a series of features c_i. Feature c_i can be determined by calculating the resultant acceleration $\overrightarrow{A_F}$:

$$\overrightarrow{A_F} = \sqrt{\overrightarrow{|x|}^2 + \overrightarrow{|y|}^2 + \overrightarrow{|z|}^2} \tag{5}$$

The resultant acceleration ($\overrightarrow{A_F}$) varies within a small range B = $[b_1, b_2]$ around g where g is the gravity force, $b_1 < g < b_2$. Therefore, if the resultant acceleration exceeds B, an abnormal walking is probable.

3.4. Tilt. Trunk tilt has an important role in the maintenance of the posture. The average and standard deviation of trunk tilt are measured during the sit to stand phase of STS test to assess the risk of a fall [31]. Moreover, energy and Hjorth parameters of the tilt vector are used as an indicator of the abnormal motion [14–16].

3.5. Postural Transition Duration. The average and standard deviation of the duration of the postural transition can be used to estimate the user's fall risk [27, 31].

3.6. Foot State. Step length is a feature of the foot in a gait cycle that can be a good indicator of the fall risk. Since a high step length decreases the stability of the user, the fall risk increases as the length of the step grows. Single support time is the time when only one limb is on the ground in a gait cycle. Double support time is the time spent when both feet are on the ground in a gait cycle. The foot age is an index of the gait which shows how old is the gait condition of the subject. Through the foot age, the falling risk can be quantified. The foot age is computed through the four gait features (step length, step center of sole pressure (CSP), distance of single supporting period, and time of double support period) [32].

The Minimum Foot Clearance (MFC) is another foot state feature that indicates the vertical distance between the lowest point of the foot of the swing leg and the walking surface during the swing phase of the gait cycle. The foot clearance is an important gait parameter that is related to the risk of falling. The low foot clearance for a step during the walking increases the probability of fall because of hitting to an obstacle. The foot clearance is extensively studied to detect trips and falls [33, 43, 44].

4. Machine Learning Algorithm

Features extracted from the input signals are processed by a machine learning algorithm in order to classify the abnormal behavior and the normal daily activity. Exploited machine learning algorithms in FPPSs are described in following.

(1) *Threshold-based Algorithm* utilizes a threshold to classify the feature set of the user gait. After extracting the desired features from the input signals, these features are compared with predefined thresholds. Since the thresholds have an important effect on the performance of the algorithm, the biggest challenge of a threshold-based algorithm is determining the thresholds. Moreover, the performance of the algorithm depends on the number of features which need to be analyzed. However, complexity and power consumption of this type of algorithms are low, so it can be adequate for devices with limited resources. Some examples of different FPPSs that exploit a threshold-based algorithm are described in the following.

Features of the acceleration signal of human upper trunk [30] in a short time interval before the fall are denoted as λ. After obtaining the ATS of the user, P(ATS $|\lambda$) states the probability of a fall occurrence during the user motion. Two thresholds P1 and P2 are specified to predict and detect a fall. As Figure 4 illustrates, the output of P(ATS $|\lambda$) is an input to the algorithm. Then, based on predefined thresholds, if P is higher than P1, the fall risk is notified, if P is higher than P2, a possible fall is noticed.

SMV, SMA, peak-to-peak, and derivative of acceleration signals are computed as feature set of user gait [35]. Afterwards, thresholds are determined to define a near fall state.

The gait status can be classified based on mean and standard deviation of stability and symmetry [34]:

(i) If index ≤ mean+std, then the gait status is normal: the subject walks normally and there is not fall risk.

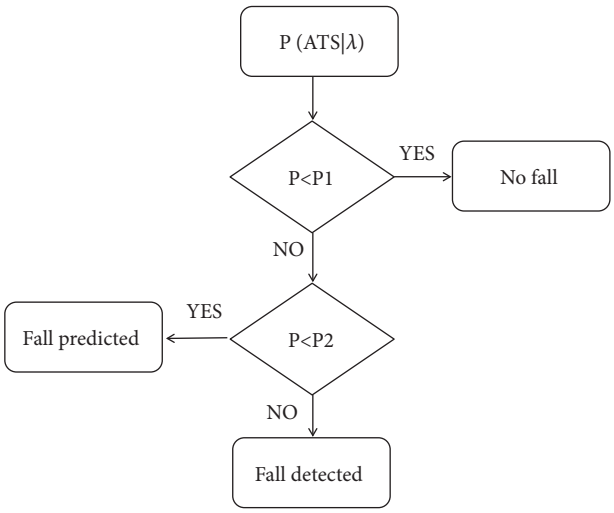

Figure 4: Threshold-based algorithm.

(ii) If mean+std < index ≤ 3∗mean, then the gait status is attentive: the subject needs to care when walking.

(iii) If index > 3∗mean, then the gait status is dangerous: the subject should present a risk to fall.

(2) *Decision Tree* (DT) is a directed tree with a root node without incoming edges and all other nodes, known as decision nodes, with one incoming edge and possible outcoming edges; a leaf node is a node without outcoming edges. At the training stage, each internal node splits the instance space into two or more parts. After that, every path from the root node to a leaf node forms a decision rule to determine which class a new instance belongs to [45]. Each internal node represents a test on an attribute or on a subset of attributes, and each edge is labeled with a specific value or range of values of the input attributes. DT is a fast algorithm but the computation cost on the tree grows as the size of the tree increases.

Figure 5 illustrates how a decision tree algorithm can be used in the classification of normal and abnormal walking [14–16]. Firstly, accelerometer and gyroscope signals are collected, then a general tilt vector is computed. Afterwards, appropriate features (e.g., energy; Hjorth parameters) are calculated from tilt vector. Then, DT is used to determine the abnormal walking.

(3) *Support Vector Machine* (SVM) finds the best hyperplane with the maximum margin to separate two classes. SVM can be defined as linear or nonlinear according to the kind of hyperplane function. SVM is a prevailing classification model for gait pattern recognizing [46–48]. SVM can be used to determine the threshold value to classify the user gait [30].

(4) *Fuzzy Logic* defines a membership function in order to assign to objects a grade of membership ranging between zero and one. For example, if X is a class of objects, with a generic element denoted by x, a fuzzy set A in X is characterized by a membership function $f_A(x)$. The value of $f_A(x)$ represents the "grade of membership" of x in A, which is a real number in the interval $[0, 1]$. The nearer the value of $f_A(x)$ to unity, the higher the grade of membership of x is in A [49].

Based on the relationship between fall risk and age, the fuzzy logic is used to prevent a fall using the sole pressure sensor to estimate the age [32]. Firstly, the fuzzy membership function for young age, μ_Y, middle age, μ_M, and elderly age, μ_E, are calculated based on the four extracted features (step length, step center of sole pressure width, distance of single supporting period, and time of double support period) of the user gait. Then, a fuzzy logic is used to estimate the foot age.

5. Evaluation Criteria

Evaluation criteria of a machine learning algorithm are described in the following. In all presented formulas, P and N represent the total number of positive and negative instances. A positive and negative instance can be defined as an abnormal/normal walk. True Positive (TP) and True Negative (TN) are defined as correct identification of a true classification of positive and negative instance, respectively. False Positive (FP) and False Negative (FN) misidentify positive and negative instances, respectively.

(1) *Specificity* or *True Negative Rate* (TNR) measures the rate of negative instances that are correctly identified as negative:

$$Specificity = \frac{\#TN}{\#TN + \#FP} \tag{6}$$

Moreover, *Generality* is computed as 1 - *Specificity*.

(2) *Sensitivity* or *True Positive Rate* (TPR) measures the rate of positive instances that are correctly identified as positive:

$$Sensitivity = \frac{\#TP}{\#TP + \#FN} \tag{7}$$

(3) *Accuracy* of an algorithm computes the number of samples correctly classified:

$$Accuracy = \frac{\#TP + \#TN}{\#P + \#N} \tag{8}$$

(4) *Error rate* is the number of wrong classifications:

$$Error\ Rate = \frac{\#FP + \#FN}{\#P + \#N} \tag{9}$$

(5) *Precision* is the percentage of the samples correctly classified as true:

$$Precision = \frac{\#TP}{\#TP + \#FP} \tag{10}$$

(6) *Recall* is the percentage of truly classified positive samples:

$$Recall = \frac{\#TP}{\#TP + \#FN} \tag{11}$$

It should be noted that one criterion alone may not be sufficient to evaluate the algorithm.

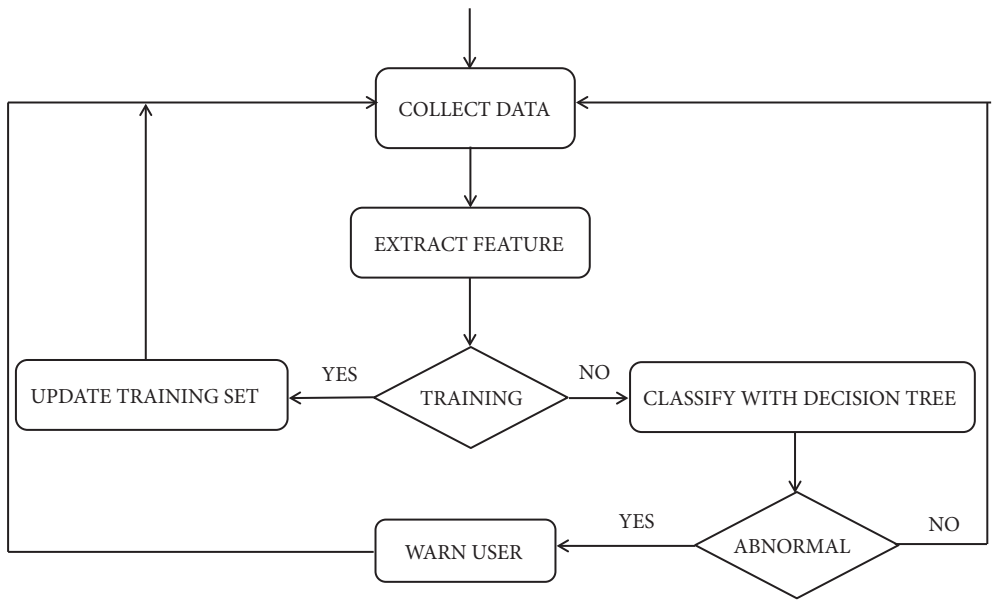

Figure 5: Fall prediction and prevention algorithm based on decision tree.

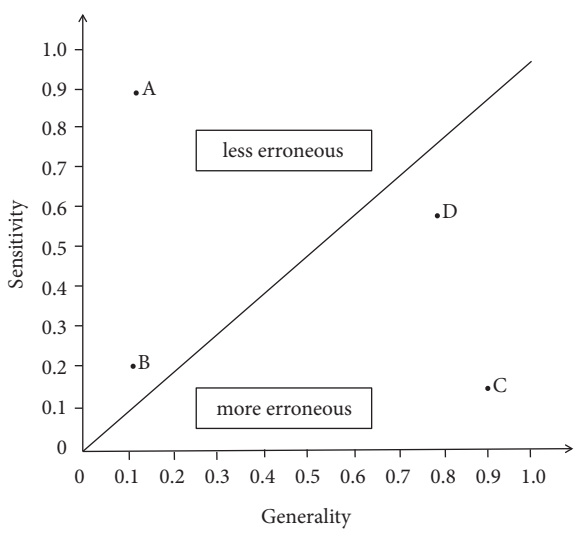

Figure 6: ROC plot of classifiers.

The Receiver Operating Characteristic (ROC) curve can be used to compare different algorithms. The ROC curve is a graphical plot that illustrates the performance of a classifier [50]. Generality and sensitivity are plotted on x and y axes of the ROC plot, respectively. The best classifier is located at the top left corner of the ROC graph, which represents 100% sensitivity and 100% specificity. The diagonal line from the left bottom to the top right corner divides the ROC space into two parts. The space above the diagonal represents classification with few errors, while the space below the line shows more erroneous results. For example, Figure 6 compares four possible algorithms: A(0.1,0.9), B(0.1,0.22), C(0.9,0.15), and D(0.8,0.6). A has the best prediction among the four instances. The further the result is from the diagonal in the above space, the better the accuracy is. C is the worst among the four instances, because it is below and far from the diagonal line. B is a good classifier but not as much as A, because it is above but not far from the diagonal line. Moreover, since D is closer to diagonal line, it is more acceptable than C.

To show how ROC curve is plotted, the output of two classifiers is illustrated in Figure 7. The x-axis shows the probability that the user gait is abnormal, and the y-axis represents the number of instances with the same probability. For instance, point (0.8, 5) means that the gait of 5 users is predicted as abnormal with probability 0.8, and the gait of all users is abnormal because it is located along the abnormal distribution. To prepare the ROC curve, firstly, a random variable X is defined and a threshold (T) is set. Everything above the threshold ($X > T$) is classified as abnormal and below the threshold ($X < T$) as normal. Then, sensitivity and generality of this classification with threshold T are computed. To generate the ROC curve, the sensitivity versus the generality for all possible thresholds should be plotted. Figure 7(a) shows a classifier with its associated ROC curve. Since the distributions of normal and abnormal cases barely overlap, the corresponding ROC curve of the classifier is close to the upper left corner of the plot. Figure 7(b) shows another classifier, where the distribution of normal and abnormal cases overlap almost completely, so the ROC curve of the classifier is close to diagonal line.

6. Experimental Results

In this section, the state-of-the-art FPPSs with accelerometer and gyroscope have been implemented and then compared according to the criteria described in Section 5.

First objective of the experiment is empirical comparison of fall factors to find the most representative one among

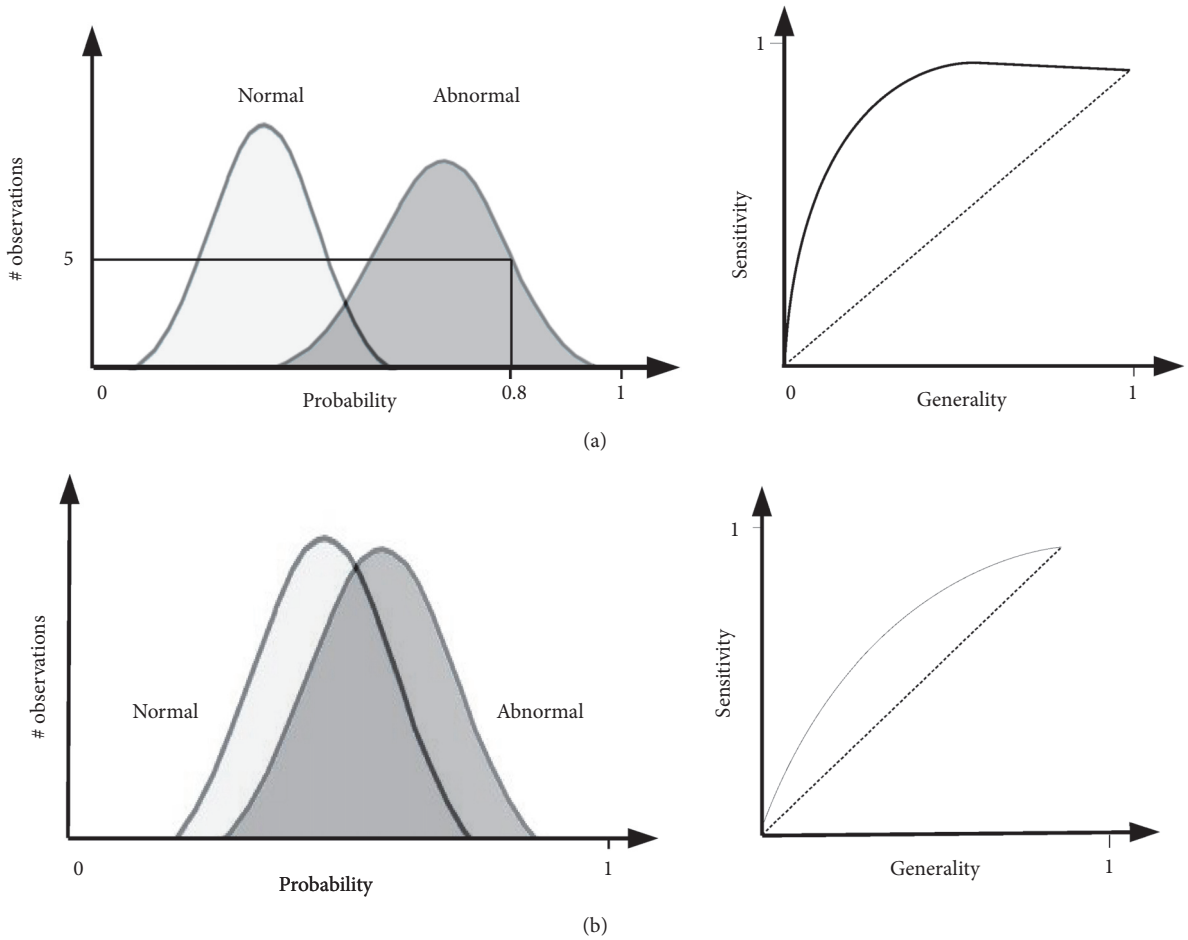

Figure 7: ROC of a good classifier (a) and poor classifier (b).

acceleration, tilt, and velocity. The second objective is evaluating different machine learning algorithm based on presented features for each fall factor in the presented dataset. It should be noted that the goal of the experiment is not finding an optimal feature set for each fall factor.

A fall occurs due to passive causes like weakness, balance deficit, gait deficit, visual deficit, and mobility limitation. The following are the most frequently used methods to simulate an abnormal gait, which can lead to a fall:

(i) Walking with straightened knee [14–16].

(ii) Walking with leg length discrepancy [14–16].

(iii) Walking on a rough surface [51].

(iv) Walking through obstacles [35].

In the experiments, an abnormal walk is modeled as irregular gaits obtained by walking through obstacles which can cause stepping, tripping, and stumbling. Thus, a flat area with different types of obstacles is prepared. Obstacles included empty boxes (height: 37 cm, length: 20 cm, and width: 17 cm) and plastic bottles (height: 20 cm; diameter: 6 cm), which are placed 60 cm far from each other.

Since the real falls cannot be experimented due to the risk of injury, only forward fall is simulated with protection. However, the applied method in this paper can easily be generalized to other type of falls (i.e., backward; lateral). Users are asked to walk through obstacles without looking them for 10 seconds. The users in the experiments are 19 men with weight in the range of 65-110 kg and height in the range of 160-185 cm and 3 women with weight in the range of 50-60 kg and height in the range of 157-165 cm. All users are without gait disturbances. Furthermore, users are in the range of 18-35 years old. Data is collected through MATLAB R2015b. WEKA tool version 3.6.13 (WEKA is an open source data mining tool that can be downloaded from http://www.cs.waikato.ac.nz/ ml/weka/) has been used to classify the obtained data.

An iPhone 4S is adopted in the experiments, equipped with the STMicro STM33DH 3-axis accelerometer and the STIMicro AGDI 3-axis gyroscope. Commonly adopted sampling frequencies range from some dozens to hundred of Hertz such that they are constant and higher than gait cycle frequency. In the experiment, the frequency is fixed to 10Hz. Since the body Center of Pressure (COP) reveals several information of user gait, the smartphone is placed on the lower back of trunk, near the real Center Of Mass (COM) position, assuming that this position moves parallel to the COP, and the same acceleration and positions will be measured [52].

In the following, velocity, acceleration, and tilt fall factors with different combinations of machine learning algorithms have been evaluated.

SMA, SVM, maximum derivative, Hjorth parameters, peak-to-peak, and energy features of acceleration are considered in the experiments. Moreover, mean, standard deviation, energy, and Hjorth parameters of tilt and mean of velocity are considered as the features in the experiment. The performance of different features with a particular machine learning algorithm was already presented in previous studies. The novelty of this paper is the comparison of different fall factors with presented features on different machine learning algorithm.

Table 1 shows the result of the experiments when the decision tree and support vector machine are selected to classify the obtained data. As reported in the last line of Table 1, a higher ROC area corresponds to a better accuracy. The comparison of the results from different fall factors shows that the tilt always has better accuracy among the other fall factors. Combination of tilt with decision tree gives 83.9% of accuracy and with support vector machines gives 65.7% of accuracy. So, the preciseness of tilt factor shows that it can be adopted as a deserved representative of fall factors in FPPSs implemented with personal monitoring device.

There are several factors that can affect the decision to choose a machine learning algorithm. In literature there are several studies which compare the performance of different machine learning algorithms [53–55]. The best machine learning algorithm cannot be universally identified because machine learning algorithms are task-dependent. In addition, the best machine learning algorithms for a particular task depends on several factors. The feature set is the primer factor which impacts on the performance. In addition, also dataset characteristic such as number of samples, type and kind of data, and skewed data can impact on the performance. In a skewed dataset, almost all samples fall in one particular class rather than in the other classes.

The comparison of the different machine learning algorithms with the presented setting in this paper shows that DT has better performance than SVM in all the combinations. Although DT has better performance comparing to the SVM, it cannot be generalized to all experiments and datasets. The reason is based on the no free lunch theorems that indicates there is not superiority for any machine learning algorithm over the others, so the best classifier for a particular task is task-dependent [56, 57]. However, it should be noted that DT requires more memory space when the size of the tree grows. Moreover, as Figure 8 shows, the tilt fall factor with DT algorithm has the best performance to detect abnormal walks, and speed has the lower performance. Since in the experiment patients tilt in a direction, it is not surprising that tilt is the most representative fall factor.

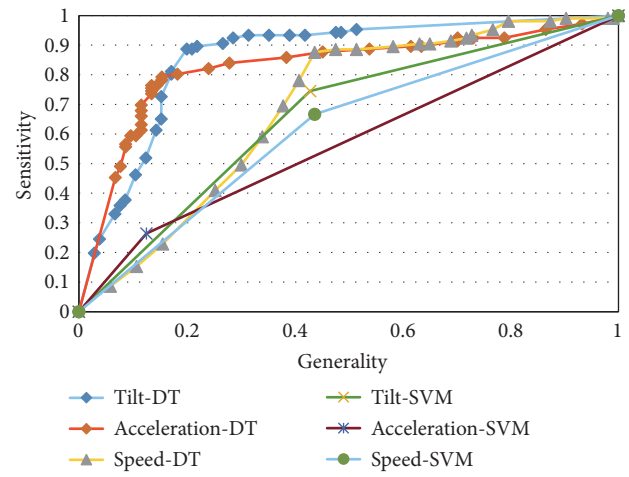

Figure 8: ROC on different approaches of 22 users with 110 samples.

7. Conclusion

This paper analyzed different aspects of fall prediction and prevention systems. It provides a comprehensive overview of various fall factors and corresponding features. Moreover, different machine learning algorithms in fall prediction and prevention systems have been reviewed. Furthermore, multiple combinations of features and fall prediction and prevention algorithms have been experimentally evaluated to find an optimal solution. Based on the presented results tilt features in combination with the decision tree algorithm present the best performance among the other permutations of fall factors and fall prediction and prevention algorithms.

Future work may include

(i) generalizing the dataset to older adults or patients with neurological disorders;

(ii) adopting new machine learning algorithms in the comparison list;

(iii) comparing systems across other performance metrics such as time, accuracy with respect to the size of dataset, number of features, memory consumption, and power consumption.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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References

[1] R. Rajagopalan, I. Litvan, and T.-P. Jung, "Fall prediction and prevention systems: Recent trends, challenges, and future research directions," *Sensors*, vol. 17, no. 11, 2017.

[2] V. R. L. Shen, H.-Y. Lai, and A.-F. Lai, "The implementation of a smartphone-based fall detection system using a high-level fuzzy Petri net," *Applied Soft Computing*, vol. 26, pp. 390–400, 2015.

[3] Y. Li, K. C. Ho, and M. Popescu, "A microphone array system for automatic fall detection," *IEEE Transactions on Biomedical Engineering*, vol. 59, no. 5, pp. 1291–1301, 2012.

[4] Y. Zigel, D. Litvak, and I. Gannot, "A method for automatic fall detection of elderly people using floor vibrations and soundProof of concept on human mimicking doll falls," *IEEE Transactions on Biomedical Engineering*, vol. 56, no. 12, pp. 2858–2867, 2009.

[5] Z.-P. Bian, J. Hou, L.-P. Chau, and N. Magnenat-Thalmann, "Fall detection based on body part tracking using a depth camera," *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 2, pp. 430–439, 2015.

[6] Y. Wang, K. Wu, and L. M. Ni, "WiFall: device-free fall detection by wireless networks," *IEEE Transactions on Mobile Computing*, vol. 16, no. 2, pp. 581–594, 2017.

[7] H. Wang, D. Zhang, Y. Wang, J. Ma, Y. Wang, and S. Li, "RT-Fall: a real-time and contactless fall detection system with commodity WiFi devices," *IEEE Transactions on Mobile Computing*, vol. 16, no. 2, pp. 511–526, 2017.

[8] K. Zhao, K. Jia, and P. Liu, "Fall detection algorithm based on human posture recognition," in *Proceedings of the International Conference on Intelligent Information Hiding and Multimedia Signal Processing*, pp. 119–126, 2016.

[9] K. H. Frith, A. N. Hunter, S. S. Coffey, and Z. Khan, "A longitudinal fall prevention study for older adults," *The Journal for Nurse Practitioners*, vol. 15, no. 4, pp. 295–300.e1, 2019.

[10] K. Khanuja, J. Joki, G. Bachmann, and S. Cuccurullo, "Gait and balance in the aging population: Fall prevention using innovation and technology," *Maturitas*, vol. 110, pp. 51–56, 2018.

[11] M. Hemmatpour, R. Ferrero, F. Gandino, B. Montrucchio, and M. Rebaudengo, "Nonlinear predictive threshold model for real-time abnormal gait detection," *Journal of Healthcare Engineering*, vol. 2018, Article ID 4750104, 9 pages, 2018.

[12] M. Hemmatpour, R. Ferrero, B. Montrucchio, and M. Rebaudengo, "A neural network model based on co-occurrence matrix for fall prediction," in *Proceedings of the International Conference on Wireless Mobile Communication and Healthcare*, pp. 241–248, 2016.

[13] M. Hemmatpour, M. Karimshoushtari, R. Ferrero, B. Montrucchio, M. Rebaudengo, and C. Novara, "Polynomial classification model for real-time fall prediction system," in *Proceedings of the Computer Software and Applications Conference*, vol. 1, pp. 973–978, July 2017.

[14] A. J. A. Majumder, I. Zerin, S. I. Ahamed, and R. O. Smith, "A multi-sensor approach for fall risk prediction and prevention in elderly," *ACM SIGAPP Applied Computing Review*, vol. 14, no. 1, pp. 41–52, 2016.

[15] A. J. Majumder, I. Zerin, M. Uddin, S. I. Ahamed, and R. O. Smith, "Smartprediction: A real-time smartphone-based fall risk prediction and prevention system," in *Proceedings of the Research in Adaptive and Convergent Systems*, pp. 434–439, ACM, October 2013.

[16] A. J. A. Majumder, F. Rahman, I. Zerin, W. Ebel Jr, and S. I. Ahamed, "iPrevention: Towards a novel real-time smartphone-based fall prevention system," in *Proceedings of the 28th Annual ACM Symposium on Applied Computing*, pp. 513–518, ACM, March 2013.

[17] P. Di, J. Huang, K. Sekiyama, and T. Fukuda, "A novel fall prevention scheme for intelligent cane robot by using a motor driven universal joint," in *Proceedings of the International Symposium on Micro-NanoMechatronics and Human Science (MHS '11)*, pp. 391–396, IEEE, 2011.

[18] Y. Hirata, A. Muraki, and K. Kosuge, "Motion control of intelligent passive-type walker for fall-prevention function based on estimation of user state," in *Proceedings of the 2006 IEEE International Conference on Robotics and Automation (ICRA '06)*, pp. 3498–3503, May 2006.

[19] A. Shumway-Cook, S. Brauer, and M. Woollacott, "Predicting the probability for falls in community-dwelling older adults using the timed up & go test," *Physical Therapy in Sport*, vol. 80, no. 9, pp. 896–903, 2000.

[20] S. W. Muir, K. Berg, B. Chesworth, and M. Speechley, "Use of the berg balance scale for predicting multiple falls in community-dwelling elderly people: a prospective study," *Physical Therapy in Sport*, vol. 88, no. 4, pp. 449–459, 2008.

[21] B. Najafi, K. Aminian, F. Loew, Y. Blanc, and P. Robert, "Measurement of stand-sit and sit-stand transitions using a miniature gyroscope and its application in fall risk evaluation in the elderly," *IEEE Transactions on Biomedical Engineering*, vol. 49, no. 8, pp. 843–851, 2002.

[22] B. J. Vellas, S. J. Wayne, L. Romero, R. N. Baumgartner, L. Z. Rubenstein, and P. J. Garry, "One-leg balance is an important predictor of injurious falls in older persons," *Journal of the American Geriatrics Society*, vol. 45, no. 6, pp. 735–738, 1997.

[23] E. T. Horta, I. C. Lopes, J. J. Rodrigues, and S. Misra, "Real time falls prevention and detection with biofeedback monitoring solution for mobile environments," in *Proceedings of the IEEE 15th International Conference on e-Health Networking, Applications and Services (Healthcom '13)*, pp. 594–600, IEEE, Lisbon, Portugal, October 2013.

[24] L. Z. Rubenstein, "Falls in older people: epidemiology, risk factors and strategies for prevention," *Age and Ageing*, vol. 35, supplement 2, pp. ii37–ii41, 2006.

[25] P. E. Roos and J. B. Dingwell, "Influence of simulated neuromuscular noise on movement variability and fall risk in a 3D dynamic walking model," *Journal of Biomechanics*, vol. 43, no. 15, pp. 2929–2935, 2010.

[26] Md. Shahiduzzaman, "Fall detection by accelerometer and heart rate variability measurement," *Global Journal of Computer Science and Technology*, vol. 15, no. 3, 2016.

[27] B. N. Ferreira, V. Guimaraes, and H. S. Ferreira, "Smartphone based fall prevention exercises," in *Proceedings of the 15th International Conference on e-Health Networking, Applications & Services (Healthcom .t13)*, pp. 643–647, IEEE, 2013.

[28] K. Cameron, K. Hughes, and K. Doughty, "Reducing fall incidence in community elders by telecare using predictive systems," in *Proceedings of the 19th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 'Magnificent Milestones and Emerging Opportunities in Medical Engineering'*, vol. 3, pp. 1036–1039, IEEE, Chicago, IL, USA, 1997.

[29] V. Guimaraes, P. M. Teixeira, M. P. Monteiro, and D. Elias, "Phone based fall risk prediction," in *Wireless Mobile Communication and Healthcare*, pp. 135–142, Springer, 2012.

[30] L. Tong, Q. Song, Y. Ge, and M. Liu, "HMM-based human fall detection and prediction method using tri-axial accelerometer," *IEEE Sensors Journal*, vol. 13, no. 5, pp. 1849–1856, 2013.

[31] V. Guimaraes, D. Ribeiro, and L. Rosado, "A smartphone-based fall risk assessment tool: measuring one leg standing, sit to stand and falls efficacy scale," in *Proceedings of the IEEE 15th International Conference on e-Health Networking, Applications and Services (Healthcom '13)*, pp. 529–533, IEEE, October 2013.

[32] T. Takeda, Y. Sakai, K. Kuramoto, S. Kobashi, T. Ishikawa, and Y. Hata, "Foot age estimation for fall-prevention using sole

pressure by fuzzy logic," in *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics (SMC '11)*, pp. 769–774, Anchorage, AK, USA, October 2011.

[33] R. Begg, R. Best, L. Dell'Oro, and S. Taylor, "Minimum foot clearance during walking: strategies for the minimisation of trip-related falls," *Gait & Posture*, vol. 25, no. 2, pp. 191–198, 2007.

[34] S. Jiang, B. Zhang, and D. Wei, "The elderly fall risk assessment and prediction based on gait analysis," in *Proceedings of the IEEE 11th International Conference on Computer and Information Technology (CIT '11)*, pp. 176–180, IEEE, Paphos, Cyprus, August 2011.

[35] A. Weiss, I. Shimkin, N. Giladi, and J. M. Hausdorff, "Automated detection of near falls: algorithm development and preliminary results," *BMC Research Notes*, vol. 3, no. 1, p. 362, 2010.

[36] M. C. Hornbrook, V. J. Stevens, D. J. Wingfield, J. F. Hollis, M. R. Greenlick, and M. G. Ory, "Preventing falls among community-dwelling older persons: results from a randomized trial," *The Gerontologist*, vol. 34, no. 1, pp. 16–23, 1994.

[37] M. E. Tinetti, J. Doucette, E. Claus, and R. Marottoli, "Risk factors for serious injury during falls by older persons in the community," *Journal of the American Geriatrics Society*, vol. 43, no. 11, pp. 1214–1221, 1995.

[38] B. J. Goldfarb and S. R. Simon, "Gait patterns in patients with amyotrophic lateral sclerosis," *Archives of Physical Medicine and Rehabilitation*, vol. 65, no. 2, pp. 61–65, 1984.

[39] R. W. Bohannon, "Correlation of lower limb strengths and other variables with standing performance in stroke patients," *Physiotherapy Canada*, vol. 41, no. 4, pp. 198–202, 1989.

[40] M. E. Tinetti, C. F. De Leon, J. T. Doucette, and D. I. Baker, "Fear of falling and fall-related efficacy in relationship to functioning among community-living elders," *Journal of Gerontology*, vol. 49, no. 3, pp. M140–M147, 1994.

[41] J. Teno, D. P. Kiel, and V. Mor, "Multiple stumbles: a risk factor for falls in community-dwelling elderly; a prospective study," *Journal of the American Geriatrics Society*, vol. 38, no. 12, pp. 1321–1325, 1990.

[42] B. Hjorth, "EEG analysis based on time domain properties," *Electroencephalography and Clinical Neurophysiology*, vol. 29, no. 3, pp. 306–310, 1970.

[43] F. Dadashi, B. Mariani, S. Rochat, C. J. Büla, B. Santos-Eggimann, and K. Aminian, "Gait and foot clearance parameters obtained using shoe-worn inertial sensors in a large-population sample of older adults," *Sensors*, vol. 14, no. 1, pp. 443–457, 2014.

[44] D. T. Lai, S. B. Taylor, and R. K. Begg, "Prediction of foot clearance parameters as a precursor to forecasting the risk of tripping and falling," *Human Movement Science*, vol. 31, no. 2, pp. 271–283, 2012.

[45] W. Dai and W. Ji, "A mapreduce implementation of c4.5 decision tree algorithm," *Journal of Database Theory and Application*, vol. 7, no. 1, pp. 49–60, 2014.

[46] R. K. Begg, M. Palaniswami, and B. Owen, "Support vector machines for automated gait classification," *IEEE Transactions on Biomedical Engineering*, vol. 52, no. 5, pp. 828–838, 2005.

[47] J. Yoo, D. Hwang, and M. S. Nixon, "Gender classification in human gait using support vector machine," in *Advanced Concepts for Intelligent Vision Systems*, pp. 138–145, Springer, 2005.

[48] D. Lai, P. Levinger, R. Begg, W. Gilleard, and M. Palaniswami, "Automatic recognition of gait patterns exhibiting patellofemoral pain syndrome using a support vector machine approach," *IEEE Transactions on Information Technology in Biomedicine*, vol. 13, no. 5, pp. 810–817, 2009.

[49] L. A. Zadeh, "Fuzzy sets, fuzzy logic, and fuzzy systems: selected papers," *World Scientific*, vol. 6, 1996.

[50] T. Fawcett, "An introduction to ROC analysis," *Pattern Recognition Letters*, vol. 27, no. 8, pp. 861–874, 2006.

[51] M. J. D. Otis and B. A. J. Menelas, "Toward an augmented shoe for preventing falls related to physical conditions of the soil," in *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics (SMC '12)*, pp. 3281–3285, IEEE, October 2012.

[52] V. Guimaraes, D. Ribeiro, and L. Rosado, "A smartphone-based fall risk assessment tool: measuring one leg standing, sit to stand and falls efficacy scale," in *Proceedings of the 15th IEEE International Conference on e-Health Networking, Applications and Services (Healthcom '13)*, pp. 529–533, Portugal, October 2013.

[53] R. Caruana and A. Niculescu-Mizil, "An empirical comparison of supervised learning algorithms," in *Proceedings of the 23rd International Conference on Machine Learning (ICML '06)*, pp. 161–168, June 2006.

[54] N. Zerrouki, F. Harrou, A. Houacine, and Y. Sun, "Fall detection using supervised machine learning algorithms: A comparative study," in *Proceedings of the 8th International Conference on Modelling, Identification and Control (ICMIC '16)*, pp. 665–670, November 2016.

[55] O. Aziz, M. Musngi, E. J. Park, G. Mori, and S. N. Robinovitch, "A comparison of accuracy of fall detection algorithms (threshold-based vs. machine learning) using waist-mounted tri-axial accelerometer signals from a comprehensive set of falls and non-fall trials," *Medical & Biological Engineering & Computing*, vol. 55, no. 1, pp. 45–55, 2017.

[56] D. H. Wolpert, "The lack of a priori distinctions between learning algorithms," *Neural Computation*, vol. 8, no. 7, pp. 1341–1390, 1996.

[57] D. H. Wolpert and W. G. Macready, "No free lunch theorems for optimization," *IEEE Transactions on Evolutionary Computation*, vol. 1, no. 1, pp. 67–82, 1997.

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Research Article

A Plurisensorial Device to Support Human Smell in Hazardous Environment and Prevent Respiratory Disease

Venere Ferraro, Lucia Rampino, and Mila Stepanovic

Department of Design, Politecnico di Milano, Italy

Correspondence should be addressed to Venere Ferraro; venere.ferraro@polimi.it

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Products embedded with wearable technologies can be a useful tool to support humans' senses in situations where they can be insufficient, mistaken, or misleading. In this article, we discuss the findings of a two-year Transnational European Research Project named "POD: Plurisensorial Device to Prevent Occupational Disease." The research was based on the evidence that human senses are not always reliable in making objective judgments. The specific field of application was coating plant, an environment that exposes workers to the risk of inhaling dangerous particles. The results obtained in the first part of the research pointed out that workers, largely relying on their sense of smell, which instead is often untrustworthy, do not protect themselves enough. Based on this ground, we designed a wearable system for providing workers with objective data both on their respiration activity and on the quality of the air in the working environment, with the ultimate goal of engaging them in wearing their personal protecting equipment (PPE). The article describes the development and testing of the solution; an example of how wearable technologies can enhance senses and improve workers' health.

1. Introduction

A report of the Scientific Committee on Occupational Exposure Limits (SCOEL) published on June 2014 highlighted that 15% of all adult respiratory diseases are a consequence of work-related exposures. Within working environments, volatile organic compounds (VOC) are one of the highest causes of asthma, lung cancer, chronic obstructive pulmonary disease, cystic fibrosis, and respiratory tract infections. Following this data, the Research Project, "POD: Plurisensorial Device to Prevent Occupational Disease," was carried out by the Design Department of Politecnico di Milano, in collaboration with the Department of Design Engineering from Delft University of Technology and Comftech, an Italian company specialized in smart textile. The project faced the issue of coating plant environments, where workers are highly exposed to the risk of inhaling hazard substances. According to the International Labour Office, prevention is the best way to reduce the number of diseases and improve workers' health. There are two levels of prevention: (i) environmental monitoring and (ii) the use of personal protective equipment (PPE). PPEs are mandatory by law but, despite this, their usage is comparatively sparse. The objective of the research was to understand why the use of PPEs is still poor and verify if the design of a wearable system based on sensor technology could enhance users' awareness about the importance of wearing protective devices.

Our research started with both a general exploration of human senses, focusing on smell, and an analysis of how workers perceive the environment through their senses.

2. How Workers Sense and Act

In order to understand how workers sense and act, we needed to both interview and observe them in a real coating plant. For such an analysis, the choice of the proper participants was relevant. Thanks to the support of Anver (Associazione Italiana Verniciatura, i.e., the Italian Painting Association), three SMEs from the northern area of Milan were identified. These three companies perform similar activities within their coating plants: coating of furniture and of small-to-medium mechanical parts.

Figure 1: Workers working in a cabin.

The three chosen coating plants have less than 20 employees. The main reason for this choice was that, in large companies, the operations of lacquering and finishing are often automated (i.e., performed by robots). Moreover, in small companies, it is easier to establish a direct contact with workers, to observe their behaviour, and to collect useful feedbacks. The first company is specialized in finishing and lacquering of metals and polymers, and the second one in finishing and lacquering of wood, steel, and metal, and so does the last one.

The user analysis, performed in each of the three companies, was divided into two parts: (i) observation: analysis of workers' behaviours in order to understand if and how they use current PPEs; (ii) interviews: with both workers and employers, in order to figure out which was their perception about the risk in the working place, what was motivating/demotivating workers in wearing the personal protective equipment, and if they were willing to accept an interactive monitoring system.

Both observation and interviews were led by three researchers and involved a total number of twenty workers (one woman and nineteen men) and were carried out between December 2015 and January 2016. We first observed the workers while performing their tasks, and then we submitted an interview addressing four main topics: (1) working activity and protective equipment, (2) mask's aesthetic and comfort, (3) safety perception, and (4) the use of personal technological devices. Hereafter, our main findings are described.

First of all, in each analyzed coating plant, we noticed the presence of a cabin where the lacquering activity is performed (see Figure 1). The cabin is equipped with an aspiration system that takes away the varnish particles from the indoor environment, so as to reduce the inner air pollution.

While in the cabin, all workers are supposed to wear a Personal Reusable Protective Mask for their personal safety but, as far as we observed, they do not. Indeed, even if the Volatile Organic Compounds (both in powder and liquid paints) have a very strong smell, after a while, getting used to such odours, the workers' perception about them decreases. Therefore, not perceiving the smell intensity anymore, they do not feel any necessity to wear the protective mask, despite being regularly exposed to dangerous particles. These workers are indeed experiencing the so-called "adaptation phenomenon," that is, the reduction in the perception of an odour following a long-term exposure to it [1].

We were really able to experience such adaptation: indeed, both during the observation and the interviews, workers were comfortable and did not seem to perceive any bad odour, while we had a completely different perception. One of us started coughing and had to leave the cabin, another one immediately felt irritation of her respiratory tract and saw blue particles (a worker was using a blue paint) on the tissue after blowing her nose, and the last one hardly stopped sneezing.

All the interviewed workers (20) stated that they wear the Protective Mask just when the so-called overspray is visible, a circumstance that occurs only when they are painting large objects or object with a complex geometry. In addition, they trust the factory aspiration system, judging it enough to protect them from the inhalation of dangerous particles and prevent them from respiratory diseases.

Other reasons for not wearing any protection are the following: the mask's discomfort due to the stiff connection to the face and the poorly breathable fabric, suffering from skin allergies (especially during summer time), and being distracted and forgetting about them. All the interviewed workers asked for a new mask designed with more attention to wearability and comfortable materials.

Moreover, the user session made it explicit that each worker relies on his/her own sense of smell and that, being immersed in the same environment, the workers tend to conform to the behaviours and opinions of others. Since their smell is altered, their perception towards the possibility of severe diseases (i.e., incurring in lung cancer, chronic obstructive pulmonary disease, cystic fibrosis, and respiratory tract infections) is modified. So, the problem becomes even more severe—workers are likely to rely on both their and other ones' subjectivity. We listened to statements like: "Well, he has been working here for ten years. If he is not wearing the mask, it means that it is not necessary"; "If all my colleagues wore the mask, I would do it as well."

According to the World Health Organization and Europe Mortality database in 2011 in Europe, it was estimated that a total of 7200 cases of respiratory diseases were related to occupational exposures to VOC and dust. The annual Inail (i.e., Italian National Institute for Insurance towards Works related Injuries) Report from 2015 confirms the European trend, putting respiratory diseases at the third place (13,5%) in Italy among occupational ones, also stressing the severity of their consequences. Such data show the importance of wearing PPEs in order to prevent the inhalation of dangerous particles.

To us, also thanks to our personal experience in the coating cabin, the severity of the risk was evident. Furthermore, an emblematic story was told to us by a worker: his father, a

nonsmoker, used to work in the same coating plant and died from lung cancer at the age of 65. Despite that, the worker at stake does not perceive the correlation between not wearing the mask and getting sick. Therefore, he does not protect himself. This story, together with the statistical data related to respiratory diseases, reinforced our willingness to introduce a medium to support workers' sense of smell and sensitize them towards the use of PPEs.

The investigated workers are not fully aware of the importance of regularly wearing protective equipment since, without feeling bad odours anymore, they do not perceive Volatile Organic Components as dangerous to their respiration system. They are thus trapped in a vicious circle: being used to certain odour reduces perception; reduced perception is disabling seizing of risks. Until confronted with an "abstract" concept (i.e., protecting their health), it is hard to make people change their behaviour; they need to perceive a tangible benefit [2]. Giving a tangible benefit, in this case, could mean excluding subjective opinion by introducing objective data that can enhance the workers' perception making them aware of the risk they are taking.

As already noted, besides the lack of proper odours perception, the workers do not wear the mask because of comfort issues. They all stressed that if the mask had been more comfortable and made of different materials, they would be willing to wear it more regularly. This was another important insight to be taken into consideration in the next steps.

Regarding the embedding of technology, it was necessary to understand if and how users were willing to accept the idea of wearing a technological apparatus and if they had any kind of preparation related to technologies. We thus described to our potential users the possibility to have a wearable system informing them about the quality of the air and monitoring their personal vital parameters. 85% of them responded that they were interested in having feedbacks about the air quality and their vital parameters. They stated that, confronted with evidences about their exposure to chemicals and their health status, they would be more motivated to wear the protective mask.

3. The Human Sense of Smell

The user session with the workers of the three coating plants confirmed us that smell, as all human senses, may generate a perception that is not fully realistic. Even if we are not always aware of it, our sense of smell plays a very important role in our everyday life, constantly monitoring the environment around us. In any moment of our live, we perceive different odours: from the coffee we drink in the morning to the soap we use for washing to the fabric softener of the clothes we wear. In general, smell's three main purposes are (i) the detection of hazards, (ii) the detection of pheromones, and (iii) the detection of food.

However, human senses have their limits that can be made more evident by factors as habits, illness (e.g., a cold is sufficient to neutralize our sense of smell), or pathology. Due to such limits, our senses can be deceived, as is evident in any case of optical illusion [3, 4].

In our case, the most important feature to stress is that, among all human senses, smell is the one that "get bored" more easily: when entering a florist or a pastry shop, we are very aware of all the aroma surrounding us but after some minutes we are no longer able to smell them. Humans have the tendency to get used to odours, at the point that they do not perceive them anymore or not with the same intensity as before [3]. According to Dalton and Wysocki, "Any individual living or working in an odorous environment can experience changes in odour perception, some of which are long lasting. Often, these individuals report a significant reduction in the perception of an odour following long-term exposure to that odour (adaptation)" [1].

This phenomenon can be readily observed in situations where ambient odours are chronically present as for the case of workers in the observed coating plants. Individuals who live or work in such an odorous environment often report that, with continuous exposure, their perception of the ambient odour intensity is greatly reduced. Furthermore, as we noticed with our users, the perceptual changes that result from daily exposure can be quite profound and durable. For example, it is commonly reported that, following extended absences (hours to days) from the odorous environment, reexposure to the odour may still fail to elicit perception at the original intensity [5]. In our case study, this perceptual change seems to represent a very persistent kind of adaptation.

4. Wearable Technology and Sensors

When the limits of our senses endanger our health, it might be the case to introduce a technological medium. Technology might resolve the problem of subjective perception by collecting objective data that can be communicated to users through smart devices. If well designed, such communication can reach the aim of changing humans' habits and behaviours without coercion [6].

In our idea, technology could enhance workers' perception of risk, providing them with objective data to base their decision on wearing PPEs upon. We focused on the use of smart technologies belonging to the class of wearable technology, which represents a large and rapidly increasing research area in sectors like medical devices, electronics, textiles, and telecommunication [7]. The purpose of wearable technologies is indeed to facilitate everyday life and also protect and inform users in order to avoid human errors, as those related to subjectivity of senses and perception [8]. These technologies are mostly based on sensors [9] and can monitor and/or stimulate, treat, and replace biophysical human functions. This way, wearable technologies led towards a stimulation and extension of our sensoriality [10].

Nowadays, the market offers wearable devices like the Philips Respironics CAPNO2mask Mainstream Monitoring Mask, a noninvasive mask for adults with respiratory disease which simultaneously delivers oxygen and measures mainstream end-tidal CO_2. Another example is the IBM Employee Wellness and Safety solution, an IoT solution for preventing

Figure 2: POD Interactive Protective System: (1) Electronic Nose Device, (2) Personal Protective Reusable Mask, (3) Chest Band, and (4) Mobile Application.

injuries at the workplace in different industries. IBM provides to workers the mobile app that operates in real time and informs the worker about the potential work-related risks.

Besides few examples like the above-mentioned two, in the field of health, wearable technologies have so far predominately focused on diet and physical activity, motivating physical activity and maintaining exercise routines. A good example is JAWBONE, a wrist-band that monitors and tracks the user's sleep, activity, and diet. All the data are provided to users via a mobile app. Another widespread use of sensor technology, usually not wearable, is outdoor or indoor environmental monitoring aimed at informing users about pollution in their cities, homes, offices, and so forth (i.e., Electronic Nose by NASA; TZOA by Woke Studios; Speck™).

Despite sparse applications, in our case, a wearable system could give more control to the user by focusing on risk prevention. According to IJsselsteijn et al. [11], in the next years, one of the strongest areas of innovation related to wearable technologies will indeed regard preventive health systems.

The value of wearable technologies also lies in their proximity to human body, synthetized in the paradigm: anytime, everywhere, and by anyone [12]. They can provide real-time feedbacks, informing the user immediately if something goes wrong.

5. Overcome the Weakness of Smell: POD Wearable System

5.1. Method. The insights from the user session, confronted with the literature review, let us to reason about designing the wearable system named POD (Plurisensorial Device to Prevent Occupational Disease) based on sensor technology that monitors both the air quality and the worker's vital parameters. Our aim was to influence the perception of risk by workers, so as to motivate them to wear the protective equipment. We generated the entire system according to the results discussed in Ferraro et al. (2018) [13], following the typical phases of a design process [14–16]:

(i) User Analysis: it lasted four months (participants selection, user observation, and semistructured interviews) engaging a total number of twenty workers.

(ii) Ideation Phase: it included a concept generation phase and a focus group with users to select the most promising concept. It lasted four months.

(iii) Concept Development: it lasted eight months and was related to the engineering and the prototyping of the system.

(iv) User Testing: it lasted two months and was performed within the first of the analyzed companies thanks to very open-minded owner willing to innovate and experiment.

We developed a system made up of (i) a wearable alert device called the Electronic Nose Device, (ii) a Smart Personal Protective Reusable Mask, (iii) a Chest Band, and (iv) a Mobile Application (Figure 2). The system POD was both engineered and prototyped.

The Electronic Nose Device, illustrated in Figure 3, gives real-time feedbacks to the user about the air quality in the coating plant. It replaces the human nose in sensing the environment. It is based on a Volatile Organic Compound sensor that monitors the level of Volatile Organic Compounds (VOCs). The selected sensor module (USM-MEMS-VOC) is based on a highly stable TGS 8100 semiconductor MEMS sensor. This module uses short response times and measurement cycles thanks to specific Digital Sampling Technology (DSP). Additionally, this sensor needs less than 20 mA in continuously operation mode and it requires 1,8V voltage supply which is suitable for an application as ours, where the device has to be operative up to 9 hours. Another advantage was the small dimension of the module (17x15x3mm) which makes it suitable for the implementation in wearable devices.

The Electronic Nose gives feedbacks leveraging on two senses not altered by the working environment: the vision and the touch (Figure 4). Indeed, the RGB LED placed on the PCB board provides three different colors: green (everything is fine), yellow (the situation is getting dangerous), and red (the VOC concentration is very high) associated, respectively,

Figure 3: Assembly of Electronic Nose Device with electronics.

Figure 4: Feedback about air quality Electronic Nose Device.

with no vibration, low vibration, and strong vibration. The data gathered from the VOC sensor are transmitted and stored via Bluetooth technology (BLE module integrated on the PCB) to the mobile app. These data can be visible to the user not only in real time but also as a long-term passive feedback, by showing both the daily output about the air quality and the air quality chart over a longer period (i.e., weekly or monthly report).

Such a device becomes a medium between the human senses and the environment, supplying the reduced perception of the smell and reminding workers to wear the mask in order to safeguard their health.

We also redesigned the mask, evaluated by the interviewed workers as unpleasant to wear. We decided to solve such a problem by focusing on the use of alternative materials (see Figure 5). In order to improve the transpiration and reduce the risk of skin irritation during summer, we replaced traditional rubber with a thermoformed spacer textile padded with soft foam. In order for the mask to be softer and smoother in contact with the head, we used thermoformed textile for the laces.

Another problem highlighted in the user session was the weight of the mask. For this reason, we decided to use the nonwoven thermoformed fabric for the carbon filters that are then welded to the mask's base. This way, by decreasing the use of plastic pieces, we reduced the overall weight of the mask.

The mask is also equipped with a temperature and humidity sensor aimed at monitoring the user's breath (humidity and respiration frequency) and checking if the mask is worn: if the mask gets in contact with the face, the sensor automatically turns on and the information is transmitted to the Mobile Application via Bluetooth. Here we choose to integrate the Sensirion SHT31 sensor which relies on innovative CMOSensor® technology that makes it very accurate. Considering that we needed a sensor easy to

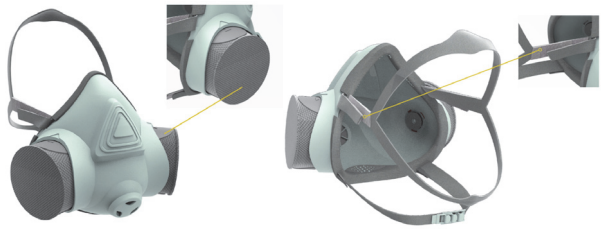

Figure 5: New mask design with thermoformed nonwoven textile filter bag and lacing detail.

Figure 6: Mobile App for the worker.

integrate in the protective mask, SHT31 was a suitable choice due to its small dimensions (2,5x2,5x0,9mm—slightly bigger if integrated as a module on the PCB). It is a low power consumption sensor; it uses supply voltage between 2,7V and 5.5V and the energy consumption is equivalent to 4,8 μW.

The Chest Band (Figure 6) is a textile band sensor to be worn under the T-Shirt throughout the entire working day. It monitors the user's breathing frequency.

All the data gathered by the three devices (i.e., the Nose, the Mask, and the Band) are transmitted via Bluetooth to a mobile application (Figure 6) that gives the user three simplified parameters: breathing rate, air quality (related to the level of VOC), and Protective Mask wearing frequency.

Thanks to the Application, the user has a complete account of his/her behaviours and physical parameters - if he/she was wearing the Protective Mask when the air was polluted and how and when his/her breathing frequency was getting worse.

These data are shown both on a daily basis and in a weekly and monthly statistic. Statistical data are intended to increase the visible benefits in wearing the Protective Mask: the worker is able to see the health progress made thanks to the mask. Indeed, he/she will realize (see following section) how his/her breathing frequency improves while wearing the mask.

This way, we created a wearable system with several features: (i) complement the human nose in real-time sensing of the environment, (ii) monitor the user respiration giving feedbacks to increase awareness about personal health, and (iii) show statistical data of the Mask wearing frequency in relation to the presence of dangerous particles.

Nowadays, the use of PPEs in dangerous working environments is the only way for workers to prevent serious disease. Existing personal equipment are "static" products. We instead developed an interactive system, made up of "dynamic" products empowered with sensors and technology.

6. Results

The wearable system (see Figure 7) was first prototyped and then tested with end users, in order to assess its qualities and flaws. In general, we wanted to check if and how the system would be perceived useful to enhance senses and improve users' health.

In more details, one of the most important objectives of this test was to understand if representing data as gradual chromatic change rather than numbers was clear and motivating for the users. At this stage, we did not focus on technical issues related to the device's precision.

Before the user testing, our expectations were that (i) the electronic nose would be a useful wearable solution to support human smell; (ii) the redesign of the Mask, improving its aesthetics and wearability, would reduce barriers in wearing it; (iii) the data elaborated by sensors would be transmitted to the user in a clear manner.

Figure 7: Mask, electronic nose, and chest band prototype.

Figure 8: On the left, worker in a cabin wearing Electronic Nose Device. On the right, worker getting near to the paint with Electronic Nose Device.

The testing of the prototype carried out in May of 2017 [13] on a total number of five workers was framed into two phases: a general observation coupled with data recorded by the sensors and collected in the working space and an unstructured interview aimed to have general feedbacks about the system and understand its efficacy. The observation was made up of two steps: (i) the workers were asked to wear the chest band and to use the electronic nose for 30 minutes; this step was useful to figure out if they understood the functioning of the electronic nose (see Figure 8); (ii) they wore both the electronic nose and the mask for 30 minutes as well (see Figure 9). We carried out five different sessions with different workers for a total number of 5 hours of testing, followed by the unstructured interviews submitted to each worker.

The functional prototypes of the Protective Mask, the Electronic Nose Device, and the real Chest Band allowed us to control the vital and environmental parameters during the observation, while the users received real-time feedbacks. The sensors showed the breathing rate value and VOC consistence in the air. These parameters were observed both when the Protective Mask was worn (on) or not (off). The purpose of comparing these parameters was to understand whether the efficacy and accuracy of sensors' information were good and fast enough and to confirm the theory that the hazard substances in the coating plant influence workers' breathing and to check whether something changes when the Protective Mask is worn.

We were following the results about air quality and breathing rate trough a demo of the mobile application. The devices (Electronic Nose, the Mask, and the Chest Band) were connected to the Mobile App via Bluetooth connection. The workers were performing working actions in the cabin, the same that they execute normally, wearing first just the Electronic Nose and the Chest Band and then also the Protective Mask.

In Figure 10, we can see how the wearable system displays the monitored parameters: (i) changing the dot colour from red to green according to the air quality; (ii) thumbs up or down for the wearing of the mask; (iii) breathing graph. It can be seen how all the parameters are interdependent. In the first image, we can see the results for breathing rate and consistence of VOC in the environment when the Protective Mask is not worn (figures on left side). In the right-side figure, we show and compare the same parameters when the mask is worn.

During the session, we noticed that the air quality was not constant. Before starting the activity, in the cabin any air contaminant was not present: indeed, the device remained on the "green" range that we identified between values of 0 and 255 (on the scale of analog read between 0 and 1023). When the activity started, the line on the graph started to increase and, depending on the distance between the worker and the object to be painted, it was increasing or decreasing. In general, we found that the level of contaminants tends to remain on the "yellow" range, numerically the range between 255 and 511 (on a scale of analog between 0 and 1023). This means that the mask wearing is required. In the presence of overspray, the line on the graph was increasing up to the "red" range, numerically the range between 511 and 767, in which wearing the mask becomes necessary. This occurred when concave objects were painted. Another case in which the line was in the "red" range was when the worker was opening the painting can, mixing and pouring paint. Summarizing the results, wearing the mask was required almost at any time. Quantifying the results, from the plot time-contaminants emerged that over one hour, 40 minutes were signaled as yellow and the remaining 20 minutes as red.

Wearing all the elements of the system during the observation sessions allowed the workers to evaluate the comfort, the materials, and the overall wearability. The observation was video-recorded, and the data collected from the prototypes were saved and subsequently analyzed. After the observation, each user was asked to partake in an unstructured interview.

The results gathered from the general observation, the sensor measuring, and the unstructured interviews gave an overview of the system efficacy in changing the consciousness of workers towards their health conditions.

The Electronic Nose was considered a necessary element in any coating plant. The workers appreciated the possibility

Figure 9: On the left, worker wearing the mask in cabin. On the right, worker wearing Electronic Nose Device, Mask, and Chest Band.

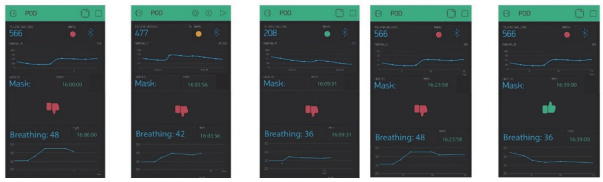

Figure 10: Monitoring results.

to wear it in a versatile way: on the pants' pocket, on the shirt's collar, and on the shirt's sleeves. The most important feature of the Electronic Nose, the feedback in form of light and vibration, received a very good evaluation. Both the employer and employees were interested in wearing one. Sentences coming from the users were the following: "Wow, I feel safer with this device"; "I would like to have it, so I would know how my breathing is and when I certainly need to wear the mask"; "It makes me feel superhuman, it smells what I'm not able to feel in the environment."

Regarding the Protective Mask, workers evaluated rather positively its wearability and general comfort; they liked the materials and the overall look of the new design.

The Chest Belt was evaluated as a noninvasive element; workers found it very comfortable and easy to understand.

The functions of all the elements resulted to be clear to users and the Mobile Application perceived quite understandable both to the workers and the employer. They were able to read the feedbacks in real time, understanding the functioning of the whole system.

The employers specifically found the electronic nose and its data on the application useful to check the efficacy of the factory aspiration system over time.

7. Discussion

A systematic literature review on wearable systems showed that personal monitoring systems on the market today provide mainly single-parameter assessment and transmission and that there is currently no smart wearable system available that integrates biosensors, intelligent processing, and alerts to support users in improving health [14]. According to the same article, "to fully realize the health and wellness benefits of smart wearable technologies, researchers and providers have to work towards adoption of these technologies by studying user requirements and developing a comprehensive approach to health and wellness services."

The research project described here started in June 2015 and lasted two years. It was executed taking into consideration the following:

(i) The Scientific Committee on Occupational Exposure Limits (SCOEL) rates that 15% of all adult respiratory diseases are a consequence of work-related exposures and are caused by the so-called Volatile Organic Compounds (VOC).

(ii) According to the International Labour Office, prevention is the best way to reduce the number of diseases and improve workers' health.

The aim of the research project was to develop a wearable device able to support the human sense of smell, therefore preventing respiratory disease. This is a novelty, since in the field related of wearable technologies, the emphasis is generally given to the ability to elicit conscious health life style, such as doing exercises (Kidd and Breazeal, 2006; Ruttkay et al., 2006; Bickmore et al., 2004; Goetz et al., 2003; and Gockley and Mataric, 2006) [15–19], giving social support (Kidd et al., 2006; Kriglstein and Wallner, 2005) [20, 21], and helping with lifestyle change (Bigelow et al., 2000; Looije et al., 2006) [22, 23]. Moreover, there are no evidences in the use of wearable technologies to "support and enhance human senses."

In this project, what we really wanted to achieve was to give more control to the *"user,"* developing a product that is *"personal"* and *"tailored"* on the specific topic of respiratory disease by focusing on *risk prevention*. The added value is the dimension of *wearable technologies* whose peculiarity is also to fulfil the paradigm: anytime, everywhere, and by anyone.

Researches in field of wearable technologies have been around for a century and have always been the domain of

engineers [14]. As Buchanan states [24], engineers are used to design for the "necessary," while designers design for the "possible." We aimed to develop an effective system able to provide objective data to the user, but we were very much concerned with how to provide those objective data and give a shape to the wearable technology.

We wanted to understand if and how wearable technologies could be perceived as an added value by workers who are subject to the reduction in the perception of odour because of the adaption phenomenon. We did not want to reason, as engineers do, on the mere *function* and *performance* but on *how valuable* is considered the use of wearable technology for the final user.

Based on those assumptions, we decided to develop the entire research activity by using a human-centered design approach, an approach to problem solving that incorporates the wants and needs of end users in every stage of the project by using qualitative methods.

The added value given by qualitative methods (observation, interviews, and focus group) is to focus on the user and his/her problems, that is, the core of the system, rather than on just functionality.

Indeed, according to Creswell [25], the use of qualitative methods is useful to explore and understand the meaning that an individual or a bunch of users belonging to the same target group confer to a specific social problem that, in our case, is the weakness of smell in the perception of risk.

8. Conclusions and Further Developments

Human senses are fundamental to interpret the world surrounding us. However, they have limits. In this article, we focused on the limits of our sense of smell.

The observation of workers within three different coating plants confirmed what is already well known in literature: our olfactory receptors get used even to strong odours if they are exposed to them over a prolonged period of time, ending up in not being able anymore to properly sense them. The long exposure to the same odour generates a significant reduction in its perception (adaptation phenomenon). Such adaptation is the main cause, for the workers we observed, of the lack of consciousness about the bad quality of the air they are inhaling.

Human practical behaviours are closely related to our sensorial perception of the environment: if the odour of potentially hazard substances (Volatile Organic Compounds) is not perceived anymore, the resulting behaviour will not be adequate to the situation. Indeed, workers do not wear Protective Equipment because they do not sense any risk.

However, when our health is in danger, the subjectivity of human perception should be overcome by introducing a technology able to complement it, so as to elicit behavioural changes. Nowadays, the development of microelectronics gives the possibility to integrate sensors in light and wearable devices, able to monitor the environment and provide users with real-time feedbacks.

The added value of wearing wearable technologies is in the possibility to provide the user with objective data and an immediate feedback, instead to rely on the subjectivity of our senses.

The overall aim of the described research project was to safeguard health condition of workers of coating factories by two actions: increasing their awareness of health risks and inducing them to wear Protective Equipment. We pursued our aim designing three interactive devices based on existing sensorial technology. The results of the user tests seem to be promising: they gave us a first confirmation that the designed system can be a valuable proposal. Nevertheless, more research is required to demonstrate the effectiveness of the system.

The research project resulted in two international patents: "Plurisensorial system adapted for the prevention of professional diseases in the working environment and method for the use of the system" and "Wearable device for controlling gaseous pollutants."

Since March 2018, the two patents are object of a research project entitled "User empowerment: shaping technology to change user behaviour" funded by the company BLS (https://www.blsgroup.it) that develops and sells respiratory protection devices. The objective of the collaboration is to improve the system and test it on a wider population of users not only in coating plants but also in other sectors where the presence of VOC is very high such as chemical industries, manufacturing companies, and agriculture. Moreover, we want to test it at a European level, in region like Spain or Netherlands, where branches of BLS are established.

In collaboration with the company, we are in the process of exploiting the results of the POD project and of translating them into a commercial product. So far, an improved working prototype was developed and tested in five different working environments (i.e., building sites, coating plants, and manufacturing companies). The results are promising and will be released in the next two months.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

In accordance with ethical obligation as researchers, the authors declare that they have no financial, commercial, legal, or professional relationship with other organizations or with the people working with them, which could influence their research.

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References

[1] P. Dalton and C. J. Wysocki, "The nature and duration of adaptation following long-term odor exposure," in *Attention, Percepttion & Psychophys*, vol. 58, pp. 781–792, Springer, 1996.

[2] W. Stroebe, "Determinants of health behavior: a social psychological analysis," in *Social Psychology And Health*, pp. 12–42, Open University, Buckingham, UK, 1995.

[3] N. Rot, "Sistematski deo [Sistematic Part]," in *Opšta Psihologija [General Psychology]*, pp. 91–126, Zavod za udžbenike i nastavna sredstva Beograd, (2010) (1966).

[4] N. A. Piotrowski, "Psychology Basics," in *Magill's Encyclopaedia of Social Science: Psychology*, vol. 2, pp. 760–773, Salem Press, 2003.

[5] M. J. E. Cometto and W. S. Cain, "Olfactory adaptation," in *Doty Handbook of Olfaction And Gustation*, pp. 257–281, Marcel Dekker, New York, NY, USA, 1995.

[6] B. Fogg, "Creating persuasive technologies," in *Proceedings of the the 4th International Conference*, p. 1, Claremont, California, April 2009.

[7] V. Ferraro, *The Designer Approach to Wearable Technologies - A Practice Based Approach*, Maggioli Editore, 2012.

[8] H. N. J. Schifferstein, E. Özcan, and M. C. Rozendaal, "Towards the maturation of design: From smart to wise products," in *Proceedings of the Design and semantics of form and movement, DeSForM '15*, pp. 77–85, Aesthetics of interaction: Dynamic, Multisensory, Wise, 2015.

[9] S. P. Gill, "Knowledge and Cognition," in *Cognition, Communication and Interaction: Transdisciplinary Perspectives on Interactive Technology*, pp. 267–269, Springer, Communication and Interaction: Transdisciplinary Perspectives on Interactive Technology, 2007.

[10] V. G. Motti and K. Caine, "Human Factors Considerations in the Design of Wearable Devices," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 58, no. 1, pp. 1820–1824, 2014.

[11] W. Ijsselsteijn, Y. de Kort, C. Midden, B. Eggen, and E. van den Hoven, "Persuasive Technology for Human Well-Being: Setting the Scene," in *Persuasive Technology*, p. 106, Springer, Berlin, Germany.

[12] D. Marculescu, R. Marculescu, N. Zamora et al., "Electronic textiles: a platform for pervasive computing," *Proceedings of the IEEE*, vol. 91, no. 12, pp. 1995–2018, 2003.

[13] V. Ferraro, M. Stepanovic, and S. Ferraris, *Wearable Technology as a Tool to Motivate Health Behaviour: A Case Study, Wearable Technologies*, Jesús Hamilton Ortiz, IntechOpen, 2018, https://www.intechopen.com/books/wearable-technologies/wearable-technology-as-a-tool-to-motivate-health-behaviour-a-case-study.

[14] M. Chan, D. Estève, J. Fourniols, C. Escriba, and E. Campo, "Smart wearable systems: current status and future challenges," *Artificial Intelligence in Medicine*, vol. 56, no. 3, pp. 137–156, 2012.

[15] C. D. Kidd and C. Breazeal, "Designing a sociable robot system for weight maintenance," in *Proceedings of the IEEE Consumer Communication and Networking Conference*, IEEE, Piscataway, NJ, USA, 2006.

[16] Z. M. Ruttkay, J. Zwiers, H. Van Welbergen, and D. Reidsma, *Towards a Reactive Virtual Trainer*, Springer, Berlin, Germany, 2006.

[17] T. Bickmore, A. Gruber, and R. Picard, "Establishing the computer–patient working alliance in automated health behavior change interventions," *Patient Education and Counseling*, vol. 59, no. 1, pp. 21–30, 2005.

[18] R. Gockley and M. J. Matarić, "Encouraging physical therapy compliance with a hands-off mobile robot," in *Proceedings of the 1st ACM SIGCHI/SIGART conference on Human-robot interaction (HRI '06)*, pp. 150–155, ACM, New York, NY, USA, 2006.

[19] J. Goetz, S. Kiesler, and A. Powers, "Matching robot appearance and behavior to tasks to improve human-robot cooperation," in *Proceedings of the 12th IEEE International Workshop on Robot and Human Interactive Communication, RO-MAN 2003*, pp. 55–60, IEEE, Piscataway, NJ, USA, 2003.

[20] C. D. Kidd, W. Taggart, and S. Turkle, "A sociable robot to encourage social interaction among the elderly," in *Proceedings of the 2006 IEEE International Conference on Robotics and Automation, ICRA 2006*, pp. 3972–3976, IEEE, Piscataway, NJ, USA, 2006.

[21] S. Kriglstein and G. Wallner, "HOMIE: An artificial companion for elderly people," in *Proceedings of the Conference on Human Factors in Computing Systems, CHI EA 2005*, pp. 2094–2098, New York, NY, USA, 2005.

[22] J. H. Bigelow, S. Cretin, M. Solomon, S. Y. Wu, J. C. Cherry, and H. Cobb, *Patient Compliance with and Attitudes Towards Health Buddy*, RAND Corporation, Santa Monica, Calif, USA, 2000.

[23] R. Looije, F. Cnossen, and M. A. Neerincx, "Incorporating guidelines for health assistance into a socially intelligent robot," in *Proceedings of the ROMAN 2006-The 15th IEEE International Symposium on Robot and Human Interactive Communication*, pp. 515–520, IEEE, Piscataway, NJ, USA, 2006.

[24] R. Buchanan, "Wicked problems in design thinking," *Design Issues*, vol. 8, no. 2, pp. 5–21, 1992.

[25] J. W. Creswell, *A framework for Design in Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*, Sage Pubblication, 2014.

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Research Article

Improving Physical Activity mHealth Interventions: Development of a Computational Model of Self-Efficacy Theory to Define Adaptive Goals for Exercise Promotion

Dario Baretta,[1] Fabio Sartori,[2] Andrea Greco,[3] Marco D'Addario,[1] Riccardo Melen,[2] and Patrizia Steca[1]

[1]*Department of Psychology, University of Milan-Bicocca 20126, Milan, Italy*
[2]*Department of Computer Science, Systems and Communication, University of Milan-Bicocca, 20126 Milan, Italy*
[3]*Department of Human and Social Sciences, University of Bergamo, 24129 Bergamo, Italy*

Correspondence should be addressed to Dario Baretta; d.baretta@campus.unimib.it

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The practice of regular physical exercise is a protective factor against noncommunicable diseases and premature mortality. In spite of that, large part of the population does not meet physical activity guidelines and many individuals live a sedentary life. Recent technological progresses and the widespread adoption of mobile technology, such as smartphone and wearables, have opened the way to the development of digital behaviour change interventions targeting physical activity promotion. Such interventions would greatly benefit from the inclusion of computational models framed on behaviour change theories and model-based reasoning. However, research on these topics is still at its infancy. The current paper presents a smartphone application and wearable device system called *Muoviti!* that targets physical activity promotion among adults not meeting the recommended physical activity guidelines. Specifically, we propose a computational model of behaviour change, grounded on the social cognitive theory of self-efficacy. The purpose of the computational model is to dynamically integrate information referring to individuals' self-efficacy beliefs and physical activity behaviour in order to define exercising goals that adapt to individuals' changes over time. The paper presents (i) the theoretical constructs that informed the development of the computational model, (ii) an overview of *Muoviti!* describing the system dynamics, the graphical user interface, the adopted measures and the intervention design, and (iii) the computational model based on Dynamic Decision Network. We conclude by presenting early results from an experimental study.

1. Introduction

Noncommunicable diseases such as cardiovascular and respiratory diseases, cancer, diabetes, and obesity are the main cause of mortality in Western countries and cause unimaginable costs for public health [1]. Although physical activity constitutes an important protective factor against such diseases [2], large part of the population does not respect the recommended physical activity guidelines and lives a sedentary life [3]. Hence, there is the need to find new, effective, and large-scale solutions to promote behaviour change in the direction of a higher physical activity.

Recent availability of effective and inexpensive sensors, generally embedded into commercial devices, such as wearables and smartphones, has opened the way to the development of smartphone applications (apps) oriented to promote health behaviour change [4]. Healthcare apps are becoming one of the most important and promising tools for delivering behaviour change interventions [5, 6]. With regards to physical activity (PA) behaviour, mobile sensors can perform direct, intense, and longitudinal measurements of physical parameters (e.g., the heartbeat) and may produce detailed records of the individual behaviour (e.g., exercise) that are immediately available for analysis [7]. Thanks to such opportunities for data collection, new technologies can rapidly manage and combine different input datasets, provide accurate predictions about the influence pattern among interested variables (e.g., behavioural, psychological),

and deliver behaviour change interventions that are adaptive to individual and context changes over time [8]. For these reasons, mobile technology has been hypothesized to support the science of behaviour change and it constitutes a preferential tool both for modeling behaviour change theories and for testing them in real world settings [4, 9, 10]. In spite of that, existing PA apps are characterized by a lack of adherence to behaviour change theories [11] and relatively little attention has been paid to the adoption of specific computational models grounded in behaviour change theories [12]. More specifically, even though digital interventions that made extensive use of behaviour change theories produce larger effects on behaviour [13], Cowan and colleagues [11] evidenced that *Health & Fitness* apps mostly included only minimal theoretical content.

Self-efficacy theory [14, 15] is one of the most prominent psychological theories about behaviour change and it lays its foundations on the construct of self-efficacy. Self-efficacy (SE) has been defined as the beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments [14]. Such beliefs affect several areas of human endeavor [15] and these effects are particularly relevant with regards to health-related behaviours [16–18]. More specifically, it has been consistently shown that self-efficacy is a key determinant for the adoption and maintenance of PA behaviour [17, 19, 20], as well as a mediator of the effects of interventions on physical activity [21–24].

Self-efficacy beliefs develop as a consequence of four sources of information: enactive mastery experience, vicarious experience, verbal persuasion, and physiological or affective states management [15]. Among them, mastery experience has been shown to be the most potent source of self-efficacy in different domains and populations [15, 25–27]. It refers to the direct experience of performing a specific task and, hence, it represents an authentic indicator of the individual ability to accomplish similar tasks in the future. Indeed, when people engage in tasks and activities, they interpret the results of their actions and they use such interpretations to develop beliefs about their capability and to subsequently act according with the created beliefs. Experiences interpreted as successful generally increase confidence while experiences interpreted as unsuccessful generally undermine it [15]. As a consequence, in light of the reciprocal influence between self-efficacy and behavior, the selection of any specific behavioral goal should be set with the aim to gradually support both the achievement of successful experiences and the increasing of self-efficacy. For this purpose, goals should be (i) doable in order to permit individuals to master successful experiences and (ii) challenging in order to adequately reinforce self-efficacy beliefs once the goal has been achieved [15, 28].

In recent years, we assisted the first attempts of developing computational models based on self-efficacy theory in order to promote PA [29, 30]. Self-efficacy theory is particularly suitable to be modeled because of its nature that is explicitly *dynamic* (i.e., it takes into account time-varying information such as individual achievements, self-efficacy beliefs and expectations) and, thus, permits adapting the intervention to the individual over the course of the intervention itself [12]. The advantages of developing a computational model based on a behaviour change theory, such as self-efficacy theory, mainly rely on the capacity of predicting directionality and magnitude of effects among variables (e.g., target behaviour and its psychological determinants),and simulating and testing how they change and influence each other across contexts and over time [31].

First computational models of self-efficacy focused on different approaches and frameworks. Pirolli [30] proposed a computational model, called ACT-R-DStress, aiming to (i) model interactions among behavioral goals, memories of past experiences, and behavioral performance, and (ii) explains and predict both the dynamics of self-efficacy and the individual performance in an exercise program. For these purposes the ACT-R-DStress exploited the computational neurocognitive architecture that characterizes the ACT-R theory's simulation environment [32]. Differently, Martin et al. [29] developed a dynamical model of social cognitive theory adopting principles from control system engineering with a focus on system identification methodologies. Specifically, *system identification* compares what happens in different states and contexts of the person over time to what was predicted by a precise mathematical model of a given theory. Such methods have been applied to PA promotion and to generate dynamical models for future predictions to be tested against social cognitive theory (for an overview see [33]).

The current paper presents an innovative computational model that is conceptually framed in self-efficacy theory with a particular emphasis on self-efficacy beliefs and goal setting constructs. The computational model is embedded in a digital behaviour change intervention delivered by *Muoviti!*, a mobile app and heart rate monitor system that aims at the promotion and maintenance of PA among adults not meeting the recommended PA guidelines. The main contribution of the current work is twofold: (i) generating a computational model that combines input data collected through mobile technology (i.e., amount of PA collected through a heart rate monitor, SE assessed through ecological momentary assessment) in order to set PA goals that are dynamically adapted to each individual's achievement and changes in SE over time and (ii) tuning the proposed computational model according to early empirical findings from real case studies.

2. Materials and Methods

2.1. Overview of Muoviti!

2.1.1. The Experimental System. The experimental system that constitutes *Muoviti!* is made of three key components (see Figure 1):

(i) A heart rate (HR) wristband needed to measure the amount of PA performed. More specifically, two commercial, low-cost and reliable HR monitors (i.e., MioAlpha, PulseON) have been tested. Such devices nonetheless provide an estimate of the relevant physiological parameters which is precise and reliable enough for our purposes [34, 35].

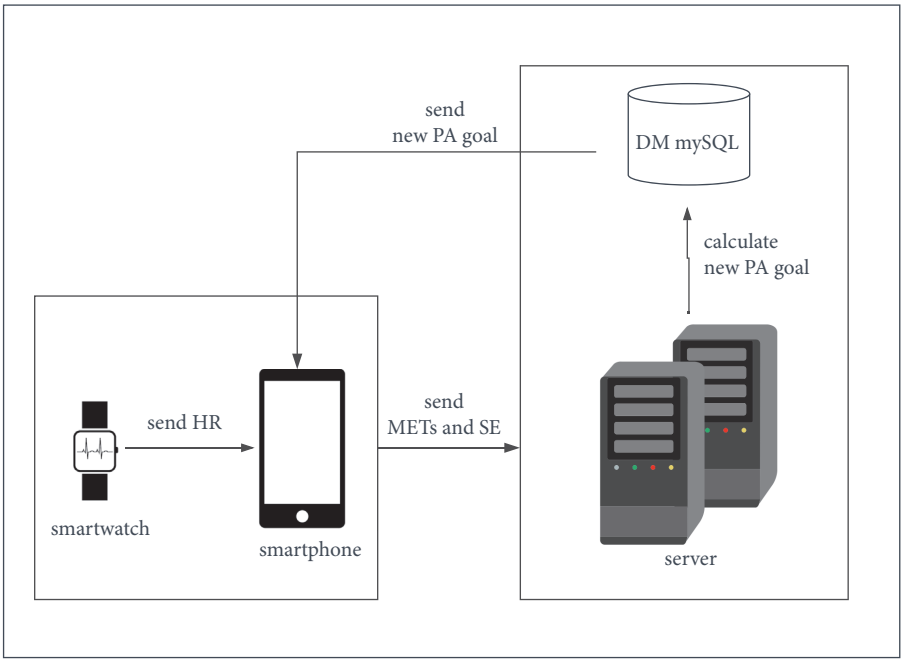
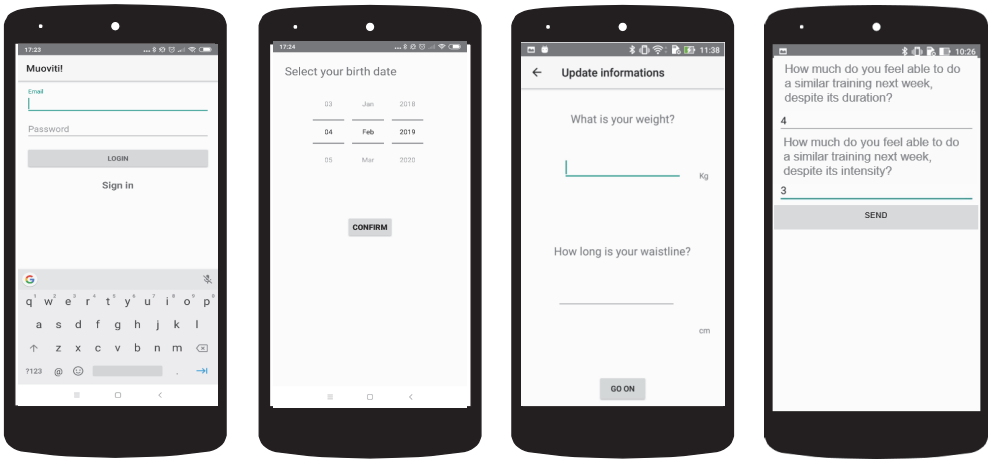


Figure 1: The general architecture of Muoviti!



1. Login phase 2. Age statement 3. Physical parameters detection 4. Self-Efficacy statement

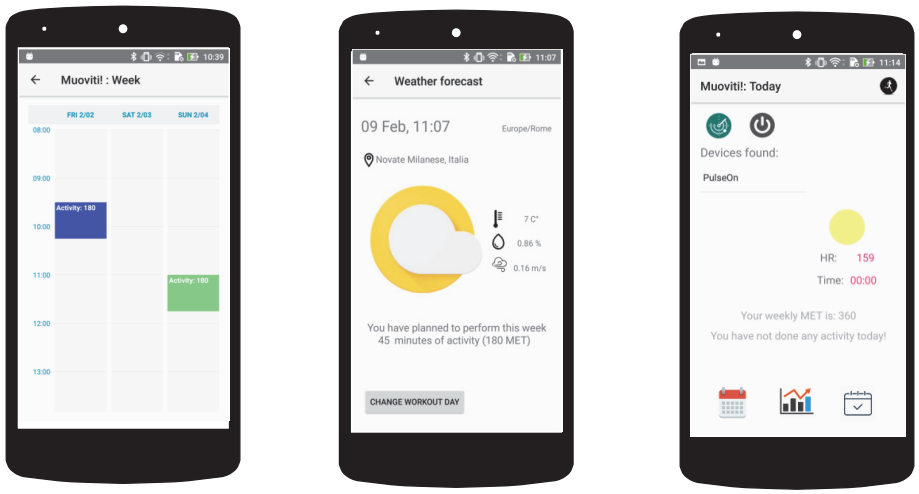
Figure 2: Screenshots from the Graphical User Interface (GUI) of the Muoviti! App.

(ii) A smartphone app which (i) handles the user interface, (ii) ecologically assesses SE through an *ad hoc* short questionnaire, (iii) collects information from the heart rate monitor, and (iv) transfers information to/from the back office.

(iii) A back office with a server that stores the data relative to each person and executes the modeling algorithm, thus formulating tailored PA suggestions for the next training period.

Muoviti! operates as follows. At the beginning of each weekly training period, a suggested PA goal for the week is generated on the basis of two different input data: (i) goal achievement during the previous week and (ii) SE beliefs in doing physical activity during the previous week. Finally, *Muoviti!* splits the weekly PA goal into daily short-term goals, translates them into concrete PA tasks (e.g., minutes of running, or fast walking), and presents them to the user (see below in the 'Computational model' paragraph).

2.1.2. Graphical User Interface. Figures 2 and 3 illustrate the main components of *Muoviti!*'s graphical user interface. During the login process, users are asked to specify the login credentials (Figure 2.1), their age (Figure 2.2), and other



1. Activity calendar 2. Training session information 3. Training session execution

Figure 3: Screenshots from the GUI of the Muoviti! App.

parameters like weight and waistline (Figure 2.3) that are useful to evaluate possible benefits or drawbacks emerging from exercising. Furthermore, the figure shows the interface for the collection of values to assess users' self-efficacy after a physical activity session (Figure 2.4). Each week the training sessions calendar is automatically updated on the basis of previous training sessions results (Figure 3.1). The user can manually place the activities suggested by the system to fit better with other duties (e.g., working hours). The calendar provides the patient with important information about the training event (Figure 3.2), like the weather forecasting, the duration and intensity of the activity to do, with the possibility for the user to change the position of the activity in the agenda. Finally, the system supports the user in self-monitoring and collecting significant data when the activity is accomplished (Figure 3.3), in particular the heart-beat rate, a visual warning about the correct execution of the activity, and the shortcuts to statistics and graphs about the results obtained.

Finally, Figure 4 illustrates how the individual performance has varied over the time, to provide people with an immediate feedback about the results obtained day by day and week by week. *Muoviti!* currently allows visualizing the heart-beat rate graph of the last training session, the curves of weight and waistline variations week by week, the burned calories graph, session by session, and the percentage of vigorous activity with respect to moderate activity.

2.2. Measures

2.2.1. Physical Activity. The computation of the PA goal for the new training period (i.e., output data) is expressed in terms of METs (Metabolic Equivalent of Task) that is a measure of the amount and quality of performed PA normalized to the physical characteristics and age of the individuals. Specifically, it METs represent the ratio of the metabolic rate (the rate of energy consumption) during a specific exercise to a reference metabolic rate:

$$1MET = \frac{kcal}{kg} * h \tag{1}$$

MET is used as a mean of expressing the intensity and energy expenditure of activities in a way comparable among persons of different weight. Actual energy expenditure (e.g., in calories or joules) during an activity depends on the person's body mass; therefore, the energy cost of the same activity will be different for persons of different weight. When the subject begins performing a PA training session, she/he asks the app to start the collection of PA data through the Bluetooth connection with the wristband. The app translates the HR collected by the wristband into the equivalent energy expenditure (METs), given by the following formula [36]:

$$MET\ minutes = 4 * Time^{MPA} + 8 * Time^{MPA} \tag{2}$$

where Time^{MPA} and Time^{VPA} are the periods of time the subject is involved in moderate physical activity (MPA) and vigorous physical activity (VPA) and parameters 4 and 8 represent the corresponding MET expenditure per minute. A PA session is defined as moderate if the registered HR values are in the range $[6 * MHR/10, 7 * MHR/10]$, while it defined as vigorous if the registered HR values are in the range $[7 * MHR/10, 8 * MHR/10]$. MHR represent the maximum heart rate depending on the subject age and it is calculated by subtracting *age* to a standard value (i.e., 220 – *age*).

2.2.2. Self-Efficacy Beliefs. SE beliefs are ecologically assessed at the end of each training session, through a set of questions to the person, each concerning a specific aspect of the physical activity. Currently, two questions are proposed to the user to evaluate the self-efficacy beliefs referring to the PA they have just performed:

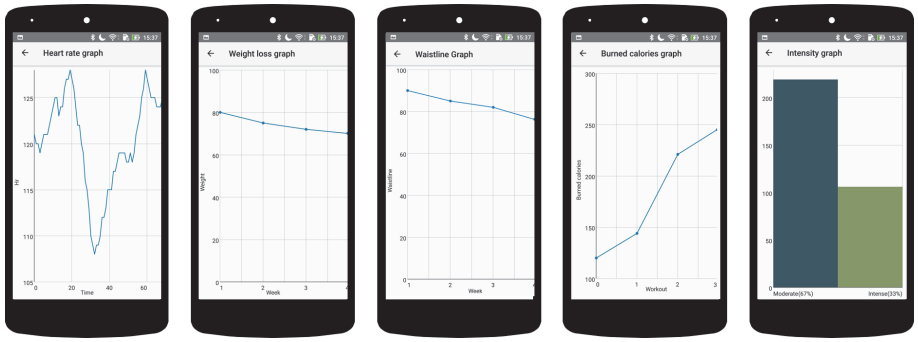


Figure 4: Screenshots from the GUI of the Muoviti! App.

(i) *How much do you feel able to do a similar training next week, despite its duration?*

(ii) *How much do you feel able to do a similar training next week, despite its intensity?*

The SE score is given by the arithmetic mean of the provided answers:

$$SE_i = \frac{\sum_{i=1}^{n} answer_i}{n} \tag{3}$$

where n is the number of questions posed to the user and answer_i is the value given by the user on a 4-point Likert scale, ranging from 1 (not able at all) to 4 (absolutely able). The advantages of assessing SE through digital ecological momentary assessment rely on the opportunity to minimize recall bias, maximize ecological validity, and better understand behaviour in real-world contexts [37].

2.3. Intervention Design. *Muoviti!* aims to homogeneously merge physical and psychological variables into a unique conceptual framework, in order to build up tailored PA goals. For this purpose, at the end of the weekly period, the app interacts with the user by notifying the degree of accomplishment of the weekly goal and sends the recorded data to the back office. *Muoviti!*'s back office aggregates PA accomplishments and SE scores from each single training session in order to get a global evaluation of the users' PA accomplishments and SE beliefs over the week. The global evaluation of PA achievements and SE beliefs over the weekly period may assume the following facets and codes:

(i) Physical activity:

(a) The weekly PA goal was achieved (PA+);

(b) The weekly PA goal was not achieved (PA-);

(ii) Self-efficacy:

(a) The weekly PA self-efficacy was high – average SE equal or higher than 2.5 (SE+);

(b) The weekly PA self-efficacy was low – average SE lower than 2.5 (SE-).

After this assessment is made, the PA goal for the next week is proposed. Table 1 shows the decision rules about how global evaluations of PA and SE are combined in order to set new goals.

Finally, according to the user preferences, the PA goal for the next training period is successively split in daily short-term goals in order to support an effective action planning. The goal setting strategies at each period are taken with the aim of obtaining a successful result in a long-term perspective that is determined according to the general guidelines for PA promotion, which state that a person should perform 600 METs per week of PA [3].

2.4. Computational Modeling. The developed computational model combines knowledge about the PA performed, measured through the data collected by the wearables and an ecological momentary assessment of self-efficacy beliefs. The model was employed to define and dynamically adapt, a PA plan consisting of suggestions about the PA goal to be carried out every week, with the aim of maximizing the probability of bringing the person to the recommended PA level at the end of the long-term training period. The mathematical model adopted is a Dynamic Decision Network (DDN), a sequence of simple Bayesian Networks (BN), each representing the person's situation at a specific training period (i.e., one week). Figure 5 shows the current decisional model in *Muoviti!* (Part (a)) and the future one (Part (b)). The basic BN embodies variables which represent the physical activity performed, the estimated self-efficacy of the period, and the possible external factors (e.g., weather) influencing the performed activity. The DDN model includes decision variables at each training stage, which represent the PA goal proposed for the week, and a utility function on the final level of PA achieved. Moreover, the mathematical model of *Muoviti!* clearly combines self-efficacy with objective measurements of PA, being able to build up a personalized plan taking into account possible different trajectories towards the final goal.

The DDN model has been preferred to other approaches present in the literature (for instance, based on neurocognitive simulation [30] or on the theory of dynamic systems [29] because it represents with accuracy the sequence of decision points (the weekly PA suggestions) that we have envisioned in our approach. An explanation of the model can be given as follows: the NEW GOAL variable (on Figure 5, part (a))

Table 1: Decision rules and rationale for setting new weekly goals.

Condition	Goal for the new training period (*newGOAL*)	Rationale for the goal setting strategy based on the relevant literature [15, 28]
(PA+) & (SE+)	Increase PA goal	Setting a harder goal is challenging but doable for the person, because it is in line with the physical capabilities and supported by strong SE beliefs
(PA+) & (SE-)	Maintain the same PA goal	Maintaining the same goal is a strategy to reinforce the self-efficacy beliefs through the achievement of the same goal and thus trains the person for successive more difficult goals
(PA-) & (SE+)	Maintain the same PA goal	Maintaining the same goal is a strategy to avoid disappointing motivations and self-efficacy beliefs, thus provides the person with a further opportunity to achieve a goal corresponding to his/her SE beliefs
(PA-) & (SE-)	Decrease PA goal	Setting an easier goal is a strategy to allow the person to become familiar with the behaviour through an easier task and reinforce self-efficacy beliefs through more likely successful experiences

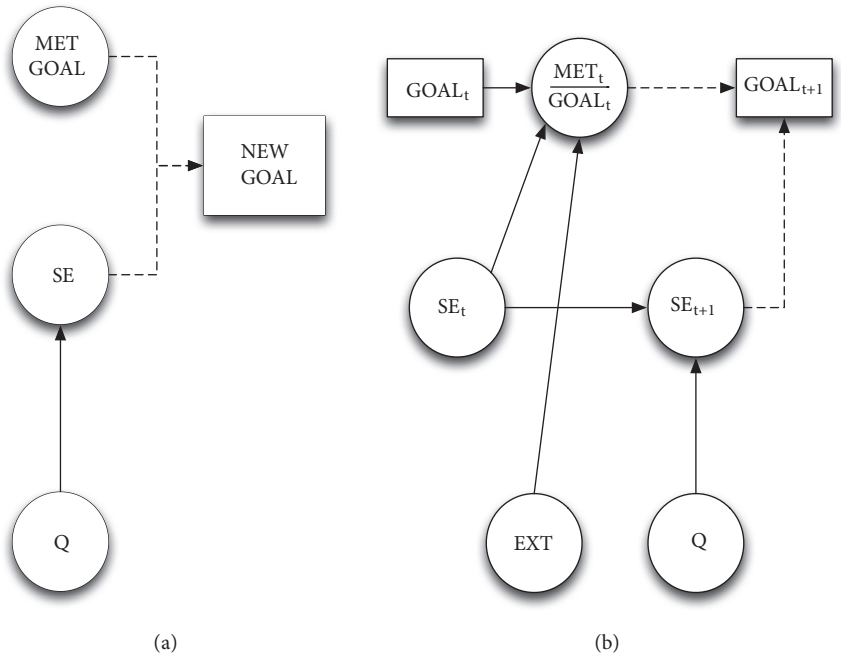


Figure 5: Part (a): the model basic decision step and Part (b): the relation between two consecutive "time slices" in the DDN model.

represents the decision to be taken at the beginning of each training period. It is influenced by the two basic variables describing the state of the subject: the SE and the level of success obtained in the preceding period, measured as the ratio of achieved METs with respect to the current GOAL. The achieved METs can be measured directly in our experimental system, and the SE can be evaluated from the result Q of a set of questions posed to the subject. Figure 5, Part (b) shows how the basic decision step is embedded in the sequence of time slices constituting the DDN. The structure of the model can be explained by considering its two main purposes:

(1) Providing an integrated estimation of SE on the basis of the self-report assessment of SE (i.e., Q) and SE autocorrelation in preceding periods. We consider that SE is a long-term developing psychological determinant of PA; therefore, its values in succeeding periods are correlated. The model conditions the SE_{t+1} value at the beginning of period t+1 to its preceding value SE_t, which has already shown its effects on the results (MET/GOAL) obtained in period t. We also introduced a variable EXT to explain away a decrease in SE when the observed PA shows a reduction due to factors external to the training (e.g., an illness or a period of bad weather).

(2) Providing planning decisions. The sequence of decisions represented by the $GOAL_t$ variables must lead the subject to achieve the desired PA level before the end of the program; the decision to be taken in each period must be compatible with this long-term target (i.e., 600 METs per week). We call the sequence of decisions from the present time until the end of the program a *strategy*. The overall objective is modeled by defining a utility function computed on the expected value assumed by the MET variable in a stable, long-term situation. The utility value distribution can be computed, for each strategy, on the basis of the present state assuming no external interference. In this way an updated assessment of the possible strategies can be carried out at each decision step.

The model tuning consists of the derivation of the conditional probability tables (CPT) from the experimental collection of data, as described in the next section.

3. Results

Muoviti!'s computational model represents a mathematical description of a behaviour change model based on self-efficacy theory that needs to be tuned according to real case studies. To this scope, we assume that potential users of *Muoviti!* can be classified into different basic profiles and that such profiles are represented by the different values in the CPTs present in the model. In this section we present early findings from a study based on real case data. For these purposes, we recruited 60 potential users of *Muoviti!*, chosen among people involved in indoor physical activity, mostly using treadmills. Participants (35 female, 25 male) were asked to use *Muoviti!* for a period of eight weeks, splitting the proposed amount of MET into two sessions, as suggested by the application. Each participant was in the 35-60 years old range, equipped with an Android smartphone and a wearable device capable to detect heart-beat rate, provided by us (i.e., PulseOn) or on their own. The study started with 120 MET as a goal to accomplish in the first week.

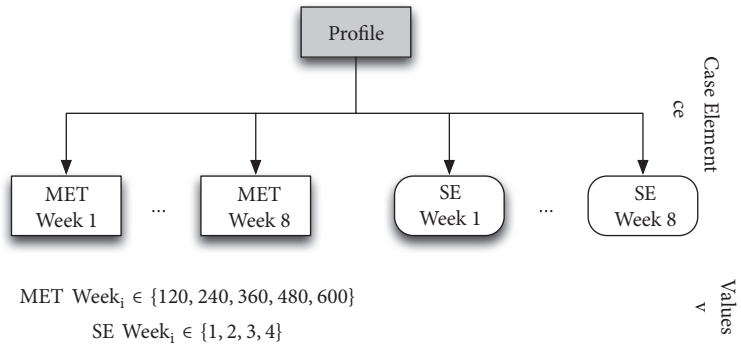


Figure 6: The case structure of our case study.

According to the results obtained, crossing self-efficacy and MET values obtained at the end of the week training session, the new goal could be increased or decreased by 120 MET with respect to the previous, or not modified, till a maximum value of 600 MET to reach. The collected data were used to build up a user profiling, suitable for the future set-up of the Dynamic Bayesian Network: each user was characterized by METs and SE values obtained in the eight weeks of the study, for a total of 16 descriptors. These descriptors were compared with an optimal user profile, exploiting the case-based reasoning paradigm and the CREPERIE platform [38, 39]. In CREPERIE, a case is a finite collection of pairs (ce_i, v_i), i ∈ [1, ∞), where case elements $ce=(id, t, n)$, where $id \in Z^+ - \{0\}$ is the case element identifier, t ∈ T identifies the range of values associated to ce (i.e., String, Integer, Double), and n ∈ String is the name of the case element; v ∈ t is the value associated to each ce. Case elements can be arranged into a vector or a tree. CREPERIE defines different kinds of similarity functions to use in the retrieval step, according to the nature of the case elements values. In particular, the following one has been adopted in our case study, given that the values are numbers:

$$sf\,(n, x\ y) = 1 - \frac{|v_{ce}\,(x) - v_{ce}\,(y)|}{\max - min} \tag{4}$$

where x and y are two cases, n is the attribute corresponding to ce(x) and ce(y), and max = $v_{ce}(n) \in x \cup y$: $v_{ce}(n) \geq v_{ce}(m)$, for all $v_{ce}(m) \in x \cup y$ and min = $v_{ce}(k) \in x \cup y$: $v_{ce}(k) \leq v_{ce}(j)$, for all $v_{ce}(j) \in x \cup y$. In other words, max and min can be substituted by the extremes of the normalization interval if needed.

Once sf(n, x, y) has been calculated for all n in x and y, the similarity between case x and y is defined as follows:

$$sim\,(x, y) = \frac{\sum_{n \in D} sf\,(n, x, y)}{\sum_{n \in D} w_n} \tag{5}$$

where $w_n \in [0, 1]$ is the weight of the attribute n, sim(x, y) is the local similarity between cases x and y, and D is the set of attributes in the cases.

Figure 6 shows the case structure adopted in our case study: the case elements were composed of 16 descriptors, eight met values reached during eight weeks of training and eight self-efficacy values calculated at the end of each week. The MET values are multiples of 120 in the range [120, 600], in accordance with the theoretical background of the model. The SE values are in the range [1, 4], according to (3). The denominator in the sf(n, x, y) calculus was equal to 480, given that the extremes of the met domain set were 120 and 600, respectively. Finally, we have considered w_n=1 for all n.

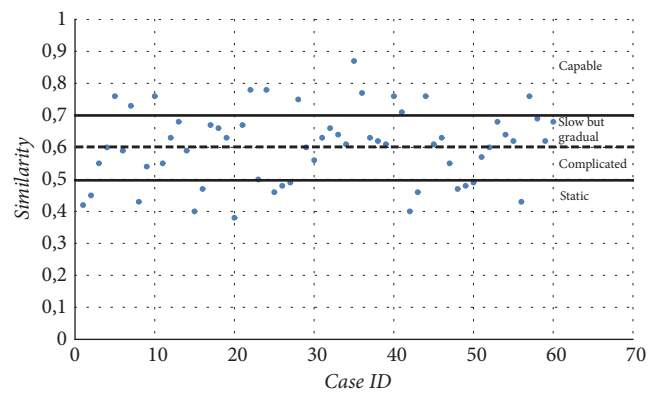


Figure 7: The profiling of Muoviti! app users according to the CREPERIE platform. Similarity values are on Y axis, while case element IDs are on the X axis.

Figure 7 shows the profiling of participants according to their similarity with the optimal profile. Four main clusters have been created: *static*, characterized by very low similarity degree with the optimal profile (less than 50%), *capable*, composed of profiles very similar to the optimal one (more than 70%), and a sort of "grey zone" with similarity between 50% and 70% where two subcategories can be identified, namely, *complicated* and *slow but gradual*. *Complicated* profiles are characterized by scarce physical performance and low self-efficacy, although they would potentially be able to reach proposed objectives; *slow but gradual* profiles are characterized by excellent physical performances, according to which they could be compared to optimal profile, but very low self-efficacy.

Table 2 shows some samples of users' data from the graph in Figure 7. The optimal profile data used in the case-based reasoning is shown at the end of the table.

Table 2: Samples of users' data referring to the current profiles emerged from the comparison with an optimal profile.

	Week							
	1st	2nd	3rd	4th	5th	6th	7th	8th
Profile 1–*Capable*								
Goal (METs)	120	240	360	480	360	480	480	600
Achievement	YES	YES	YES	NO	YES	YES	YES	NO
Self-Efficacy	HIGH	HIGH	HIGH	LOW	HIGH	LOW	HIGH	LOW
Profile 2–*Slow but gradual*								
Goal (METs)	120	240	360	360	360	480	480	360
Achievement	YES	YES	YES	YES	YES	YES	NO	NO
Self-Efficacy	HIGH	HIGH	LOW	LOW	HIGH	LOW	LOW	LOW
Profile 3–Complicated								
Goal (METs)	120	240	240	240	360	480	360	240
Achievement	YES	YES	YES	YES	YES	NO	NO	YES
Self-Efficacy	HIGH	LOW	LOW	HIGH	HIGH	HIGH	LOW	HIGH
Profile 4–*Static*								
Goal (METs)	120	120	240	120	120	240	120	120
Achievement	NO	YES	NO	NO	YES	NO	YES	YES
Self-Efficacy	HIGH	HIGH	LOW	HIGH	HIGH	LOW	LOW	LOW
Optimal Profile								
Goal (METs)	120	240	360	480	600	600	600	600
Achievement	YES	YES	YES	YES	YES	YES	YES	YES

4. Discussion and Conclusions

This paper presented an innovative approach to promote PA behaviour change among inactive adults. The approach is based on the development of a computational model grounded in self-efficacy theory and on the integration of mobile technologies and dynamic decision networks. The main aim of *Muoviti!* is to suggest personalized PA goals that adapt to individuals' changes in PA and self-efficacy over time. Early findings revealed the presence of four clusters of user profiles, reflecting the respective progression patterns towards the long-term goal. However, further research is needed to confirm such results by tuning the computational model around a greater number of real case studies. After having tuned the mathematical model in an experimental setting, *Muoviti!* will be tuned in real life contexts too. The purpose of this additional research phase is to develop a mathematical model that takes into account external (e.g., weather, time of the day, and day of the week), demographical (sex, age), and psychological (e.g., stress, outcome expectancies, and action control) factors that may influence the exercise behaviour. Furthermore, in the same vein, future research will aim to tune the current computational model in different populations (e.g., clinical populations) and contexts (e.g., rehabilitation settings) in order to validate its scalability. Finally, next works will be also devoted to develop an effective Android app for distribution: to this aim, many steps should be completed. In particular, the adherence of our approach to recent GDPR regulations must be implemented. At the current stage for development, personal data (like the heartbeat rate) of the users are stored inside their smartphones, while elaborations of the system are anonymized and stored in a cloud platform to be easily retrieved and used. Anyway, this is not sufficient to allow full sharing and downloading of the app through usual channels, like play-stores and websites. For this reason, at the end of this preliminary phase of analysis, where permissions to exploit user data have been only signed by the participants for research scopes, our strategy in future developments of the Muoviti! app will be completely revised.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

References

[1] A. Boutayeb and S. Boutayeb, "The burden of non communicable diseases in developing countries," *International Journal for Equity in Health*, 2005.

[2] B. K. Pedersen and B. Saltin, "Exercise as medicine - Evidence for prescribing exercise as therapy in 26 different chronic diseases," *Scandinavian Journal of Medicine and Science*, 2015.

[3] Who, *Global Recommendations on Physical Activity for Health*, World Health Organization, Geneva, Switzerland, 2010.

[4] K. Patrick, E. B. Hekler, D. Estrin et al., "The pace of technologic change: implications for digital health behavior intervention

research," *American Journal of Preventive Medicine*, vol. 51, no. 5, pp. 816–824, 2016.

[5] N. Lathia, V. Pejovic, K. K. Rachuri, C. Mascolo, M. Musolesi, and P. J. Rentfrow, "Smartphones for large-scale behavior change interventions," *IEEE Pervasive Computing*, 2013.

[6] S. Pagoto and G. G. Bennett, "How behavioral science can advance digital health," *Translational Behavioral Medicine*, 2013.

[7] E. B. Hekler, P. Klasnja, V. Traver, and M. Hendriks, "Realizing effective behavioral management of health: the metamorphosis of behavioral science methods," *IEEE Pulse*, Article ID 2271681, 2013.

[8] I. Nahum-Shani, S. N. Smith, B. J. Spring et al., "Just-in-time adaptive interventions (JITAIs) in mobile health: key components and design principles for ongoing health behavior support," in *Proceedings of the Annals of Behavioral Medicine*, 2016.

[9] W. J. Nilsen and M. Pavel, "Moving behavioral theories into the 21st century: technological advancements for improving quality of life," *IEEE Pulse*, Article ID 2271682, 2013.

[10] D. Spruijt-Metz, E. Hekler, N. Saranummi et al., "Building new computational models to support health behavior change and maintenance: new opportunities in behavioral research," *Translational Behavioral Medicine*, vol. 5, no. 3, pp. 335–346, 2015.

[11] L. T. Cowan, S. A. van Wagenen, B. A. Brown et al., "Apps of steel: are exercise apps providing consumers with realistic expectations?: a content analysis of exercise apps for presence of behavior change theory," *Health Education and Behavior*, 2013.

[12] W. T. Riley, D. E. Rivera, A. A. Atienza, W. Nilsen, S. M. Allison, and R. Mermelstein, "Health behavior models in the age of mobile interventions: Are our theories up to the task?" *Translational Behavioral Medicine*, 2011.

[13] T. L. Webb, J. Joseph, L. Yardley, and S. Michie, "Using the Internet to promote health behavior change: A systematic review and meta-analysis of the impact of theoretical basis, use of behavior change techniques, and mode of delivery on efficacy," *Journal of Medical Internet Research*, 2010.

[14] A. Bandura, "Self-efficacy: toward a unifying theory of behavioral change," *Psychological Review*, vol. 84, no. 2, pp. 191–215, 1977.

[15] A. Bandura, "Self Efficacy: the exercise of control," *American Journal Os Health Promotion*, 1997.

[16] A. Luszczynska and R. Schwarzer, "Social cognitive theory," in *Predicting Health Behaviour*, 2005.

[17] P. Steca, L. Pancani, F. Cesana et al., "Changes in physical activity among coronary and hypertensive patients: A longitudinal study using the Health Action Process Approach," *Psychology & Health*, vol. 32, no. 3, pp. 361–380, 2016.

[18] P. Steca, L. Pancani, A. Greco et al., "Changes in dietary behavior among coronary and hypertensive patients: a longitudinal investigation using the health action process approach," *Applied Psychology: Health and Well-Being*, vol. 7, no. 3, pp. 316–339, 2015.

[19] A. E. Bauman, R. S. Reis, J. F. Sallis, J. C. Wells, R. J. F. Loos, and B. W. Martin, "Correlates of physical activity: why are some people physically active and others not?" *The Lancet*, vol. 380, no. 9838, pp. 258–271, 2012.

[20] L. S. Rovniak, E. S. Anderson, R. A. Winett, and R. S. Stephens, "ocial cognitive determinants of physical activity in young adults: A prospective structural equation analysis," in *Proceedings of the Annals of Behavioral Medicine*, 2002.

[21] S. Ashford, J. Edmunds, and D. P. French, "What is the best way to change self-efficacy to promote lifestyle and recreational physical activity? A systematic review with meta-analysis," *British Journal of Health Psychology*, 2010.

[22] V. Burke, L. J. Beilin, H. E. Cutt, J. Mansour, and T. A. Mori, "Moderators and mediators of behaviour change in a lifestyle program for treated hypertensives: a randomized controlled trial (ADAPT)," *Health Education Research*, 2008.

[23] C. D. Darker, D. P. French, F. F. Eves, and F. F. Sniehotta, "An intervention to promote walking amongst the general population based on an "extended" theory of planned behaviour: a waiting list randomised controlled trial," *Psychology & Health*, 2010.

[24] G. R. Dutton, F. Tan, B. C. Provost, J. L. Sorenson, B. Allen, and D. Smith, "Relationship between self-efficacy and physical activity among patients with type 2 diabetes," *Journal of Behavioral Medicine*, 2009.

[25] S. L. Britner and F. Pajares, "Sources of science self-efficacy beliefs of middle school students," *Journal of Research in Science Teaching*, 2006.

[26] C. W. Loo and J. L. F. Choy, "Sources of self-efficacy influencing academic performance of engineering students," *American Journal of Educational Research*, 2013.

[27] L. M. Warner, B. Schüz, J. K. Wolff, L. Parschau, S. Wurm, and R. Schwarzer, "Sources of self-efficacy for physical activity," *Health Psychology*, 2014.

[28] E. A. Locke and G. P. Latham, "Building a practically useful theory of goal setting and task motivation: A 35-year odyssey," *American Psychologist*, 2002.

[29] C. A. Martin, S. Deshpande, E. B. Hekler, and D. E. Rivera, "A system identification approach for improving behavioral interventions based on Social Cognitive Theory," in *Proceedings of the American Control Conference*, 2015, https://doi.org/10.1109/https://doi.org/10.1109/ACC.2015.

[30] P. Pirolli, "A computational cognitive model of self-efficacy and daily adherence in mHealth," *Translational Behavioral Medicine*, vol. 6, no. 4, pp. 496–508, 2016.

[31] E. B. Hekler, S. Michie, M. Pavel et al., "Advancing models and theories for digital behavior change interventions," *American Journal of Preventive Medicine*, vol. 51, no. 5, pp. 825–832, 2016.

[32] J. R. Anderson, D. Bothell, M. D. Byrne, S. Douglass, C. Lebiere, and Y. Qin, "An integrated theory of the mind. Psychological Review," *Psychological Review*, 2004.

[33] E. B. Hekler, D. E. Rivera, C. A. Martin et al., "Tutorial for using control systems engineering to optimize adaptive mobile health interventions," *Journal of Medical Internet Research*, vol. 20, no. 6, p. e214, 2018.

[34] S. E. Stahl, H.-S. An, D. M. Dinkel, J. M. Noble, and J.-M. Lee, "How accurate are the wrist-based heart rate monitors during walking and running activities? Are they accurate enough?" *BMJ Open Sport & Exercise Medicine*, 2016.

[35] G. Valenti and K. R. Westerterp, "Optical heart rate monitoring module validation study," in *Proceedings of the Digest of Technical Papers - IEEE International Conference on Consumer Electronics*, 2013.

[36] T. Armstrong and F. Bull, "Development of the world health organization global physical activity questionnaire (GPAQ)," *Journal of Public Health*, 2006.

[37] S. Shiffman, A. A. Stone, and M. R. Hufford, "Ecological momentary assessment," in *Proceedings of the Annual Review of Clinical Psychology*, 2008.

[38] L. Manenti and F. Sartori, "etadata support to retrieve and revise solutions in case-based reasoning," *International Journal of Metadata, Semantics and Ontologies*, 2011.

[39] F. Sartori, A. Mazzucchelli, and A. Di. Gregorio, "Bankruptcy forecasting using case-based reasoning: The CRePERIE approach," *Expert Systems with Applications*, 2016.

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Research Article

An Energy Efficient Wearable Smart IoT System to Predict Cardiac Arrest

AKM Jahangir Alam Majumder,[1] Yosuf Amr ElSaadany,[2] Roger Young Jr.,[1] and Donald R. Ucci[2]

[1] *University of South Carolina Upstate, SC, USA*
[2] *Miami University, OH 45056, USA*

Correspondence should be addressed to AKM Jahangir Alam Majumder; majumdaa@miamioh.edu

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Recently, many people have become more concerned about having a sudden cardiac arrest. With the increase in popularity of smart wearable devices, an opportunity to provide an Internet of Things (IoT) solution has become more available. Unfortunately, out of hospital survival rates are low for people suffering from sudden cardiac arrests. The objective of this research is to present a multisensory system using a smart IoT system that can collect Body Area Sensor (BAS) data to provide early warning of an impending cardiac arrest. The goal is to design and develop an integrated smart IoT system with a low power communication module to discreetly collect heart rates and body temperatures using a smartphone without it impeding on everyday life. This research introduces the use of signal processing and machine-learning techniques for sensor data analytics to identify predict and/or sudden cardiac arrests with a high accuracy.

1. Introduction

Heart problems have a significant impact on the quality of life of any who suffer from them. Through the widespread use of new technologies, there is a potential for advanced healthcare systems. The development of smart wearable IoT system for health monitoring is revolutionizing our lives [1]. Medical services have made large advancements in recent years. Computing and communication technologies have the potential to offer a wider variety of services for patients. Through this advancement, a patient's quality of life would improve and provide a benefit to a large portion of the population.

Through the availability and advancement of wearable IoT devices, it aids patients in monitoring and controlling their health metrics. An example of the benefits is that a patient can be made aware of the status of their condition with the aid of such devices at any time. That information can then be made available to the treating health care professional to provide prompt action for a condition or save the life of the user in an emergency. Connected health is proving to be a major application for developing technologies.

The concept of connected healthcare systems and smart embedded IoT devices offers a potential for both commercial companies and individuals to benefit. The goal is to use investigations performed on new technologies to enable the creation, enhancement, and expansion of connected health systems with the objective of developing a system that can help patients obtain a better awareness of their health status and provide early medical warnings.

The goal of the IoT is to enable things to be connected anytime and anyplace, with anything and anyone ideally using any path/network and any service [2, 3]. This goal requires more development in many areas including communication and applications. Many research and development entities are involved in development activities. Cisco defines the Internet of Everything (IoE) as connectivity of people, data, things, and processes in networks of connections [3]; in other words, IoE is a network of computers and devices of all types and sizes, all communicating and sharing information.

According to Cisco, there will be 50 billion devices connected to the Internet by 2020 [4]. IoT can be described as a network of networks.

A special dedicated IEEE standard is under development for the architectural framework of the IoT, namely, IEEE P2413 [5]. This standard defines IoT as a system of interconnected people and physical objects along with Information and Communication Technology (ICT) to build, operate, and manage the physical world via smart networking, pervasive data collection, predictive analytics, and optimization [6]. The IoT standard provides a reference model, defines architectural building blocks, and affords development mechanisms for the relevant systems.

As the Internet continues to grow, one of the key enablers is the IPv6 [7] global deployment which supports the ubiquitous addressing of any communicating "smart thing". It will provide access to billions of smart things allowing new models of IoT interconnection and integration. However, as a result of network expansion, more requirements will be added to network functions, network management, and network composition. IPv6 must enable the interconnection of heterogeneous IoT components together with heterogeneous applications. 6LoWPAN [8] is an optimized version of IPv6 for Low Power Wireless Personal Area Networks. It is basically IPv6 implemented on resource-constrained IoT devices.

IoT security is one of the main research topics as there is a need to provide security for the growing number of connected devices. For example, there is a need to ensure that IoT devices are only providing information to authorized entities [20]. IoT hardware development has many related research issues as new devices are introduced and many of them are small and have limited battery life. Moreover, the IoT sensor devices must be integrated into the Internet using communication protocols. These protocols must consider the low energy of the sensor battery especially when sensors are deployed in remote locations.

There are many protocols developed and more to be developed that consider the use of low power for IoT devices. For example, an efficient service announcement and discovery protocol in IP-based ubiquitous sensor networks is proposed [8]. The protocol adopts a fully distributed approach to ensure optimal acquisition times, low energy consumption, and low generated overhead, with timely reaction to topology changes. The protocol is capable of realizing optimal acquisition times with minimal cost in terms of energy and generated overhead, making it suitable for mobile networks.

The Internet Engineering Task Force has done the major standardization work for the Constrained Application Protocol (CoAP) that allows seamless integration of low power devices into the Internet [21]. CoAP can run on most devices that support User Data Protocol and the network architecture that use this protocol is a hot research topic [22–26]. IoT devices use different protocols (Bluetooth, Zigbee, etc.) and different networks (LANs; WANs). Thus, an IoT platform has three building blocks: Cloud Computing is used as an enabling platform that supports IoT-based systems to allow connecting a large number of devices and sensors. IoT-based healthcare applications can use Cloud Computing platforms to facilitate sensors communication, instead of implementing separate means to have all the sensors communicate directly.

1.1. Major Contributions. In this paper, our aim is to develop a smart IoT system that is unique and stands out when it comes to eHealth based IoT systems for predicting a personalized cardiac arrest, because they naturally combine the detection and communication components. Our major contributions are as follows:

(i) *Developing a multisensory smart IoT-based cyber-human system for heart abnormality prediction.*

(ii) *Proposing a smartphone-based heart rate detection system using a wearable Body Area Sensor (BAS) system.*

(iii) *Designing, developing, and implementing a low power communication module to send data to the smartphone.*

(iv) *Implemening a mobile system for remote supervision of users, which can be used to detect personalized health crisis.*

The rest of the paper is organized as follows: in Section 2, we describe the background and relevant related work. In Section 3, we discuss the solution process of designing our system architecture and we explain the circuit design of our system. In Section 4, we discuss the data collection process and follow with Sections 5 and 6, which are data analysis, results, and evaluation of our smartphone-based prototype system. Finally, in Section 7, we conclude the paper with some future research directions.

2. Related Works

There are many research projects that attempt to characterize a user's heart abnormality; however, most of them have lack of key components. Many individuals currently perform research in eHealth and many companies have taken advantage of this work by designing systems that connect patients with doctors around the world. We examine two different categories of related systems: comprehensive health care using embedded systems and connected eHealth smartphone applications. Our proposed system is more related to connected eHealth smartphone applications since we are developing an application on smartphone that connects with a smart IoT device while most companies focus on comprehensive health care systems that allow users to interact with one another and benefit from resources.

2.1. Comprehensive Health Care Systems. "PatientsLikeMe" focused on helping patients answer the question: "Given my status, what is the best outcome I can hope to achieve, and how do I get there?" They answered patient questions in several forms like having patients with similar conditions connect to each other and share their experiences [27]. But, they did not mention data security and the usability of the system.

Another related system is called "DailyStrength". It is a social network centered on support groups, where users provide one another with emotional support by discussing their struggles and successes with each other. The site contains online communities that deal with different medical conditions or life challenges [28]. It is very similar to

"PatientsLikeMe" in the sense that both of them are free platforms that involve patients and doctors interacting. Two major discrepancies between them are that "DailyStrength" does not involve research institutes and does not have a mobile application. Also, both systems are not IoT-based system.

In another work, a robust model was developed that included multiple pulse parameters, EEG, and skin conductance sensors into a shirt [42]. Another system was developed for connecting facial expressions and voice recognition with EEG patterns [43]. Other researchers proved that EEG alone exhibits characteristics for different emotions [44]. Facial recognition software has been compared with heart rate variability in order to better understand patterns associated with various emotions [45]. It has also been proven that certain pulse patterns are associated with physical stress and not from emotional stress [46]. But, their systems are mobile and they did not use IoT as a platform for their system.

Another comprehensive health care system is called "Omnio" which is an all-in-one application for Medical Resources [29]. It provides, among its services, clinical resources, diagnostic resources, disease guides, and drug information. Everyday Health [30] is a company which owns websites and produces content relating to health and wellness. It has higher ratings and publishes many health articles that can be very helpful for patients. In addition, it has a smart search that provides users with easy access their materials.

2.2. Connected eHealth Mobile Applications. Even though all the systems mentioned above provide health services, they do not provide any smart devices that can be used to monitor user's daily activities and alert them when needed. There are many heart monitors that provide users with their ECG signals so they can keep track of their condition but none of which who alert the users upon emergencies. A Smart Elderly Home Monitoring System (SEHMS) designed and developed on an Android™-based smartphone with an accelerometer; it could detect a fall of the user [31]. It provides a smartphone user interface to display health information gathered from the system. The main advantage of SEHMS is that it has the remote monitoring facility for elderly who and chronically hostile patients. But it cannot warn the user in case of emergency.

Remote Mobile Health Monitoring (RMHM) is a system that provides monitoring of a user's health parameters such as his or her heart rate, which is measured by wearable sensors [32]. It allows care givers and loving one to monitor the user's to facilitate remote diagnosis. The system does not have the capability of monitoring in real time.

The idea of predicting heart attacks remains a challenge and that is the focus of our research. Every research group specifies its own approach on how they plan to achieve its objective. We decided to use a combination of body temperature and ECG to predict heart abnormalities. Other systems have different approaches with different hardware implementations. None of them were discussed about power consumption rate during data collection. Our system uses a low power Bluetooth module to collect a longitudinal data wirelessly using a smartphone.

In [33, 34], authors presented a comparison between different data mining techniques for heart attack prediction. They present just prediction algorithms rather than a complete system with a data collection device and a computing platform. The best techniques that are most commonly used for predicting heart problems are: Decision Tree, Naïve Bayes, Neural Network, and K-mean. Our research not only includes a complete system with an IoT device and a computing platform, but also uses one of those data mining techniques (Decision Tree) to predict heart problems. This makes our system unique in the sense that we created a low power smart IoT system and used a data mining technique in our prediction algorithm. Upon testing our prediction algorithm, we obtained results with a high accuracy for all our healthy and unhealthy test subjects. We illustrate the difference between our system and the other related works in Tables 1 and 2.

To address the drawbacks of the above-mentioned research and systems, in this paper, we propose a smart IoT-based heart rate monitoring system. Our system is designed to address directly some of the drawbacks of the existing systems and potentially yield good prediction results. The most important aspect of our system is the warning that allows the user to prevent an injury before it actually happens. To the best of our knowledge, our system is the first smart IoT-based health assistance which uses a subject-specific Body Area Sensor signals for predicting heart related injuries.

3. System Architecture

The strength of our system relies on existing wireless communications to provide low power with maximum freedom of movement to users in their physical activity. In addition, we have used small, light-weight smart IoT devices that are user friendly, like the smartphone and the wrist-band.

To integrate the sensors, we used the output of the embedded sensors to perform an extensive set of experiments for evaluating and discriminating between normal and abnormal heart rate patterns. Subjects wear the embedded sensors and carry their smartphone in their pocket or hold it in their hands. The embedded ECG and temperature sensors constantly collect the heart parameters while the subject is living a normal life. After receiving the data through a low power Bluetooth communication channel, the smartphone will process the data to classify whether the user's condition is normal or abnormal. A quantitative heart rate analysis is performed in the Android platform which gives the user the option of viewing his/her real-time plots of the ECG signal and body temperature.

To determine abnormal heart patterns, we first establish a criterion for normal heart rate. Quantitative analysis of heart rate stability and pulse symmetry will yield a series of parameters, like heart rate, RR intervals (RR interval is the duration between two consecutive R peaks in an ECG signal), and ST segments (ST segment is the flat section of the ECG signal between the end of the S wave and the beginning of the T wave. It represents the interval between ventricular depolarization and repolarization). We then design an early warning system to monitor those parameters for signs of

Table 1: Qualitative comparison of existing work based on different features.

Approach	Use IoT Device	Mobility	Low Power System	Cyber Physical System	Cost Effective
PatientsL-ikeMe [27]	No	Yes	No	No	No
Daily Strength [28]	Yes	Yes	No	No	No
Om-nio [29]	Yes	Yes	Yes	Yes	No
Everyday Health [30]	Yes	No	No	No	No
SEHMS [31]	No	Yes	No	Yes	No
RMHM [32]	No	No	No	Yes	No
PHM [33]	Yes	Yes	No	Yes	No
Qardiocore [34]	No	No	No	Yes	No
Maksimović [35]	No	No	No	Yes	No
Stecker [36]	No	No	No	Yes	No
Mancini [37]	No	No	No	Yes	No
Sun [38]	No	No	No	Yes	Yes
Communicore [39]	No	No	N0	Yes	No
Kavitha1 [40]	Yes	No	No	Yes	No
Jagtap [41]	No	No	No	Yes	No
Our Approach	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

Table 2: Quantitative comparison of existing work based on different features.

Approach	Average Max HR	Approximate Accuracy	Average Max Sampling Rate	Number of Device (s) Used	Power Consumption in Watts
PatientsL-ikeMe [27]	160	90%	120	1	~ 500 mWatt
Daily Strength [28]	156	85%	110	1	N/A
Om-nio [29]	140	80%	100	1	N/A
Everyday Health [30]	144	85%	80	1	N/A
SEHMS [31]	155	78%	90	2	N/A
RMHM [32]	162	82%	140	2	N/A
PHM [33]	145	70%	150	1	N/A
Qardiocore [34]	135	78%	110	1	N/A
Maksimović [35]	155	85%	105	2	N/A
Stecker [36]	167	77%	130	1	N/A
Mancini [37]	151	87%	135	2	~ 600 mWatt
Sun [38]	160	75%	95	1	N/A
Communicore [39]	148	72%	150	1	N/A
Kavitha1 [40]	156	68%	155	1	N/A
Jagtap [41]	148	72%	145	2	N/A
Our Approach	**135**	**95%**	**160**	**1**	**~ 444 mWatt**

cardiac arrest during any activity. Although the system continuously monitors ECG patterns, the planned design only triggers a warning if the ECG patterns and body temperature of the user reaches a certain threshold level, wherein the user might face a potential heart attack. At that moment, the system transmits a warning to the subject in the form of a message or a vibration alert. Figure 1 illustrates the prototype embedded smart IoT system.

The IoT device constantly collects data from the user and sends it to smartphone via a Bluetooth communication module. All the processing and data analysis take place in the application where the user has the option to view user real-time plots. These plots provide the user a basic idea of his/her body's status. The user does not have maintained a record of his/her data to ensure that s/he is in a healthy or unhealthy state since the application's job is to alert the user upon an emergency. Finally, when the algorithm senses an abnormality it immediately alerts the user.

3.1. Hardware. The initial prototype system consists of a low power Bluetooth chip, an Arduino Uno™, a pulse sensor, and a temperature sensor as shown in Figure 2. The other components are the power supply unit along with a smartphone with an application.

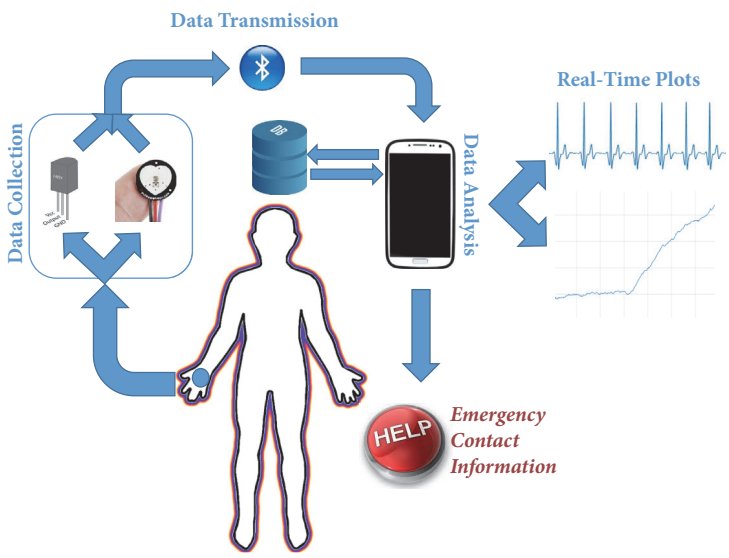


Figure 1: Proposed system architecture.

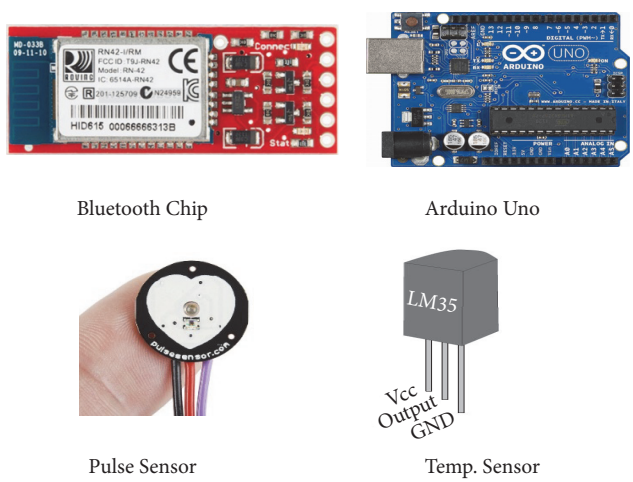


Figure 2: Hardware components for early prototype system [9–12].

The Arduino simply serves as an Analog to Digital Converter (ADC) [47]. An Arduino is an open-source physical computing platform based on a simple I/O board and a developmental environment that implements the processing/wiring language. The Arduino is programmed to read analog signals from the pulse and temperature sensors and create a data packet to convert the signals into digital form. Subsequently, it sends those packets to the phone as a response to the data sending request. It also manages the Bluetooth communication by coordinating with the RN42 Bluetooth chip. The Bluetooth chip basically equips the Arduino with the ability to connect to the smartphone application.

The data read from the sensors is always an analog value between 0 and 5 volts since that is the operating voltage of this microcontroller. The Arduino then maps those voltage values to digital values ranging from 0 to 1023. Since the y-axis for ECG signals is also a voltage, all we had to do is scale the digital values to back voltage.

Basically, we read the sensor value from the Arduino through analog pin 0 and then multiply it by 5 and divide it by 1023 to get the correct voltage value. This only applies to the pulse sensor since the expected output from the temperature sensor is in degrees Celsius.

To avoid the inaccuracy in simultaneous reading from multiple analog pins, we not only need a delay between each reading, but also need to read from the same analog pin twice. We read the temperature data from the sensor twice and send the second reading, then do the same for the pulse sensor. We need to send different symbols before the sensor readings to be able to parse the data at the receiving end (android application). Before sending a temperature reading we send

a '/' and before sending a pulse reading we send a '-', which makes data parsing simple.

3.1.1. Hardware Modifications. After testing our early prototype system, we worked on modifying the hardware to develop a better IoT device that can later on be used as a user friendly wearable device. In this section, we will discuss the new hardware components used, the design of the wearable device, and the performance of the device (power consumption /current draw).

(1) New Hardware Components. Rather than using the Arduino Uno, we decided to use the **Arduino Mini** instead. They both have the same microcontroller, clock speed, operating voltage, and range of input voltage. The Arduino Uno has an area of 36.63 cm^2 which is almost 7 times larger than the Arduino Mini. When developing a user friendly wearable device, it is important to have smaller components to be able to design a compact device.

To be able to upload code to the device using Mini USB Adapter, we also needed a **0.1 μF (micro-farad) capacitor** connected in series between the reset pin of the Arduino Mini and the reset pin of the Mini USB Adapter. We used a **PCB soldering board** to solder all the hardware components together. The board, which has dimensions of 5 cm x 7 cm (almost the same size of the Arduino Uno), has all the hardware components soldered to it. To power the device, we used a **7.4 Volt Lithium Ion battery** with a current supply of 2200 mAH (milli-amperes per hour). This battery has an outlet plug that gives it the ability to recharge. So, we also bought a **Pin Battery Connector Plug** to insert the battery in. This allows us to solder the pin plug to the board without soldering the battery itself, allowing the user to remove the battery when it needs to be recharged. All the components that we added (shown in **Bold** in this section) are shown in Figure 3.

(2) Design of the Wearable Device. After soldering all the hardware components on the PCB board, we design the system using Velcro strips to make it wearable. The device is designed such that the Mini USB Adapter can be connected only when we need to modify code on the Arduino. The final design of the device is shown in Figure 4, where Figure 4(a) shows the device with the Mini USB Adapter attached and Figure 4(b) shows the device without the Mini USB Adapter.

Figure 4(b) shows the device when the battery is active; hence, the LEDs of the Arduino Mini, Bluetooth, and pulse sensor are all on. The wires connected to the battery can be easily plugged in and out of the IoT device to allow the user to power the device on and off. The battery is placed between two PCB soldering boards. The temperature sensor's connection mounts over the Bluetooth chip and under the lower PCB board, where it will be in contact with the user's skin when the device is worn. The pulse sensor extends to the palm where it should be wrapped around the user's index finger. It is easy to measure pulse from finger during daily activities of the user. Finally, the Velcro is glued to the bottom of the lower PCB board and covered in black leather to give the device a better appearance. A complete smart wearable IoT device is shown in Figure 5.

(3) Smart IoT Device Performance. In this section, we explain the power consumption of the IoT device in different modes. When the IoT device is powered, the Bluetooth enters the idle mode where it blinks on and off waiting for a connection request. When the Android device connects to the IoT device through the application, the Bluetooth's LED stops blinking and is set to green indicating a successful connection.

The performance of the device can be determined by measuring the current consumption which tells us how long the device can be powered. The voltage supplied from the battery is constant since the Arduino Mini takes the voltage it needs and supplies to the devices connected to it. The typical way to determine the performance of the device is by checking the amount of current that is drawn from the battery in the different modes. The two modes in which we test the device are the idle mode and the connected/transmitting mode. The measuring unit of the battery is in milliamp hour (mAH) which is an energy measure. A battery with 2200 mAH will work for an hour if the current drawn from it is always 2200 mA. Similarly, if the current draw is 1100 mA, the battery would last two hours. Therefore, to measure how long the device can be powered in the on state without the battery draining, we need to calculate the average current draw of the IoT device. Table 3 shows the current draws, the device's lifetime, and the power consumption during the two modes for the IoT device.

The performance of the smart IoT device shows that the system can collect data for a long period of time in both modes which makes it very useful for users. When the battery is too low on power to operate the device, it can be recharged by simply plugging the battery's wires to a charger.

3.2. Software. To receive and analyze data from the IoT device, we use a heart rate and body temperature collector interface in the smartphone. As described in the hardware section, we developed a Bluetooth communication channel that is capable of transmitting data from the pulse and temperature sensors to the smartphone. On receiving data from the sensors, the system processes the data to identify any abnormality in the heart rate.

To transmit data to the smartphone through Bluetooth channel, we opened a socket from the Android application that connected to the transmitting signals of the Bluetooth module. To communicate with the Arduino, we created a software serial object and specified the transmitting and receiving pins. When the Bluetooth is supplied with power, it immediately enters the pairing mode, where it waits for any device to connect to it. Then the smartphone Bluetooth adapter is opened through the application and it starts searching for the devices. After a successful connection, the application will produce a message on the screen informing the user that the connection was successful, and the Bluetooth chip's LED will turn from red (pairing mode) to green (connected mode). The detail user interface of our system is shown in Figure 6.

After connecting to the IoT device, the application will automatically start receiving the sensors' data. The application parses the temperature and pulse data into separate arrays that are then sent to different pages where they are

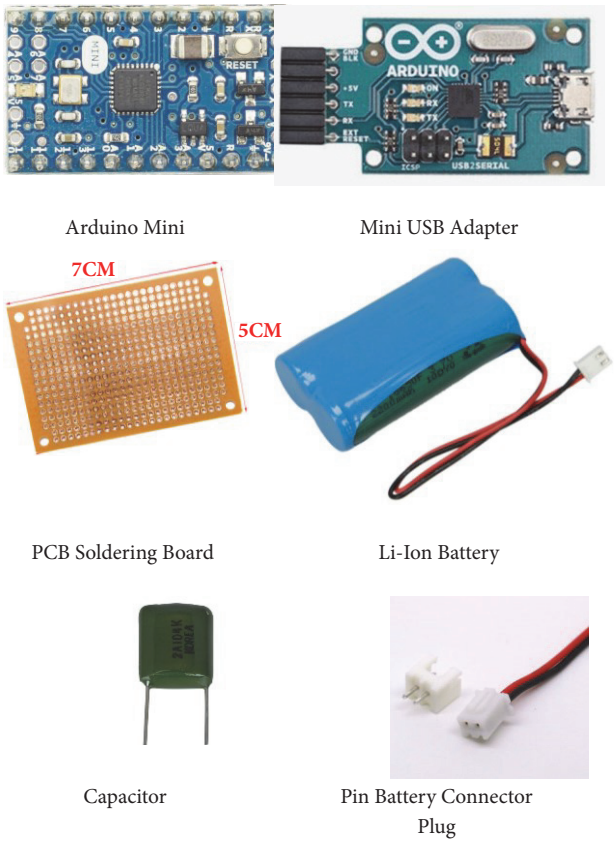
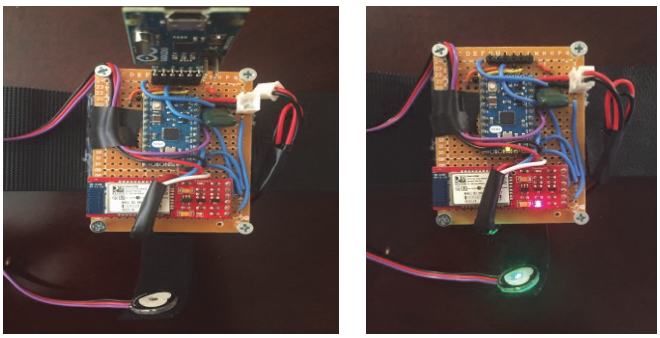


Figure 3: Hardware components for improved version of the system [13–18].



(a) With USB adapter (b) Without USB adapter

Figure 4: Wearable IoT device.

plotted in real time. The user has the option of either viewing the separate plots for each sensor data or viewing a page that has both plots in real time. While data is being plotted, the algorithm is constantly examining the ECG signal waiting for any abnormality.

The user will have the option of either signing up or logging in depending on whether the user has an account or not. If the user has an account s/he can simply enter the username and password to login. If not, clicking on the sign-up button will take the user to another page where s/he will be asked to enter some information to create an account. The user will then be directed to the home page of the application where s/he will have different options. The user will need to connect to the IoT device before s/he can start viewing his/her data. This can be done by pressing the connect button which will take the user to another page where s/he can find the device.

In the connect page, at first the user needs to turn on the Bluetooth of the Android device. By pressing the "TURN ON" button, the Android device will respond to the application's request, asking the user if the application can open the Bluetooth and by hitting yes, the Bluetooth turns on. The user can then go to the home page where s/he will have several options between viewing his/her real-time plots

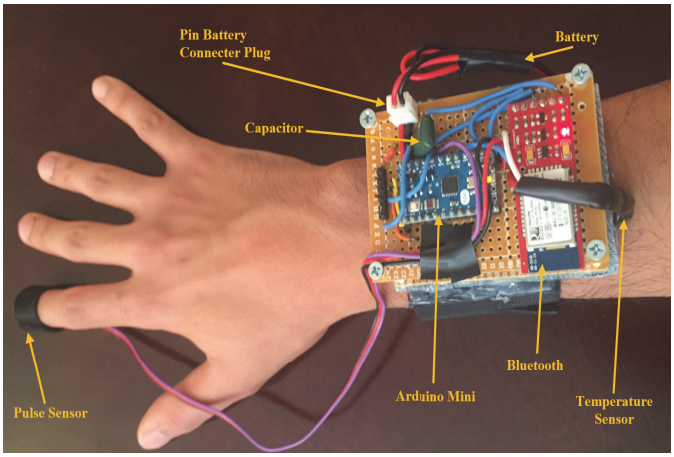


Figure 5: Wearable smart IoT device.

Table 3: Performance metrics of IoT device.

Mode of operation	Current Draw (mA)	Lifetime (Hours)	Power Consumption (mW)
Idle	26	84	192.2
Connected	60	36	444

Table 4: Statistics about subjects participating in our data collection.

Gender	Age [yrs.]	Height [cm]
F: 4	23-26: 8	150-159: 3
M: 16	27-34: 9	160-169: 5
	35-39: 3	170-179: 10
		180-189: 2

of the sensed data or going to the decision page. The decision page will basically have information that describes the user's current health status. The time axis in real-time graphs shows that the graph retrieves the current time from the Android device and displays it in real time as the axis moves with incoming data points.

4. Data Collection

After we finalized the system and were retrieving accurate results, we began testing on test subjects. Since, we cannot test our system with real people who have a chronic heart disease, we recruited a group of participants, a variety of age groups, and a range of heights (see Table 4 for statistics).

The data collection process can be divided into two parts, reading the data from the sensors and sending it to the smartphone. For the first part, one sensor gets the heart's pulse rate and the other one gets the body temperature. The sensors data is parsed and plotted on the device's screen.

4.1. Data Collection Interface. The sampling frequency or rate at which we are collected sensor data is the key challenge in data collection process. For our system, we send the data from the two sensors simultaneously, so intuitively, the sampling rate for our system would be less than the sampling rate of a system that reads data from just one sensor. Given that the body temperature does not undergo as many changes as the ECG signal, we increased the ECG's sampling rate by decreasing the temperature's sampling rate. We fixed the sampling rates for the temperature sensor and the ECG signal at 5 Hz and 160 Hz, respectively. Figure 7 shows the block diagram that describes the sensor data collection interface. The Bluetooth chip is also connected to the Arduino which enables the IoT device to transmit the sensed data to the smartphone application.

First, the user wears the device as described in the hardware section and then uses the application to connect to the Bluetooth interface as described in the software section. From this point the user only needs to interface with the application where s/he can navigate through the different options.

4.2. Test Subject Data Collection. Our proposed system is used to collect data from the users and store it in the smartphone's database and it can plot and process the data in real time. To be able to write our algorithm, we had to collect data from test subjects while doing different activities. The three scenarios that we consider for each subject are: sitting, walking, and climbing (upstairs). We believe that those different scenarios can help us understand how everyone's heart behaves during different activities.

4.3. Test Subject Sample Data. The data collected show that the system has a data collection system that is capable of gathering data under any circumstances, such as in the three scenarios described above. In this section, we show the sample ECG data for test subjects. The sample temperature sensor data are just plots to demonstrate the accuracy of the sensor.

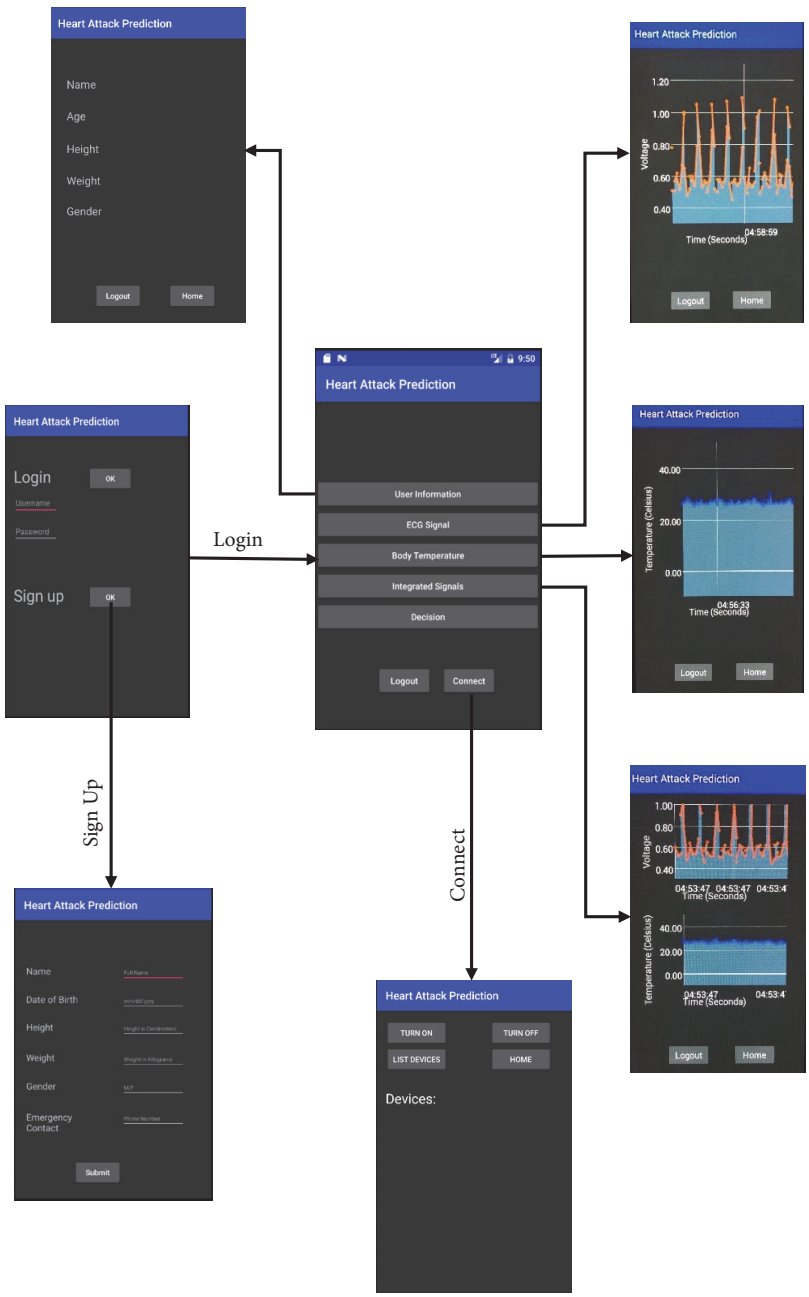


FIGURE 6: Smartphone user interface for data collection and for real-time graph.

4.3.1. Temperature Data. In this subsection, we present the detailed data for our temperature sensing process. Temperature does not need much analysis except for converting the data points to the time domain and smoothing the signal for better visual representation. The "noisiness" in temperature signal indicates a need for smoothing. The y-axis represents the temperature in Celsius and the x-axis shows the number of data points. To convert the data points to time in seconds, we need to use the sampling frequency which for this case was 100 Hz. The sampling rate that was used here was just to demonstrate the plot in an easier way since 700 hundred data points can be easily mapped to 7 seconds using 100 Hz. However, the sampling rates used for our system are still 5 Hz for the temperature data and 160 Hz for the ECG data. Figure 16 shows a set of data when converted from data points to time in seconds.

The temperature sensor used in our work has an accuracy of +/- 0.5, which allows it to capture changes in temperature very quickly as shown in the 7 second plots in Figure 8. The one on the left shows the temperature decreasing while the one on the right shows the temperature increasing.

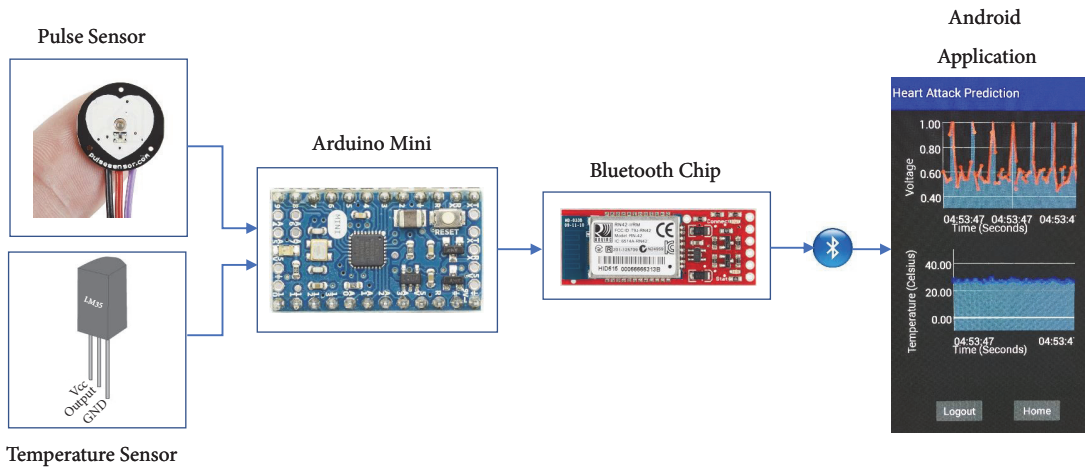


Figure 7: Data collection interface.

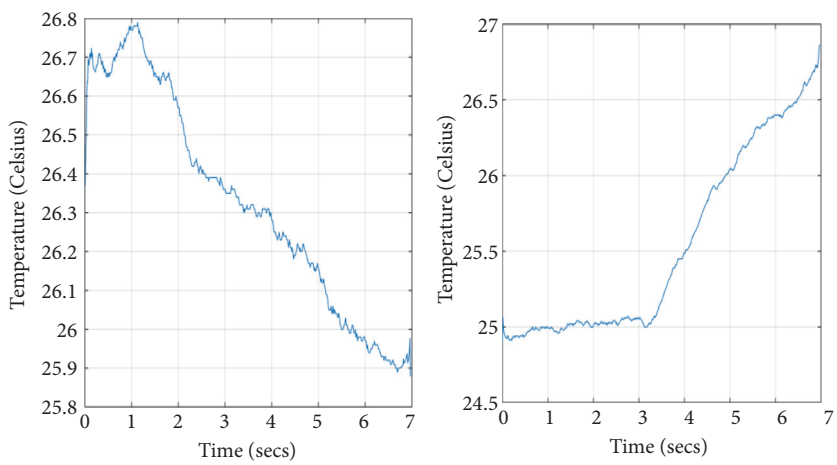


Figure 8: Temperature sensor data accuracy.

4.3.2. ECG Data. ECG data was collected from test subjects and analyzed on MATLAB. In this section, we show the data of four test subjects in the three scenarios, two males and two females. We were able to collect data for the walking scenario using treadmills and for the climbing upstairs scenario using stair steppers at the rec center. For each scenario, we show the ECG signal and its corresponding heart rate. The heart rate was ultimately calculated using the Fourier transform method to make sure it is accurate [48]. Table 5 shows the information of the four test subjects.

It is observed that the data collected for test subject 1 while sitting had no problems. Variations occurred when the data collected while walking and climbing upstairs. This is a result of the sensor moving while the subject was performing the different activities. We collected data for multiple times before we start analyzing. However, we decided to present the noisy data obtained for subject 1 to show the major distinction between noisy and proper ECG data. Therefore, the heart rates for subject 1 for the last two scenarios are displayed as N/A. A sample ECG signals for sitting, walking, and climbing upstairs for a test subject shown in Figure 9.

5. Data Analysis Techniques

Our data analysis was mostly done using MATLAB. In signal processing, noise is a general term for unwanted alterations that a signal may suffer during collecting, storing, transmitting, or processing data [49]. We collected data from analog sensors and transmitting them over a low power Bluetooth communication channel. We need data enhancement techniques before we can start analyzing the data as the reading can be affected by noise through the process. Since temperature values do not usually have many fluctuations, we are more concerned about the enhancement of the ECG signals.

5.1. Noise Reduction: Filtering. Extracting features from a noisy signal can give a heart rate of 200 when the actual heart rate is 80. Therefore, we ensure that, before we send our signal to the feature extraction method, almost every unwanted part of the signal is removed.

5.1.1. Baseline Wander Removal. The baseline wander is a problem that shows ECG signals in a wavy fashion rather than

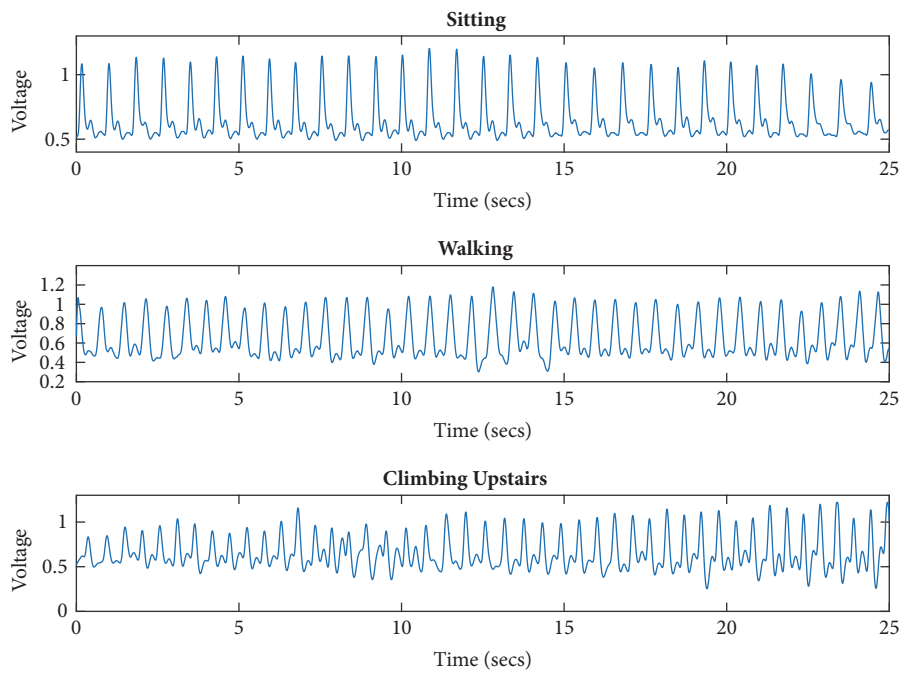


Figure 9: ECG signals for sitting, walking, and climbing upstairs for test subject 1.

Table 5: Test subject information.

Test Subject	Weight (lbs)	Height (cm)	Age	Scenario	Heart Rate
Subject 1 (Female)	125	173	20	(i) Sitting (ii) Walking (iii) Climbing Upstairs	(i) 107 (ii) N/A (iii) N/A
Subject 2 (Male)	141	177	24	(i) Sitting (ii) Walking (iii) Climbing Upstairs	(i) 72 (ii) 98 (iii) 108
Subject 3 (Male)	163	180	23	(i) Sitting (ii) Walking (iii) Climbing Upstairs	(i) 72 (ii) 100 (iii) 134
Subject 4 (Female)	128	184	23	(i) Sitting (ii) Walking (iii) Climbing Upstairs	(i) 79 (ii) 89 (iii) 105

being more of a constant envelope. A high pass filter to the signal improves the "look" of the signal because it removes the low frequency component that manifests itself as a sine-like pattern of the baseline. Removing the baseline wander gives a better signal which can help us process data more accurately. Equation (1) describes the process of reducing noise using base line wonder, where w_c is the cut-off frequency and N is the filter order:

$$|H(\omega)|^2 = \frac{1}{1 + (\omega_c/\omega)^{2N}} \quad (1)$$

First, we smooth the signal using the MATLAB built in function 'smooth', which gives us that sine-wave-like signal, then we subtract that sine-wave-like (low frequency component) from the collected ECG signal.

5.1.2. Removal of High-Frequency Component. The time domain operation of a low pass filter for signals is the mathematical operation called the moving average (often addressed to as smoothing). The enhanced version was achieved by applying a low pass filter with a very satisfying result as can be seen in the plot. The key when using high pass or low pass filters is to choose the correct cut-off frequency.

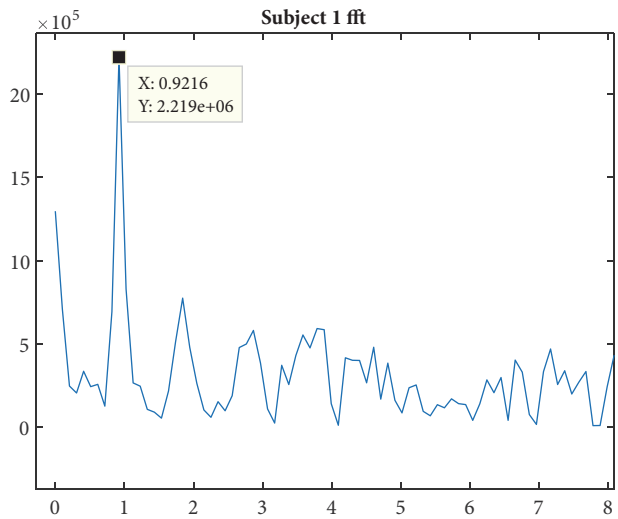


Figure 10: Fourier transform of an ECG signal.

Choosing the wrong cut-off frequency can result in huge alterations in the signal and irrelevant or, worse, erroneous data decisions. Equation (2) describes the operation of low pass filtering.

$$|H(\omega)|^2 = \frac{1}{1 + (\omega/\omega_c)^{2N}} \tag{2}$$

We apply a moving average which is achieved by using the smooth function in MATLAB. Using the correct window for smoothing is essential as it can affect the signal's expected output. For the ECG signal we used a smoothing window of 20 data points.

5.2. Extracting Features. After noise reduction, we extracted heart rate, RR intervals, and ST segments from ECG signals. We used these features as inputs of our prediction algorithm along with the body temperature. In the next subsections, we describe the process of extracting features from the ECG signal.

5.2.1. Heart Rate. We extracted heart rate or Beats per Minutes (BPM) from collected ECG signals. We can calculate BPM using several techniques including taking the number of QRS peaks in a given time, using autocorrelation, or using Fourier transform. The first technique sometimes yields inaccurate results; however, when a signal has no baseline wander problem, this technique should work. Autocorrelation and Fourier transform techniques yield very accurate results.

(1) Autocorrelation. In autocorrelation, a signal is correlated with a shifted copy of itself as a function of delay or lag. Correlation indicates the similarity between observations as a function of the time lag between them. We used this technique to analyze our data as the collected ECG signals are periodic. First, we calculate the difference between two peaks which gives the length of one period in data points. Dividing that number of data points by the sampling frequency gives us the time in seconds of one period. Inversing and multiplying it by 60 give us the total beats per minute.

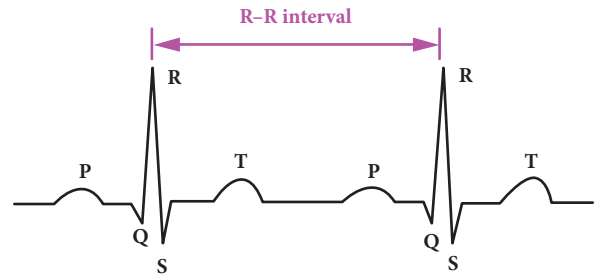


Figure 11: R-R interval of an ECG signal [19].

The mathematical equation for the autocorrelation function for signal processing is shown in

$$R(k) = \sum_{n=N1}^{N2-k} x(m) * x(m+k) \tag{3}$$

The equation shows the summation of the product of a signal (x(m)) and a shifted version of it (x(m + k)). From the equation, one can intuitively understand that, at lag zero, the signal will have the highest amplitude since it is a multiplication of itself without any shift.

(2) Fourier Transform. The Fourier transform extracts the frequencies and harmonics of the signal. So, we find the location of the maximum harmonic in the frequency plot.

The first significant harmonic in the signal is shown approximately around 0.92 (the red circle) as shown in Figure 10, which represents the beats per second. Simply multiplying this by 60 gives us the beats per minute. The other peaks in the signal represent either noise or information are irrelevant in terms of calculating the heart rate.

The equations for the Fourier and inverse Fourier transforms are shown below in (4) and (5), respectively [50].

$$F(\omega) = \int_{-\infty}^{\infty} f(t) * e^{-i\omega t} dt \tag{4}$$

$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} F(\omega) * e^{i\omega t} d\omega \tag{5}$$

where $F(\omega)$ is the frequency domain of a given signal and $f(t)$ is the time domain of the signal. For our data analysis, we used an "fft" function in MATLAB that gives us the plot of the signal in the frequency domain. From there, we get the location of the maximum harmony and multiply it by 60 to get the beats per minute.

5.2.2. R-R Intervals. Another feature that we extracted from the ECG signal is called the R-R interval, which is the interval between successive R peaks in an ECG signal. For normal ECG signals, the R-R intervals do not fluctuate or suddenly change in a drastic manner. We recorded R-R intervals by having the standard deviation of the signal. Figure 11 gives a visual representation of an RR interval

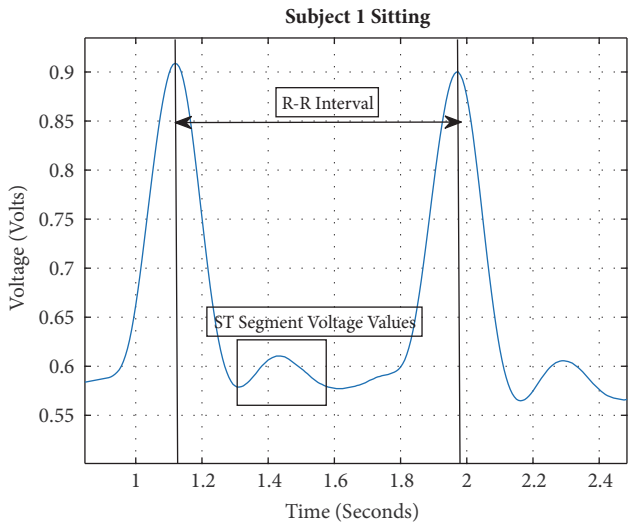


Figure 12: Sample ECG with R-R interval and ST segment.

Basically, we find the R peaks and subtract the peaks locations in time, giving us the duration between each beat. We find the peaks using a threshold value that ensures that all the R peaks are included. To do that, we get the maximum of the signal and subtract it by a specified percentage to ensure that all the intervals are above the threshold value. The reason for this was because not all the R peaks have the same voltage value, the voltage values of the peaks usually fluctuate which is why we dynamically calculate that threshold value based on the portion of the ECG signal with which we are dealing. We create arrays that store the R-R intervals of the ECG signal to calculate the variability of the durations.

5.2.3. ST Segments. Also, another feature is that we extracted ST segment voltage value from the ECG signals. We take the ST segment into consideration for heart attack predictions since elevated ST segments are one of the biggest indicators of heart attacks. Figure 12 shows the sample data from one of our test subjects. To calculate the ST segment voltage value, we take the average of the points shown in the rectangle.

This produces a number that represents the ST segment voltage value. The R-R interval is basically the range between both peaks. We take a 20 percent from that range and add it to the location of the first peak which gives us the point where we would start adding the voltage values. Then we take 50 percent of the range and subtract it from the location of the subsequent peak, which gives us the point where we would stop adding the voltage values. Those voltage values are shown in the box in Figure 12.

After adding all the voltage values, we divide by the number of points to get the average voltage value representing the ST segment. Typically, the voltage values of a normal ECG would be much lower than the voltage values of an ECG with an elevated ST segment. We also use a standard deviation analysis to detect if an ST segment suddenly changed. Note that using percentages of the R-R interval to get the locations of the ST segment voltage values and then averaging them is not a conventional way to calculate the voltage value of the ST segment. This is based on our analysis, which used trial and error, and that method to extract the ST segment voltage value provided us with the best results.

5.3. Algorithm. The algorithm is the most important part of the system. The algorithm functions as shown in the flow chart in Figure 13. The first step is to read the data from the sensors at 5 Hz for the temperature data and 160 Hz for the ECG data. We then maintain a sampling window of 5 seconds on which to perform all computations. After selecting the sample window, we reduce the noise by applying the filtering techniques discussed in Section 5.1. After removing all the noise components from the signals, we extract the three features from the ECG and pass on those features along with the temperature data to our prediction algorithm. If the results from the algorithm indicate that the current sample window is normal, the window shifts by 1 second and takes the next 5 seconds of data. If the algorithm detects an abnormality, it immediately warns the user. Using a moving window of 1 second creates the need more computation but it provides faster and more accurate feature extraction and prediction results. This means the next sample window will have 1 second of new data and 4 seconds of data from the previous sample window.

Our prediction algorithm is based on a predictive machine-learning model called J48 Decision Tree [51]. This model decides the target value of a new sample based on various attribute values of the available data. We apply that model to our algorithm with the result that the target value would indicate whether the patient is having a heart attack or not, and the available data would be contained in the extracted features. We note that the decision tree is a general model that can be used in many applications in many different ways. We designed a novel algorithm; Heart Attack Prediction using a **Decision Tree based on a Standard Deviation Statistical Analysis** (DTSDSA); that uses the decision tree model with a standard deviation statistical analysis. We examine the method by which the extracted features are processed at the decision tree. Using a standard deviation statistical analysis, we determine whether the features are abnormal or abnormal. Figure 14 shows the structure of our decision tree which refers to the prediction algorithm block in Figure 13. Our algorithm uses warning levels from 0 to 4 to determine the degree of abnormality for each incoming window.

We employ a sample window and a moving window. The sample window contains the part of the ECG signal that is being processed while the moving window specifies the amount by which that sample window is shifted to start taking the next sample window. Figure 15 illustrates the appearance of both of the windows on one of our test subjects for both sensors. As shown in Figure 14, the sample window is 5 seconds and the moving window is 1 second. This provides an overlap of 4 seconds for subsequent sample windows. We note that, for the 30 second ECG signal shown below, if we did not have a moving window, we would have only had 6 sample windows (30 seconds/5 second windows). This means that the features would only be updated 6 times throughout the entire 30 seconds. The way we implemented it, we get 26

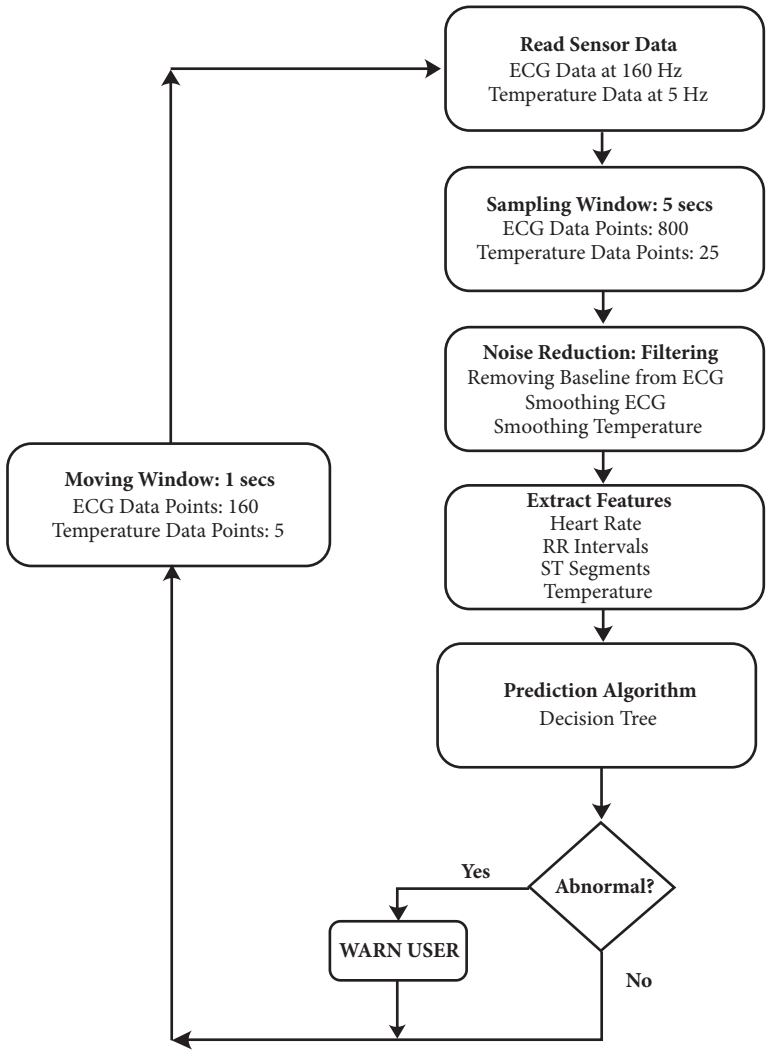


Figure 13: Flow diagram of our algorithm.

results instead of 6 for the entire 30 seconds. This represents a far more practical method since heart rates change very fast, especially during cardiac events.

For each sample window, the feature extraction function returns a single value for the heart rate, in a one-dimensional array with the RR interval durations, and a one-dimensional array with the ST segment voltage values. Since heart rates are the most important feature that describe the heart's status, we start by checking variations in the heart beats first. We do so by making sure that the heart rate is consistent using our standard deviation analysis. Any heart rate while walking or running is obviously going to be higher than the heart rate while sitting or resting. Since we have a wide range of heart rates that are considered normal, we were not able to simply apply a thresholding technique where a heart rate above a certain threshold value would be a sign of potential heart failure. Heart rates can vary from 55 all the way to 150 depending on the person and what the person is doing.

By using our standard deviation statistical analysis, we only detect an issue with the heart rate when it suddenly fluctuates out of the normal range. If the current heart rate has an error above 7 percent, we set the warning level to 1. For example, if a person's average heart rate is between 80 beats per minute for 20 seconds then suddenly goes up to 100, the error would be 25 percent. We only proceed to check the R-R intervals if there is a problem with the current heart rate. For the R-R intervals and ST segments arrays, with which we are dealing, we calculate the standard deviation of the sample window for both features. If the R-R intervals' error is higher than a certain percentage, we set the warning level to 2 and proceed to check the ST segment. If the ST segment also has an error higher than what is considered to be normal, we set the warning level to 3 and proceed to check the body temperature. At this point, we already know that this sample window is abnormal. We still check the body temperature to see if the warning level would go up to 4 or not since up to this point, it can be a false reading based on errors in feature extraction due to noisy signals. Since the temperature is a single value, we calculate the error the same way we did for the heart rates only with different thresholds. We then return

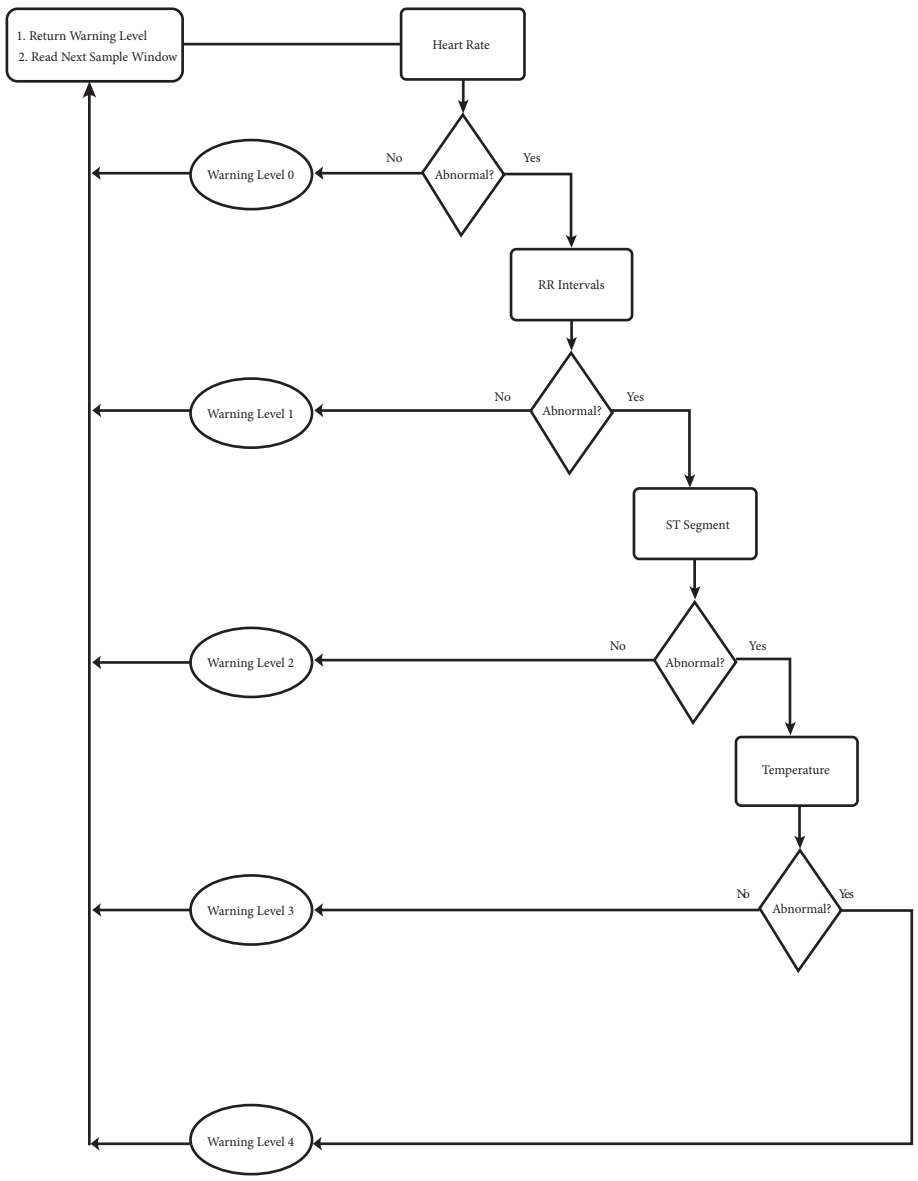


Figure 14: Flow diagram of decision tree algorithm.

the warning level for each sample window to process that warning and read the next sample window.

We created a dynamic buffer that attends to the processing of warnings that are returned for each sample window. The buffer is responsible for collecting the warning levels and making a decision. To implement the buffer, we created another window called the prediction window along with a moving window. This window initially waits to collect the results from 8 sample windows (8 warnings). The moving window then shifts the prediction window 2 spots to the right. A decision is made on each prediction window based on a ratio that is calculated from the warning levels. Figure 16 shows the technique by which the prediction and moving windows are established. The moving window is equivalent to 2 warnings and the prediction window is equivalent to 8 warnings, which results in 10 prediction windows for the 30 second segment.

Assuming that the body temperatures are normal, the worst case would be a prediction window with all 3's which gives a sum of 24. We add all the warning levels and divide by 24. If the ratio is 0.5 or above, we trigger a warning to the user. The results shown in Figure 16 are from an ECG signal that was very noisy and did not have any characteristics of a proper ECG. The algorithm therefore started detecting abnormalities in the third prediction window. Running this algorithm on normal ECG's for healthy subjects gave us ratios that were either zero or close to zero. Those were our first indications that the algorithm does indeed work. However, our next step was to run the algorithm on real test subjects with heart failures for more validation. The

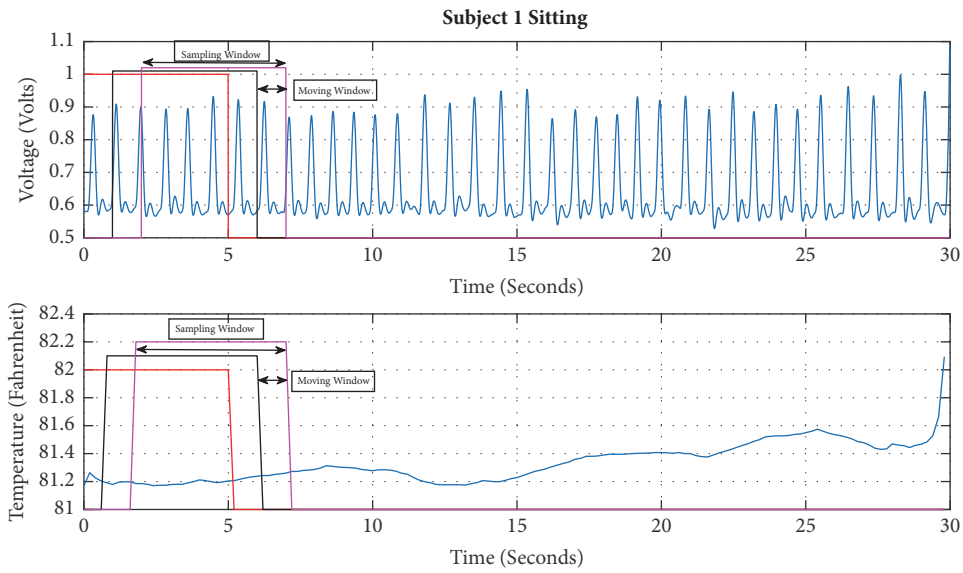


Figure 15: Illustration of sample and moving windows.

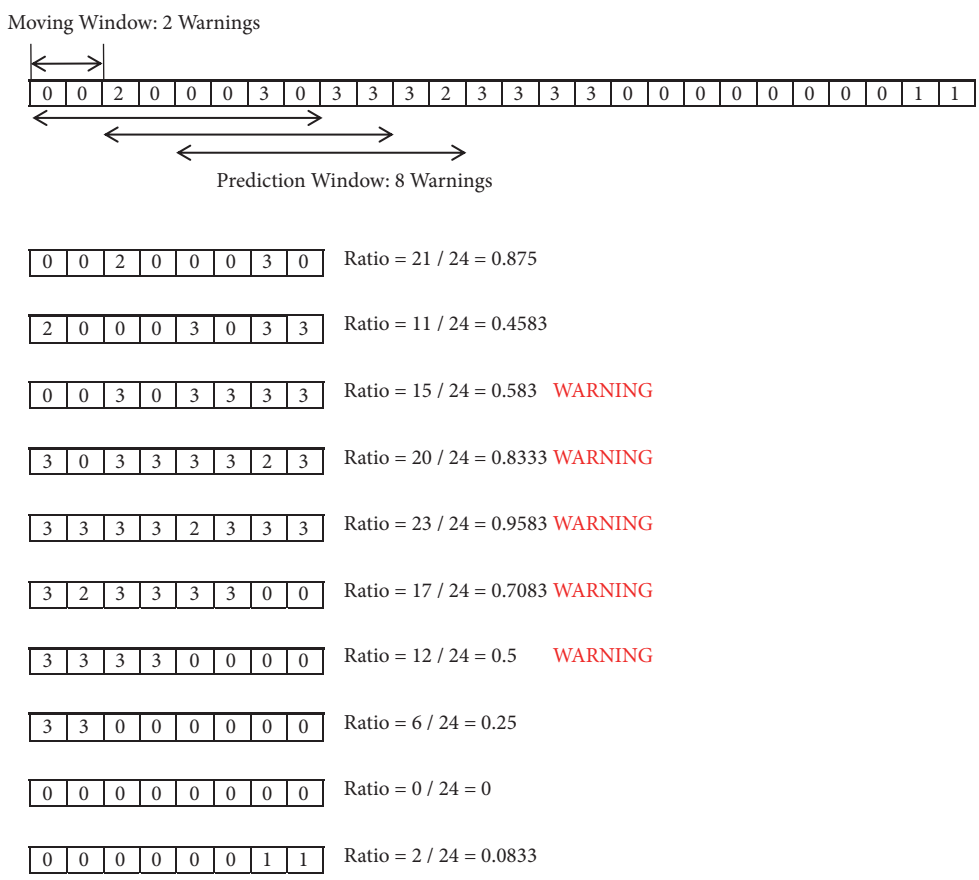


Figure 16: Algorithm results using prediction window.

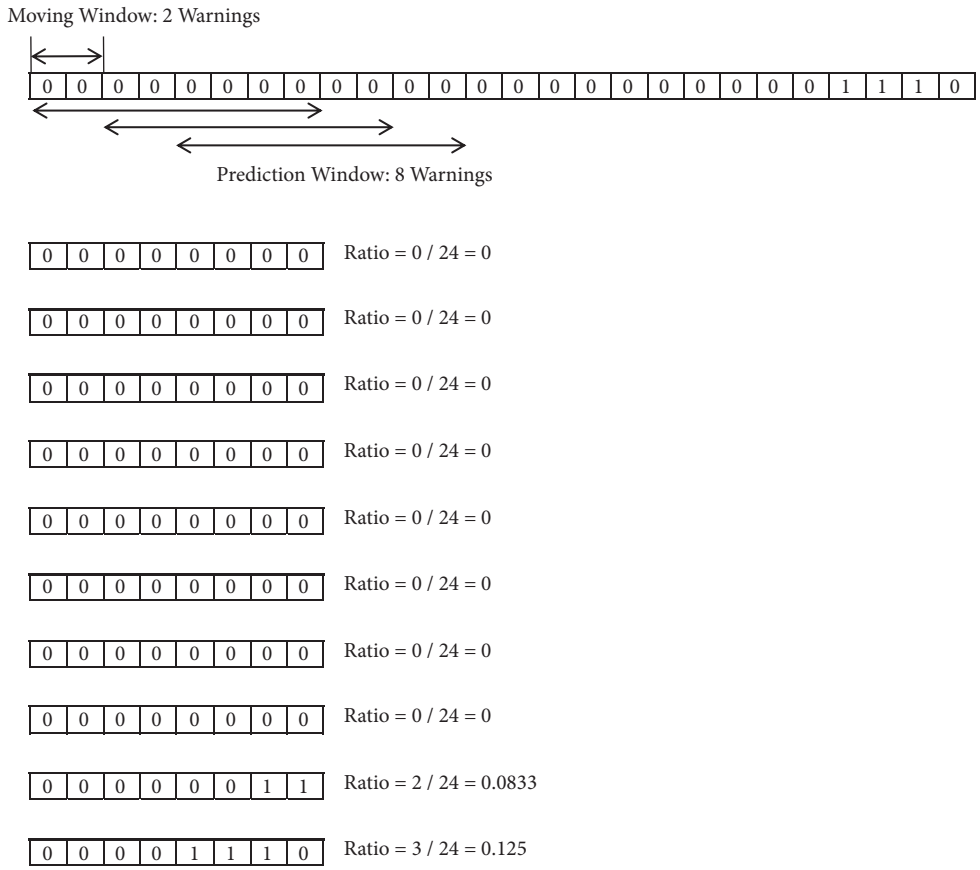


Figure 17: Prediction algorithm results for test subject 1 while walking.

results are shown and discussed in more detail in the next section.

6. Results and Evaluation

To evaluate our proposed system, we developed a prototype application and investigated its performance. We evaluated the prototype with extensive experiments. In this section, we explain how the data is analyzed and performance is measured for healthy and unhealthy subjects.

6.1. Healthy Test Subjects. The results shown are for one test subject in the three different scenarios. Since all subjects had normal body temperatures, we will show the ECG signals and the results of the prediction algorithm for each sample window. The test subject's information is shown in Table 6.

The ECG signal while walking is considered as a normal and, therefore, no warning will trigger. The ECG signal while walking also consider as normal. But, we had a couple of false warnings while walking. We use the prediction window to eliminate the false warnings in our algorithm. Figure 17 shows that the results from the prediction algorithm had three warnings of level one while walking. Therefore, there was no need to warn the user since it was a false error.

The algorithm triggered a few warnings as well while the test subject was climbing upstairs. As shown in Figure 18, there are a few warnings for each prediction window, but, none of which above 50 percent, threshold level for indicating a myocardial infarction (MI).

6.2. Unhealthy Test Subjects. We were able to download datasets from a database online that has records of patients who suffered from sudden cardiac deaths. We also ran the algorithm on our 20 healthy test subjects and the results validated that the algorithm works with a high accuracy for the healthy test subjects. Table 7 shows the information of each test subject [52].

The results showed that the algorithm gives no warnings for all scenarios that had different heart rates. However, to validate our algorithm using only healthy subject data is not enough. Even though we ran our algorithm on noisy data, we still cannot conclude that our algorithm can predict heart problems. Therefore, we downloaded 10 datasets from a database online that has ECG signals for patients that suffered from sudden cardiac deaths. The ECG signals we selected for each test subject was moments before the subject passed away.

We tested our algorithm on the ECG signals from all the subjects shown in Table 7 and the results were accurate as expected. We show some details of the algorithm's results for the subject 5 from Table 7. Figure 19 shows the ECG signal for subject 5.

Before showing the prediction algorithm results, we will explain the results from the feature extraction to show why the algorithm triggered warnings.

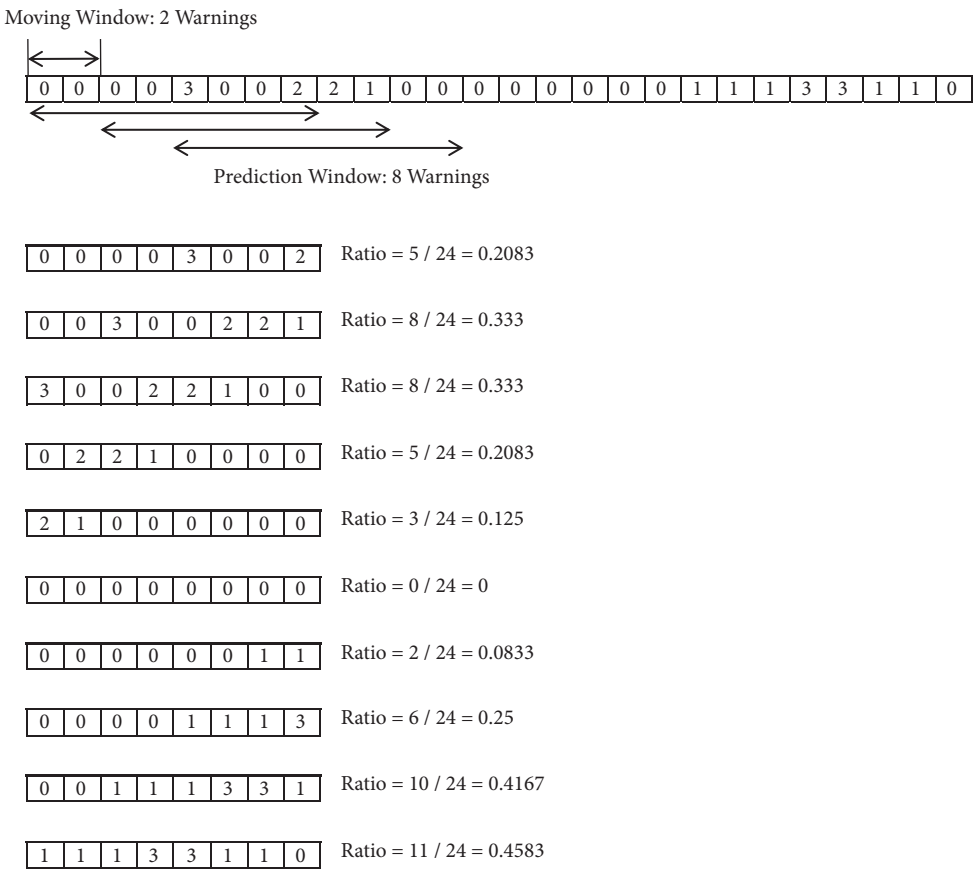


Figure 18: Prediction algorithm results for subject 1 while climbing upstairs.

Table 6: Information for test subject 1.

Subject	Gender	Age	Scenario	Average Heart Rate
1	Male	24	(i) Sitting (ii) Walking (iii) Climbing Upstairs	(i) 84 (ii) 108 (iii) 135

Heart Rates for First 11 Sample Windows

71.94	131.89	71.942	119.90	119.90	131.89	71.942	71.942	71.942	71.942	131.89

Sample Window 2

(1) Heart Rate Error = 100 ∗ |131.89 − 71.94| / 71.94 = 83.3% ⟶ Warning level 1

(2) As shown in Figure 20, the R-R Intervals had very high fluctuations which explain why the heart rate jumped from 71.94 to 131.89 in just one second. ⟶ Warning level 2

(3) As shown in Figure 21, the ST segment voltage values were also fluctuating in an abnormal fashion. ⟶ Warning level 3

The prediction results for the ECG signal are shown in Figure 22. The warning result from the second sample window, the one we discussed, is highlighted in yellow. We observed a remarkable fluctuation in all the features and the algorithm triggered warnings of level 3 for almost all the sample windows as expected for a patient who had a history of cardiac surgery and passed away shortly after the signal was recorded.

7. Conclusion

In this paper, we designed and developed an integrated smart IoT system to predict and monitor heart abnormality in

Table 7: Information of unhealthy test subjects.

Subject	Gender	Age	History	Medication	Underlying Cardiac Rhythm
1	Male	43	Unknown	Unknown	Sinus
2	Female	72	Heart Failure	Digoxin; Quinidine gluconate	Sinus
3	Female	30	Unknown	Unknown	Sinus
4	Female	72	Mitral valve replacement	Digoxin	Atrial fibrillation
5	**Male**	**75**	**Cardiac surgery**	**Digoxin; Quinidine**	**Atrial fibrillation**
6	Male	34	Unknown	Unknown	Sinus
7	Female	89	Unknown	Unknown	Atrial fibrillation
8	Male	66	Acute myelogenous leukemia	Digoxin; Quinidine	Sinus
9	Female	82	Heart failure	None listed	Sinus
10	Male	68	History of ventricular ectopy	Digoxin; Quinidine Gluconate	Sinus

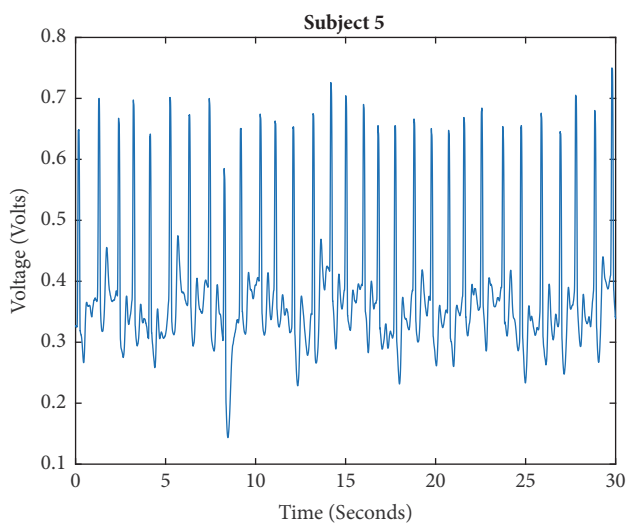


Figure 19: ECG signal of unhealthy subject 5.

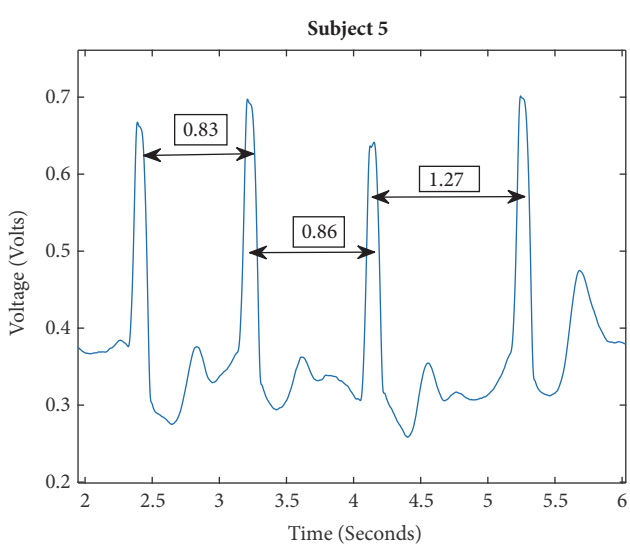


Figure 20: R-R Intervals on sample window 2.

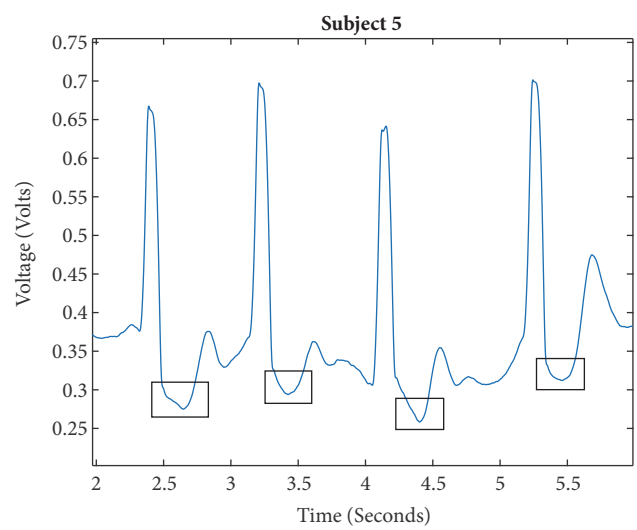


Figure 21: ST segments on sample window 2.

user. We also managed to create a low power consumption communication channel between the smart IoT device and the smartphone application. This research provides users a noninvasive device that allows them to better understand how they may feel about their ECG. The results from different data sets are also presented to show that this approach provides a high rate of classification correctness in distinguishing between at normal and abnormal ECG patterns. The system may also find multiple applications in behavior detection for people with various disabilities.

To test the chronological durability and long-term feasibility of our approach in the future, we plan to test our system with data from the people who suffer from heart problems. We plan to test the power consumption rate for whole working life of the device during test on the field. We also plan to measure the different physiological parameters of the user during daily activities. Additionally, the system can be used in the smart home monitoring system for future wireless technology. Also, we can enhance the system by

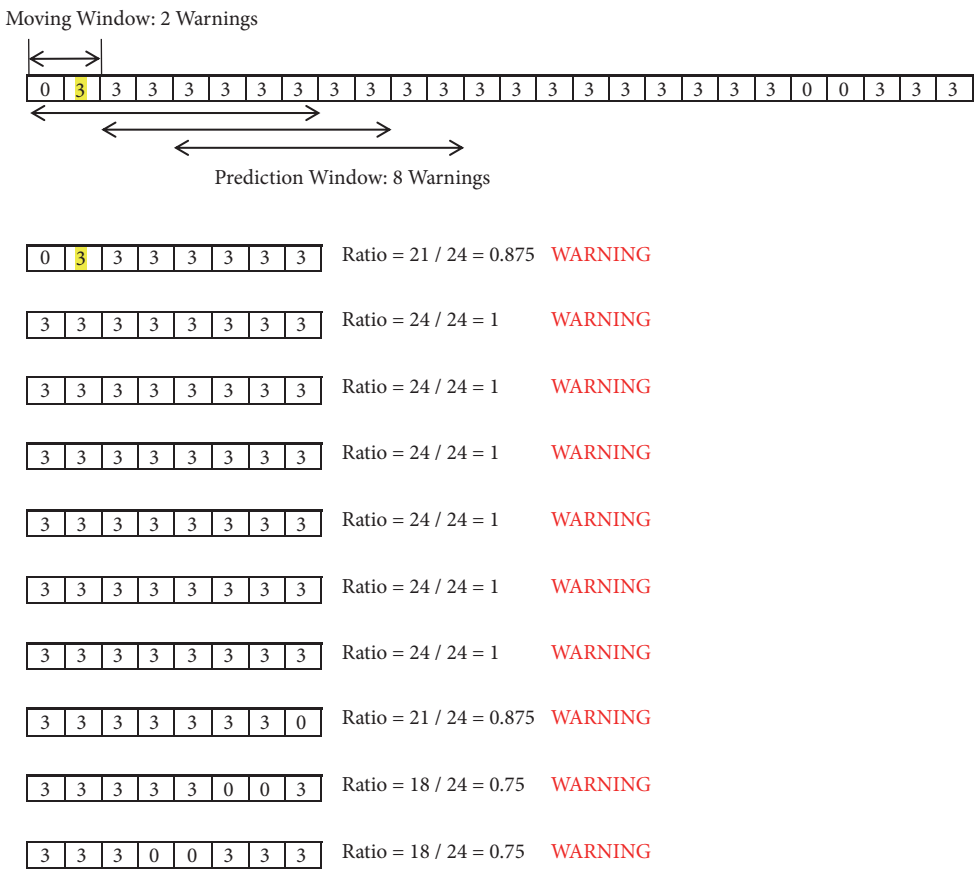


Figure 22: Prediction algorithm results for unhealthy subject 5.

adding more sensors, like, Galvanic Skin Response (GSR), accelerometer, to the IoT device.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Disclosure

This paper is based on the MS thesis work by the author Yosuf Amr ElSaadany [53].

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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References

[1] ITU-T Global Standards Initiatives Recommendation ITU-T Y.2060 (06/2012) http://www.itu.int/en/ITU-T/gsi/iot/Pages/default.aspx.

[2] O. Vermesan and P. Friess, *Internet of Things: Converging Technologies for Smart Environments and Integrated Ecosystems*, River Publishers Series in Communications, 2013.

[3] R. Clarke, *Smart Cities and the Internet of Everything: The Foundation for Delivering Next-Generation Citizen Services*, Cisco, 2013.

[4] D. Evans, *The Internet of Things How the Next Evolution of the Internet Is Changing Everything*, Cisco IBSG.

[5] IEEE Standards Association, P2413 - Standard for an Architectural Framework for the Internet of Things (IoT), https://standards.ieee.org/develop/project/2413.html.

[6] IEEE Standards Association (IEEE-SA), Internet of Things (IoT) Ecosystem Study, IEEE 2015.

[7] IETF, Internet Protocol Version 6 (IPv6) Specification, Network Working Group, The Internet Society (1998).

[8] B. Djamaa and R. Witty, "An efficient service discovery protocol for 6LoWPANs," in *Proceedings of Science and Information Conference, SAI 2013*.

[9] https://www.sparkfun.com/products/12576.

[10] https://robotechshop.com/shop/arduino/arduinoboard/arduino-uno-r3-china/?v=7516fd43adaa.

[11] https://www.sparkfun.com/products/11574.

[12] https://www.slideshare.net/AmeerKhan3/zigbee-based-patient-monitoring-system-21031306.

[13] https://store.arduino.cc/usa/arduino-mini-05.

[14] https://store.arduino.cc/usa/arduino-usb-2-serial-micro.

[15] http://www.ebay.com/itm/100PCS-7CM-X-5CM-PCB-Soldering-Printed-Circuit-Board-Blank-/220845344036.

[16] http://18650-battery.net/wp-content/uploads/2016/03/74V-2200mAh-18650-Rechargeable-Li-ion-Battery-0-2.jpg.

[17] http://www.jameco.com/z/MY-1–1-uF-100-Volt-Mylar-Capacitor_26956.html.

[18] https://www.aliexpress.com/store/product/50-SETS-JST-XH-2-5-2-Pin-Battery-Connector-Plug-Female-Male-with-140MM-Wire/506373_32598005148.html.

[19] https://upload.wikimedia.org/wikipedia/commons/c/c1/ECG-RRinterval.svg.

[20] J. Penney, *Choosing An IoT Security Provider*, 2016, http://info.deviceauthority.com/blog-da/choosing-an-iot-security-provider.

[21] Internet Engineering Task Force, The Constrained Application Protocol (CoAP), https://tools.ietf.org/html/rfc7252.

[22] P. Sethi and S. R. Sarangi, "Internet of things: architectures, protocols, and applications," *Journal of Electrical and Computer Engineering*, vol. 2017, Article ID 9324035, pp. 1–25, 2017.

[23] P. P. Pereira, J. Eliasson, and J. Delsing, "An authentication and access control framework for CoAP-based Internet of Things," in *Proceedings of the 40th Annual Conference of the IEEE Industrial Electronics Society*, 2014.

[24] H. Khattak, M. Ruta, and P. di Bari, "CoAP-based Healthcare Sensor Networks: a survey," in *Proceedings of the 11th International Bhurban Conference on Applied Sciences and Technology*, 2014.

[25] M. Kovatsch, "CoAP for the Web of things: From tiny resource-constrained devices to the web browser," in *Proceedings of the 4th International Workshop on the Web of Things (WoT 2013), UbiComp '13 Adjunct*, Switzerland, Zurich, Sept. 2013.

[26] Internet Engineering Task Force (IETF), The Constrained Application Protocol (CoAP), https://tools.ietf.org/html/rfc7252, 2012.

[27] Patients Like Me, https://www.patientslikeme.com/.

[28] DailyStrength, http://www.dailystrength.org/.

[29] Omnio, http://omnio.com/.

[30] Everyday Health, http://www.everydayhealth.com/.

[31] J.-V. Lee, Y.-D. Chuah, and K. T. H. Chieng, "Smart elderly home monitoring system with an android phone," *International Journal of Smart Home*, vol. 7, no. 3, pp. 17–32, 2013.

[32] Y. Zhang, H. Liu, X. Su, P. Jiang, and D. Wei, "Remote mobile health monitoring system based on smart phone and browser/server structure," *Journal of Healthcare Engineering*, vol. 6, no. 2, Article ID 590401, pp. 717–738, 2015.

[33] P. Pawar, V. Jones, B.-J. F. van Beijnum, and H. Hermens, "A framework for the comparison of mobile patient monitoring systems," *Journal of Biomedical Informatics*, vol. 45, no. 3, pp. 544–556, 2012.

[34] Qardiocore, https://www.getqardio.com/qardiocore-wearable-ecg-ekg-monitor-iphone/.

[35] M. Maksimović, V. Vujović, and B. Perišić, "A custom Internet of Things healthcare system," in *Proceedings of the 10th Iberian Conference on Information Systems and Technologies (CISTI '15)*, Aveiro, Portugal, June 2015.

[36] E. C. Stecker, K. Reinier, C. Rusinaru, A. Uy-Evanado, J. Jui, and S. S. Chugh, "Health insurance expansion and incidence of out-of-hospital cardiac arrest: A Pilot study in a US metropolitan community," *Journal of the American Heart Association*, vol. 6, no. 7, 2017.

[37] M. E. Mancini, M. Cazzell, S. Kardong-Edgren, and C. L. Cason, "Improving workplace safety training using a self-directed CPR-AED learning program.," *AAOHN journal : official journal of the American Association of Occupational Health Nurses*, vol. 57, no. 4, pp. 159–169, 2009.

[38] Feng-Tso S., Cynthia K., Heng-Tze C. et al., "Activity-aware mental stress detection using physiological sensors," *Mobile Computing, Applications, and Services*, pp. 211–230, 2012.

[39] Communicore. (1996). Sudden cardiac arrest: A treatable public health crisis. Retrieved July 20, 2017, http://publicsafety.tufts.edu/ems/downloads/sca_whtp.pdf.

[40] G. Kavitha and E. Mariya, "Endowed heart attack prediction system using big data," *International Journal of Pharmacy & Technology IJPT*, vol. 9, no. 1, p. 285, 2017.

[41] S. Jagtap, "Prediction and analysis of heart disease," *International Journal of Innovative Research in Computer and Communication Engineering*, vol. 5, no. 2, 2017.

[42] C. Min, M. Yujun, S. Jeungeun et al., "Smart clothing: connecting human with clouds and big data for sustainable health monitoring," *Mobile Networks and Applications*, vol. 21, no. 5, pp. 825–845, July 2016.

[43] G. Chanel, J. J. M. Kierkels, M. Soleymani, and T. Pun, "Short-term emotion assessment in a recall paradigm," *International Journal of Human-Computer Studies*, vol. 67, no. 8, pp. 607–627, 2009.

[44] P. C. Petrantonakis and L. J. Hadjileontiadis, "Emotion recognition from EEG using higher order crossings," *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no. 2, pp. 186–197, 2010.

[45] F. Bousefsaf, C. Maaoui, and A. Pruski, "Remote assessment of the heart rate variability to detect mental stress," in *Proceedings of the 7th International Conference on Pervasive Computing Technologies for Healthcare and Workshops, PervasiveHealth 2013*, pp. 348–351, Venice, Italy, May 2013.

[46] E. M. Tapia, S. S. Intille, W. Haskell et al., "Real-time recognition of physical activities and their intensities using wireless accelerometers and a heart rate monitor," in *Proceedings of the 11th IEEE International Symposium on Wearable Computers*, pp. 37–40, Boston, MA, USA, October 2007.

[47] https://learn.sparkfun.com/tutorials/analog-to-digital-conversion.

[48] N. Sani, W. Mansor, K. Lee, N. Zainudin, and S. Mahrim, "Determination of heart rate from photoplethysmogram using fast fourier transform," in *Proceedings of the International Conference BioSignal Analysis, Processing and Systems (ICBAPS)*, 2015.

[49] T. Vyacheslav, *Signal Processing Noise, Electrical Engineering and Applied Signal Processing Series*, ISBN 9781420041118, CRC Press, 2010.

[50] https://en.wikipedia.org/wiki/Fourier_transform.

[51] K. Thenmozhi and P. Deepika, "Heart Disease prediction using classification with different decision tree techniques," *International Journal of Engineering Research and General Science*, vol. 2, no. 6, 2014.

[52] https://physionet.org/physiobank/database/sddb/.

[53] Y. ElSaadany, *A Wireless early prediction system of cardiac arrest through IoT. [Dissertation, thesis]*, 2017, https://etd.ohiolink.edu/.

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Research Article

The Impact of an Augmented Reality Application on Learning Motivation of Students

Tasneem Khan, Kevin Johnston, and Jacques Ophoff

Department of Information Systems, University of Cape Town, Cape Town 7701, South Africa

Correspondence should be addressed to Jacques Ophoff; jacques.ophoff@uct.ac.za

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Guest Editor: Francisca Rosique

The research on augmented reality applications in education is still in an early stage, and there is a lack of research on the effects and implications of augmented reality in the field of education. The purpose of this research was to measure and understand the impact of an augmented reality mobile application on the learning motivation of undergraduate health science students at the University of Cape Town. We extend previous research that looked specifically at the impact of augmented reality technology on student learning motivation. The intrinsic motivation theory was used to explain motivation in the context of learning. The attention, relevance, confidence, and satisfaction (ARCS) model guided the understanding of the impact of augmented reality on student motivation, and the Instructional Materials Motivation Survey was used to design the research instrument. The research examined the differences in student learning motivation before and after using the augmented reality mobile application. A total of 78 participants used the augmented reality mobile application and completed the preusage and postusage questionnaires. The results showed that using an augmented reality mobile application increased the learning motivation of students. The attention, satisfaction, and confidence factors of motivation were increased, and these results were found to be significant. Although the relevance factor showed a decrease it proved to be insignificant.

1. Introduction

The use of augmented reality (AR) in education is an important topic of research [1]. AR enables the addition of virtual objects into real environments to facilitate real-time interaction [2]. Research on AR applications in education is still in an early stage, and there is a lack of research on the effects and implications of AR in the field of education [3–5].

The use of AR has become more accessible as it no longer requires specialised equipment and may easily be used on mobile devices [3, 5]. Most people now own mobile devices, and the use of these devices has increased, thereby enabling greater access to AR [1, 6]. The applications for mobile AR in education are increasing rapidly [7], and the feasibility of mobile AR has increased due to advances in mobile technology [4, 8]. AR mobile applications are available for several areas of education [2], and education related AR applications are now more commonly found on mobile devices [4, 9].

The use of AR may increase student learning motivation and contribute to improved academic achievement [10, 11]. There is insufficient research on the impact of using mobile AR in education, and there is room to explore the potential of AR to improve student learning motivation and contribute to improved academic achievement [4, 7, 10]. "The potential of AR in education remains unexplored and, there is a limited amount of studies investigating student motivation with the use of AR" ([4], p. 587). This research extends previous studies performed in other countries that looked specifically at the impact of AR technology on student learning motivation [4, 8, 11–13], with a case study from a university in South Africa.

The purpose of this research was to measure the learning motivation of undergraduate health science students at the University of Cape Town (UCT) before and after using a particular AR mobile application. The main research question was as follows: *What are the differences in student learning motivation before and after using the AR mobile application?* The main research question was underpinned by several

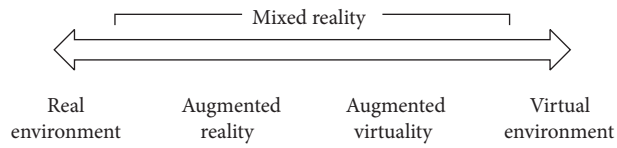

Figure 1: Milgram's mixed reality continuum [14].

subquestions examining how the attention, relevance, confidence, and satisfaction aspects of learning motivation were affected by using the AR mobile application. Empirical data was collected to answer these questions.

The remainder of this paper proceeds as follows. First, the conceptual background related to the use of AR in education and our theoretical model is presented. The next section discusses the methodology in detail, and this is followed by the analysis and research findings. Finally, implications are summarised, along with opportunities for future research.

2. Literature Review

The literature review includes literature published between 2013 and 2018 to ensure that the information included was recent and relevant. The Google Scholar H-5 index was used as the inclusion criterion for journals referenced [9].

2.1. Augmented Reality. AR combines real and virtual worlds, supplementing the real world with computer-generated virtual objects in real-time [1, 3, 12, 13, 18]. According to one of the most commonly accepted definitions, AR is said to be a technology that has three key requirements: combining of real and virtual objects in a real environment, aligning of real and virtual objects with each other, and real-time interaction [2, 4, 7, 14, 19]. Figure 1 shows Milgram's mixed reality continuum which is a taxonomy of the ways in which real and virtual elements may be combined [14]. The continuum ranges from a completely real environment to a completely virtual environment [5, 14]. Based on this continuum, mixed reality may be defined as a situation in which real and virtual objects are combined [5]. AR lies closer to the real environment end of the continuum as can be seen in Figure 1 [5, 14]. AR may be considered as a mixed reality technology which contains more reality, as this technology includes virtual objects in the user's real environment, enabling interaction with virtual content [1, 5, 7, 14]. In the case of mobile AR, the technology involves the addition of digital elements to the real world through a smartphone camera. Examples of mobile AR applications include Pokémon GO, which is a location-based mobile AR game that enables users to catch various digital Pokémon creatures around their area and AR GPS DRIVE/WALK NAVIGATION which provides an AR-powered navigation system [20]. Virtual reality differs from AR, as in virtual reality the real world is shut out and the user steps into a digital world using a virtual reality headset such as the Oculus Rift or Samsung Gear VR [21].

AR no longer requires specialised equipment and may easily be used through computers or mobile devices [3, 5]. A lightly AR supplements the real world with a relatively small amount of virtual information, while a heavily AR contains frequently accessible virtual information [5, 19]. The amount of virtuality within the real world determines the type of technology required to support the AR, as different display and tracking technologies result in different degrees of immersion [4, 5]. Immersive technologies such as head-mounted displays are used to support heavily AR and foster more immersion than mobile devices, which can support lightly AR [4, 5]. An example of a lightly AR would be the Pokémon GO mobile application, which can be used through a smartphone [20]. An example of a heavily AR is the Star Wars Jedi Challenges mobile application which requires the user to use a headset [22].

Many people now own mobile devices and therefore have access to AR [1, 6]. The use of AR for learning has been made more feasible due to advances in mobile technology and the increased use of smartphones [4, 8, 9, 18]. Smartphones and tablets are ideal to facilitate AR experiences, due to fast processors, graphics hardware, and various onboard sensors [18].

2.2. Augmented Reality in Education. The educational value of AR is closely linked to the way in which it is designed, implemented, and integrated into formal and informal learning environments [5]. An important consideration is how AR technologies support and afford meaningful learning [5]. Considering AR as a concept rather than a certain type of technology would be productive for educators [5]. The involvement of educators is important to facilitate the development of favourable AR applications for teaching, which increases the potential for AR to be incorporated in education [18]. AR applications have been developed for many areas of education [2].

Some of these AR applications have been used in previous studies [8, 11, 23]. Gopalan et al. [8] tested the impact of AR enhanced science textbooks on lower secondary school students in Malaysia. Chiang et al. [11] tested the use of an AR based mobile learning system for natural science inquiry activities on fourth-grade students in Taiwan. The system guided students towards target ecology areas and displayed the corresponding learning tasks or related learning materials [11]. Akçayır et al. [23] tested the use of an AR enhanced laboratory manual in science laboratories on first-year students in Turkey. This study tested the impact of the Anatomy 4D mobile application on the learning motivation of undergraduate health science students at UCT.

2.2.1. Advantages of Using Augmented Reality in Education. AR provides new ways of interacting with the real world and can create experiences that would not be possible in either a completely real or virtual world [3, 24]. AR has the unique ability to create immersive hybrid learning environments that combine real and virtual objects [3]. AR technologies enable users to experience scientific phenomena that are not possible in the real world, such as certain chemical reactions, making inaccessible subject matter available to students [3, 5, 23]. The manipulation of virtual objects and observation of phenomena that are difficult to observe in the real world can be facilitated through AR [5]. This type

of learning experience can encourage thinking skills and increase conceptual understanding of phenomena that are either invisible or difficult to observe as well as correct any misconceptions [5]. AR addresses learning difficulties that are often encountered with visualising unobservable phenomena [5].

The skills and knowledge that students develop through technology-enhanced learning environments may be developed more effectively through AR technology [5]. The cognitive workload may be reduced by integrating multiple sources of information [3, 18]. The immersion and interaction features offered by AR may encourage students to engage in learning activities and may improve student motivation to learn [4, 8, 18]. AR provides highly interactive experiences and can generate authentic learner activity, interactivity, and a high level of realism [18]. Interaction with the world is important in the learning process, and, apart from reality, AR is one of the best ways of facilitating this interaction [18].

2.2.2. Challenges with the Use of Augmented Reality in Education. Users of AR technology may experience usability issues and technical problems, and some students may find this technology complicated [3]. One of the main challenges of AR applications is usability; however, ease of use is also reported as an advantage [3]. There is no evidence to suggest that usability issues are directly related to AR technology and may instead stem from inadequate technology experience, interface design errors, technical problems, or negative attitudes [3]. The combination of real and virtual objects may cause confusion as students may face difficulty navigating between fantasy and reality [5]. The use of AR technology within a learning environment requires multitasking, as students need to engage with large amounts of information and multiple technological devices to accomplish complex tasks [5]. This may result in a cognitive overload and a feeling of being overwhelmed or confused [3, 5]. The confusion indicates the authenticity of an AR system; however, this may be unproductive in a learning environment as students may lose track of the real environment [5]. Some studies report that AR decreases cognitive load, while others report cognitive overload [3, 5]. Schools may place constraints on the adoption of AR technology, and educators may be reluctant to use AR as this technology often requires innovative teaching approaches to be implemented [5]. The content available through AR applications is often inflexible, which restricts the teacher's control over the content and prevents adaptation to accommodate student needs [5]. The availability of authoring tools may resolve this challenge by allowing users to revise and create AR applications [5]. Another challenge may be that the stability of mobile AR technology is not guaranteed, and difficulties may be encountered if the technology lacks well-designed interfaces and guidance as this may result in the technology being too complicated [3, 5]. Users may also need time to get familiar and comfortable with AR technology [8].

2.3. Motivation in the Context of Learning. "Motivation provides a source of energy that is responsible for why learners decide to make an effort, how long they are willing to sustain an activity, how hard they are going to pursue it, and how connected they feel to the activity" ([4], p. 586). Motivation is a student's desire to engage in the learning environment [4, 18]. Motivation is necessary for students to make an effort towards learning and to increase academic performance [8], as motivation plays an important role in the learning process [12]. An important factor in increasing student motivation is the use of effective learning strategies [11]. Motivation is important in promoting and sustaining self-regulated learning, which often results in improved academic performance [4]. Students that are academically motivated tend to engage, persist, and expend effort to complete tasks compared to unmotivated students [4]. A lack of motivation could be a major obstacle to learner success, emphasising the importance of creating and sustaining motivation [4, 18].

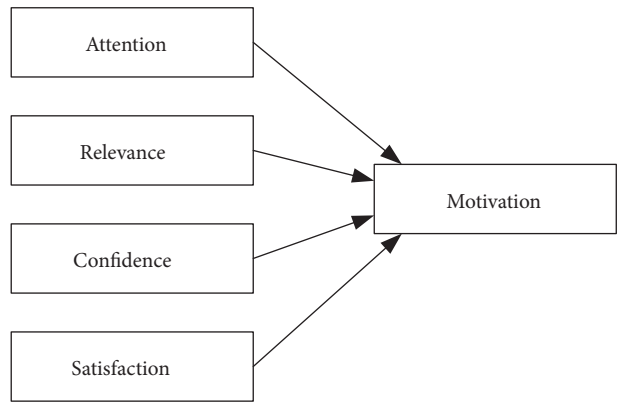

Figure 2: Keller's ARCS model of motivational design [15].

2.3.1. The Intrinsic Motivation Theory. The intrinsic motivation theory explains motivation in the context of learning [25]. Key factors that influence intrinsic motivation are challenge, curiosity, control, and fantasy [25]. Willpower and positive attitude are required to sustain motivation for learning [25]. Intrinsic motivation can influence students to participate in academic activities without external pressure or the expectation of external rewards [25]. Participation is influenced based on a desire to experience the fun, challenge, and uniqueness of the academic activity [25]. Studies have shown that AR can have consistent positive impacts on student motivation [4, 8, 11–13]. There are studies which prove that AR can specifically increase student motivation in science learning [8]. The increased student motivation may be largely attributed to the elements of curiosity, fantasy, and control presented using AR technology [26], as student motivation may be directly influenced using an attractive or stimulating medium or learning material [25].

This led to the main research question (RQ) (RQ 1): *What are the differences in student learning motivation before and after using the AR mobile application?* The attention, relevance, confidence, and satisfaction (ARCS) model was used to answer RQ 1.

2.4. ARCS Model. The attention, relevance, confidence, and satisfaction (ARCS) model of motivational design as shown in Figure 2 was used to understand the impact of AR

technology on student motivation towards learning [4, 8, 11, 13]. Based on the ARCS model, the design of the AR technology must attract student *attention*, it must be *relevant* to the students, the students must be *confident* with the technology, and the students must feel *satisfied* after using the technology [11].

Based on the ARCS model, research questions (RQ) 2.1, 2.2, 2.3, and 2.4 were developed to determine the impact of using an AR mobile application on each of the ARCS factors [4, 8, 11, 13].

2.4.1. Attention. Attention can be gained through perceptual arousal or inquiry arousal [17, 27]. Perceptual arousal can be gained using novel, surprising, and uncertain events which hold attention. Inquiry arousal can be gained using challenging questions or problems which stimulate curiosity [4, 27]. Attention may be grabbed through a variety of methods including participation, humour, conflict, variety, and real-world examples [28]. The attention factor is the most important as it initiates the motivation for students [27]. Once interest has been created, students are usually willing to invest their time and pay attention [27].

Based on the attention factor, *research question 2.1 was proposed: How was the attention aspect of learning motivation of UCT undergraduate health science students affected by using the AR mobile application?*

2.4.2. Relevance. Relevance can be established through using language and examples that are familiar to the students [17, 27]. Strategies to achieve relevance include goal orientation, motive matching, and familiarity [27]. Goal orientation can be achieved by making students aware of how the knowledge will help the student today as well as in the future [17, 27]. Motive matching involves assessing the students' needs and reasons for learning to provide choices that are conducive to their motives [27]. Familiarity involves providing examples that tie in with the student's experience and relate to the subject matter [27]. Pappas [28] mentions links to previous experience, perceived present worth, perceived future usefulness, modelling, and choice as strategies to establish relevance. Studies reported that a benefit of AR technology is the ability to provide immediate and relevant information and guidance [8, 11].

Based on the relevance factor, *research question 2.2 was proposed: How was the relevance aspect of learning motivation of UCT undergraduate health science students affected by using the AR mobile application?*

2.4.3. Confidence. Confidence involves establishing positive expectations for achieving success among students [27]. The confidence level is often correlated with motivation; therefore, it is important that the design of lessons provides students with a method for estimating the probability of their success [27]. Examples include a syllabus and grading policy, rubrics, or a time estimate in which to complete tasks [27]. Confidence may be built through timely and relevant feedback which provides positive reinforcement for personal achievements [27]. Pappas [28] mentions facilitating self-growth, communicating objectives, providing feedback, and giving learners control as ways to raise confidence.

Based on the confidence factor, *research question 2.3 was proposed: How was the confidence aspect of learning motivation of UCT undergraduate health science students affected by using the AR mobile application?*

2.4.4. Satisfaction. Students must obtain some type of reward from learning experiences [27]. Satisfaction may be in the form of a sense of achievement, praise, or entertainment [27]. Feedback and reinforcement are also important elements [27]. Satisfaction is based upon motivation, and, to keep students satisfied, they should be given the opportunity to use (or apply) their newly learned skills as soon as possible in a relevant setting [27]. Pappas mentions [28] praise or rewards and immediate application as ways to increase satisfaction.

Based on the satisfaction factor, *research question 2.4 was proposed: How was the satisfaction aspect of learning motivation of UCT undergraduate health science students affected by using the AR mobile application?*

2.5. Instructional Materials Motivation Survey. The Instructional Materials Motivation Survey (IMMS) was developed to measure student learning motivation following the ARCS model [11, 13]. Appendix A shows the IMMS, and Appendix B shows the scoring guide for the IMMS [17]. The scoring guide shows which statements in the IMMS relate to each of the four ARCS factors and highlights the statements that have been stated in a negative manner. The IMMS is "a 36-item situational measure of people's reactions to instructional materials" ([29], p. 204); the IMMS has been used as a pre- and postinstrument to test motivational needs and reactions to a new technology such as AR [29]. The IMMS instrument has been validated and successfully used in several previous research studies assessing the impact of the use of technology on student learning motivation [4]. Previous studies have used the IMMS to develop questionnaires in the form of a five-point Likert scale [4, 8, 13]. The "IMMS has a documented reliability coefficient of 0.96" ([4], p. 589); this can be seen in Appendix C along with the reliability coefficients for the attention, relevance, confidence, and satisfaction measures. In the papers by Wei et al. [18] and Solak and Cakir [13], the results of the IMMS questionnaire showed that student learning motivation improved significantly due to the introduction of AR technology. AR technology has been found to increase student learning motivation for attention, relevance, confidence, and satisfaction factors [4, 11]. The IMMS was used in this research and the results were analysed to answer the research questions.

3. Methodology

The intrinsic motivation theory was used to understand motivation in the context of learning [25]. The ARCS model of motivational design was used to understand the impact of AR technology on student motivation towards learning [4, 8, 11, 13]. The impact on student learning motivation was measured by comparing the learning motivation of students before and after using an AR mobile application, using a preusage and postusage questionnaire.

The target participants were undergraduate health science students at UCT, studying towards a Bachelor of Medicine and Bachelor of Surgery (MBChB). The target participants were taking an anatomy course offered by the UCT Department of Human Biology. The department had not found or used any AR mobile applications prior to this study. Approval for the students to use the application was obtained from the course convenor.

The numbers of participants used by Budiman [12], Chiang et al. [11], Di Serio et al. [4], Gopalan et al. [8], and Solak and Cakir [13] were 112, 57, 69, 70, and 130, respectively. The sample size for this research was 78 participants who used the AR mobile application and completed the preusage and postusage questionnaires. This sample size is close to the average sample size of 87.6 calculated based on the five previous studies which also investigated the impact of using AR on student motivation.

The participants could not be separated into a control and experimental group following the design of many previous studies (e.g., [8, 11, 13]), as this could result in some students obtaining an unfair (dis)advantage in the course. The curriculum provides students with a detailed understanding of the normal structure and function of the human body and how these are affected when the body suffers from disease. The impact of disease and the role of healthcare services are studied in a case-based group learning manner, supported by lecturers and practical sessions. Students learn core material as well as clinical skills, interpretation of data, professional values and ethics, and certain procedural skills directly related to the cases studied. Therefore, data collection was based on the procedure used by Di Serio et al. [4] where quantitative data was collected in two steps using a preusage and postusage questionnaire.

3.1. Research Instruments. A preusage and postusage questionnaire were used as instruments for data collection. The questionnaires were in the form of a five-point Likert scale and were designed based on the IMMS used in previous studies [4, 8, 13]. IMMS was chosen based on the successful use in previous studies to determine the impact of AR technology on student motivation [4, 8, 11, 13].

All the questions in the preusage questionnaire were related to student motivation regarding the use of the anatomy notes for the course, which included a textbook and lecture slides. All the questions in the postusage questionnaire were related to student motivation regarding the use of the Anatomy 4D mobile application. The questionnaires were submitted for ethical approval before conducting data collection. Appendix D shows the questions for the preusage questionnaire and Appendix E shows the questions for the postusage questionnaire. Ethics approval was obtained from the university before proceeding with data collection. The participants were required to provide consent before completing the preusage and postusage questionnaire and the anonymity of all respondents was ensured as no personally identifiable information was requested or captured.

In addition, Google Forms was used to create and distribute a short online interview that consisted of six open-ended questions. This online interview was distributed to two lecturers in the UCT Faculty of Health Sciences. The purpose of this online interview was to gain insight into the views of these lecturers regarding the use of AR.

3.2. AR Mobile Application. In previous studies the AR educational tools used were designed specifically for the courses [4, 8, 11, 13, 23]. The AR mobile application used in this study was not designed specifically for the course; instead the Anatomy 4D mobile application designed by DAQRI was used as the educational AR tool [16, 30]. The relevance of this mobile application to second-year MBChB students was verified by a course convenor in the UCT Faculty of Health Sciences prior to the study.

Anatomy 4D is a free application that uses AR to enable interaction with pictures of the human body. The application uses a target image, shown in Figure 3, and the camera on a mobile device to display an AR model of the human body [16]. A screenshot of the Anatomy 4D mobile application is displayed in Figure 4 [16]. The Anatomy 4D mobile application was chosen based on its accessibility. All participants used both the anatomy notes as well as the AR mobile education application.

4. Data Analysis

Empirical data were analysed following the methods used by Chiang et al. [11], Di Serio et al. [4], Gopalan et al. [8], Keller [17], and Solak and Cakir [13]. The overall mean values of the preusage and postusage questionnaire were used to compare student learning motivation and to determine if there was a statistically significant difference in motivation [4].

The Cronbach alpha values were calculated for both the preusage and postusage questionnaires to determine the reliability of the results, based on the use of this test by Chiang et al. [11], Gopalan et al. [8], and Solak and Cakir [13]. Mean values were calculated for both the preusage and postusage questionnaires for the four factors that measured student motivation based on the ARCS model [4, 17]. The significance of the difference between mean values for the four factors was determined and the differences in mean values were compared to answer the research questions.

The results were used to determine if there was a statistically significant difference for any of the four factors [4]. A statistically significant difference indicates how much each of the four factors of motivation was impacted using an AR mobile application.

Before performing analysis, the data collected from the preusage and postusage questionnaires was exported to Microsoft Excel. The questionnaires contained some questions that were stated in a negative manner, indicated in Appendix B which shows the scoring guide for the IMMS. The values for these questions were recoded before the mean value for each ARCS factor and the overall mean values were calculated [17].

4.1. Questionnaires. Microsoft Excel was used to calculate the mean value for each ARCS factor for both the preusage and postusage questionnaires. The calculated values are displayed in Table 1; the percentage differences indicate that

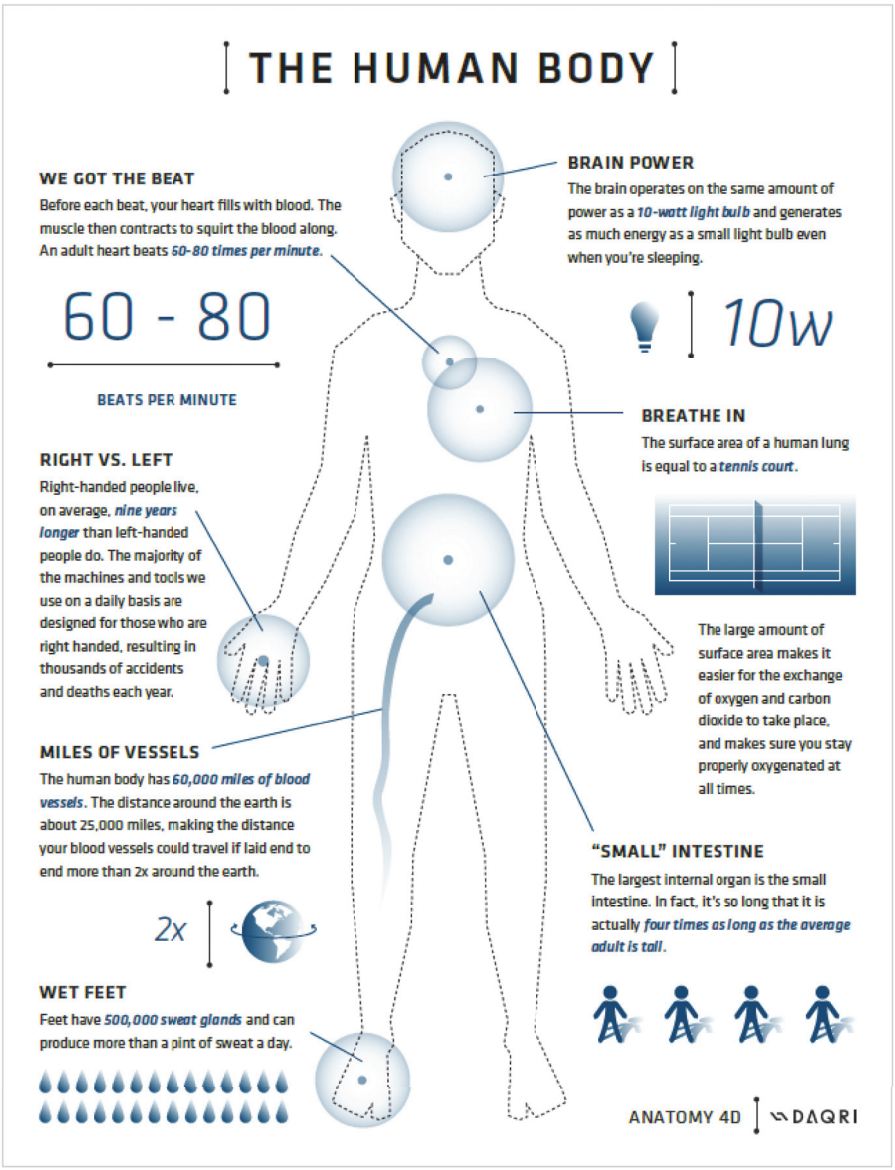

Figure 3: Anatomy 4D target image [16].

Table 1: Mean values for ARCS factors.

	Preusage	Postusage	Percentage difference
Attention	2.93	3.83	30.72% increase
Relevance	3.37	3.26	3.26% decrease
Confidence	2.98	3.30	10.74% increase
Satisfaction	2.96	3.33	12.50% increase
Overall	3.05	3.49	14.43% increase

the mean values for attention, confidence, and satisfaction increased while the relevance factor decreased. This allows a comparison of the learning motivation of students before and after using the AR mobile application.

Although the postusage mean values for each ARCS factor and the overall mean value showed either an increase or decrease, it was necessary to determine whether the change in each mean value was significant. Significance indicates that the difference in mean value is greater than a value that would be expected by chance [31]. The null hypotheses for each factor were that the postusage mean value was equal to the preusage mean value. A significance level of 0.05 was used; therefore p values less than 0.05 were considered significant while p values greater than 0.05 were considered insignificant [31]. The probability for each ARCS factor was computed using the central limit theorem where a value for z was obtained [31]. The p value was then obtained using the z tables [31]. The calculation results and p values for each ARCS factor are shown in Table 2. The overall mean value obtained for

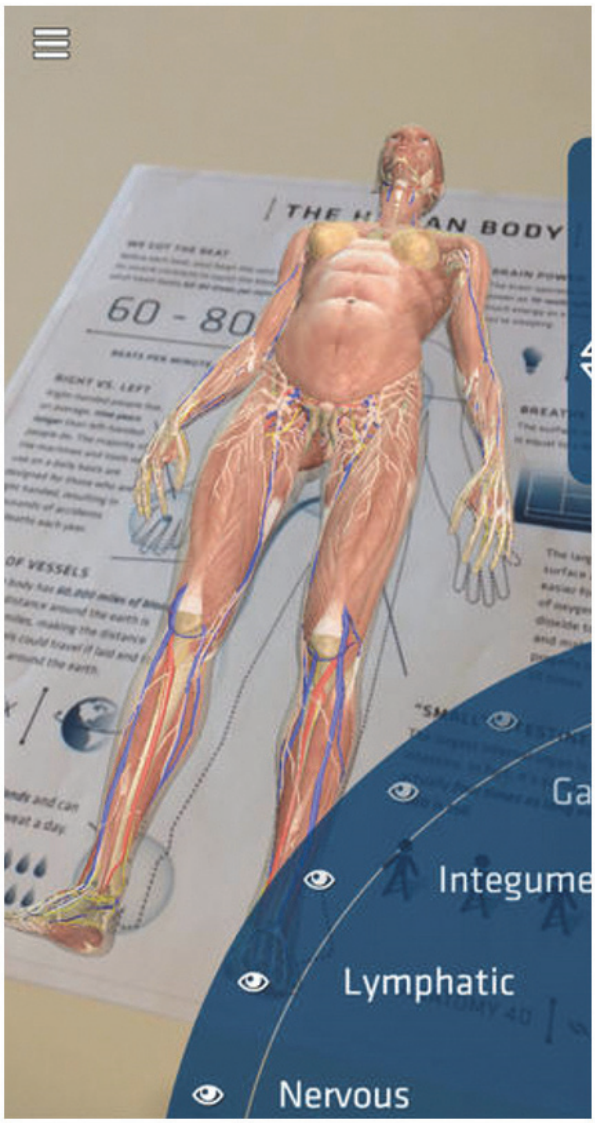

Figure 4: Anatomy 4D mobile application screenshot [16].

the postusage questionnaire was 14% higher than the value obtained for the preusage questionnaire.

The comparison of mean values for the preusage and postusage questionnaires is shown in Figure 5.

A Cronbach alpha test was performed using IBM SPSS to measure the reliability of the results for each ARCS factor and the overall reliability. IBM SPSS was used by Akçayır et al. [23] and Gopalan et al. [8]. The Cronbach alpha reliability test was used to see how well the questions for each ARCS construct fit together. Cronbach's alpha is a measure of internal consistency: an alpha score of 0.7 or higher is regarded as acceptable, an alpha score of 0.8 or higher is regarded as good, and an alpha score of 0.9 or higher is regarded as excellent [32]. The Cronbach alpha values for each ARCS factor and the total scale are displayed in Table 3.

4.2. Online Interviews. In addition to collecting data from student participants in the course, two lecturers in the UCT Faculty of Health Sciences were also interviewed. The interview was conducted online and consisted of open-ended questions. Of interest were their views regarding the use of AR in the classroom.

Lecturer X in the Division of Anatomical Pathology and Lecturer Y in the Division of Clinical Anatomy and Biological Anthropology in the UCT Department of Health Sciences were interviewed. Both lecturers support the use of AR to teach health science courses at UCT as Lecturer X said that "*students are often attracted by the use of technology as a learning tool*" and "*augmented reality may prove to be useful in teaching anatomy and anatomical pathology*." However, Lecturer X also stated that "*although AR represents an exciting new technology in Higher Education, we should caution ourselves against embracing it blindly*." Although Lecturer X stated that "*the advantages [of AR] cannot be stated at this point*," Lecturer Y stated that the advantages of augmented reality include "*making learning fun, appealing to multiple learning styles and increasing motivation to learn*."

"*Tools should be critically examined and researched in order to weigh their potential benefits, the advantages [of AR] cannot be stated at this point. Research will need to be conducted at the time of implementation, to see if it does offer advantages to higher education teaching and learning in the Health Sciences*." Challenges highlighted by the lecturers include

(i) training of staff and students on the application of the equipment

(ii) technical difficulties

(iii) possessing of a support team to assist with necessary software and hardware

(iv) access to internet off campus

The lecturers stated that AR may improve student motivation towards learning as it could "*make learning more enjoyable and interactive*" and be "*a 'fun' way to learn*." "*Augmented reality could improve student's intrinsic motivation towards learning. However, it must be stated that this is speculative, and research would be the only reliable way to answer this question*." Lecturer X "*would like to explore the use of a smartphone app, that could be used to bring AR into the Pathology Learning Centre*." In contrast, Lecturer Y would "*recommend [AR] as an additional resource*" and views AR "*as a helpful and attractive additional learning resource*."

5. Discussion of Findings

The overall Cronbach alpha value and the Cronbach alpha values obtained for each ARCS factor were all greater than 0.7. An alpha score greater than or equal to 0.7 indicates an acceptable value, while an alpha value of 0.8 or higher indicates a good value [32]. Therefore, the Cronbach alpha values obtained indicate that the results obtained were reliable [32]. Obtaining reliable data that return Cronbach alpha values exceeding 0.7 is consistent with findings from previous studies [8, 11, 13]. The reliability of the data was

Table 2: Significance of differences in mean values.

Attention	
Hypotheses	H_0: $\mu = 2.93$; H_1: $\mu > 2.93$
Calculation	$P(\times > 2.93) = P\left(z > \frac{3.83 - 2.93}{1.13 \div \sqrt{78}}\right) = P(z > 7.03)$
***p* value**	p value < 0.00001
Significance	The result is significant at $p < 0.05$
Relevance	
Hypotheses	H_0: $\mu = 3.37$; H_1: $\mu < 3.37$
Calculation	$P(\times < 3.37) = P\left(z > \frac{3.26 - 3.37}{1.13 \div \sqrt{78}}\right) = P(z > -0.76)$
***p* value**	p value $= 0.223$
Significance	The result is not significant at $p < 0.05$
Confidence	
Hypotheses	H_0: $\mu = 2.98$; H_1: $\mu > 2.98$
Calculation	$P(\times > 2.98) = P\left(z > \frac{3.30 - 2.98}{1.30 \div \sqrt{78}}\right) = P(z > 2.17)$
***p* value**	p value $= 0.015$
Significance	The result is significant at $p < 0.05$
Satisfaction	
Hypotheses	H_0: $\mu = 2.96$; H_1: $\mu > 2.96$
Calculation	$P(\times > 2.96) = P\left(z > \frac{3.33 - 2.96}{1.34 \div \sqrt{78}}\right) = P(z > 2.44)$
***p* value**	p value $= 0.0073$
Significance	The result is significant at $p < 0.05$
Overall	
Hypotheses	H_0: $\mu = 3.05$; H_1: $\mu > 3.49$
Calculation	$P(\times > 2.96) = P\left(z > \frac{3.49 - 3.05}{1.27 \div \sqrt{78}}\right) = P(z > 3.06)$
***p* value**	p value $= 0.001107$
Significance	The result is significant at $p < 0.05$

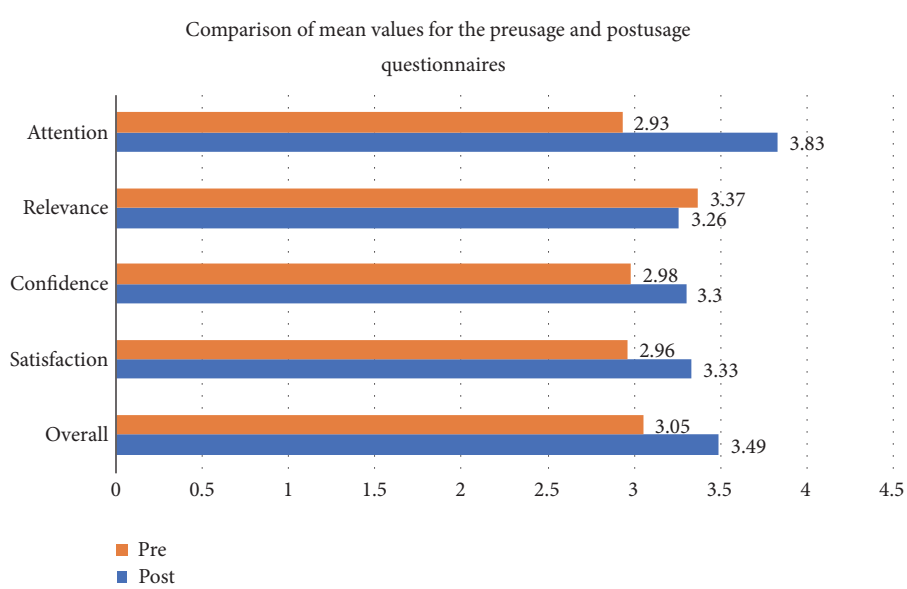

Figure 5: Comparison of mean values for the preusage and postusage questionnaires.

Table 3: Cronbach alpha values.

ARCS subscales	Cronbach alpha values
Attention	0.845
Relevance	0.836
Confidence	0.840
Satisfaction	0.744
Total scale	0.833

expected, given the high Cronbach alpha values of the Instructional Materials Motivation Survey (IMMS) upon which the preusage and postusage questionnaires were based. The values for the reliability estimates of the IMMS (all above 0.8) are shown in Appendix C while the Cronbach alpha values obtained for the findings (all above 0.7) are shown in Table 3.

Based on the information provided in Table 2, the significance of the change in mean value for each ARCS factor was determined. The increases in mean values for the attention, confidence, and satisfaction factors were significant at the 0.05 level. This indicated that the increase in mean values obtained for these factors was significant. The decrease in mean value for the relevance factor was not significant at the 0.05 level. Although the null hypothesis for the relevance factor could not be rejected, this did not mean that the null hypothesis held true [31]. This rather indicated that the decrease in mean value obtained was not significant. The results of the significance test indicate that the increases in mean values for the attention, confidence, and satisfaction factors are significant while the decrease in the mean value of the relevance factor is insignificant.

5.1. Advantages and Challenges. The lecturer in the Division of Anatomical Pathology, Lecturer X, did not outline any advantages of AR, stating that the "advantages cannot be stated" without conducting more research. However, Lecturer X did say that "augmented reality could improve student's intrinsic motivation towards learning." Lecturer Y stated that one of the advantages of augmented reality included "increased motivation to learn." According to Di Serio et al. [4], Gopalan et al. [8], and Wei et al. [18] the immersion and interaction features offered by AR may encourage students to engage in learning activities and may improve student motivation to learn. The data collected indicated that the use of AR did, in fact, increase the motivation to learn, or the intrinsic motivation, of the target participants.

One of the challenges highlighted by both lecturers was "technical difficulties," as reported by Akçayır and Akçayır [3]. Another challenge stated by Lecturer X was "training staff and students on the application of the equipment." This is related to the challenge outlined by Gopalan et al. [8] who stated that users may need time to get familiar and comfortable with AR technology.

5.2. Attention. The attention factor was used to measure the attention of students with regard to the prelearning material, the anatomy notes, and the postlearning material, the Anatomy 4D mobile application [11]. The 31% increase in the mean value was significant and indicated that the Anatomy 4D mobile application was better able to hold the attention of the students than the anatomy notes. The increase in attention indicated that perceptual arousal was gained using the Anatomy 4D mobile application which led to the increase in attention [17, 27]. The significant increase in attention is encouraging as the attention factor is the most important as it initiates the motivation for students [27]. RQ 2.1 asked, How was the *attention* aspect of learning motivation of UCT undergraduate health science students affected by using the AR mobile application? Based on this finding, RQ 2.1 was answered: after using the AR mobile application, the attention aspect of learning motivation of UCT undergraduate health science students showed a significant increase of 31%.

5.3. Relevance. The relevance factor was used to measure the relevance of the prelearning material, the anatomy notes, and the postlearning material, the Anatomy 4D mobile application [11]. Relevance can be established through using language and examples that are familiar to the students [17, 27]. The 3% decrease in the mean value of relevance indicated that the Anatomy 4D mobile application was less relevant than the anatomy notes. The decrease in relevance indicated that students were more familiar with the anatomy notes than with the Anatomy 4D mobile application. The decrease in relevance may be attributed to the fact that the Anatomy 4D mobile application was not designed specifically for the course as in previous studies by Akçayır et al. [23], Chiang et al. [11], Di Serio et al. [4], Gopalan et al. [8], and Solak and Cakir [13]. However, the 3% decrease was found to be insignificant which indicated that the difference in mean value is not greater than a value that would be expected by chance [31]. This indicated that there was not sufficient evidence at the 0.05 level of significance to conclude that the decrease in the mean value of the relevance factor was significant. Therefore, the decrease observed in the mean value for the relevance factor was insignificant. Based on this, both the anatomy notes and the Anatomy 4D application showed relevance given the mean values of 3.37 and 3.26, respectively. RQ 2.2 asked, How was the relevance aspect of learning motivation of UCT undergraduate health science students affected by using the AR mobile application? Based on this finding, RQ 2.2 was answered: after using the AR mobile application, the relevance aspect of learning motivation of UCT undergraduate health science students showed a slight decrease of 3%, which was found to be insignificant.

5.4. Confidence. The confidence factor was used to assess the confidence of students with regard to the prelearning material, the anatomy notes, and the postlearning material, the Anatomy 4D mobile application [11]. The increase of 11% in the mean value of confidence indicated that students felt more confident with the Anatomy 4D mobile application than the anatomy notes. The increase in confidence indicated that the Anatomy 4D mobile application may have established positive expectations for achieving success among students [27]. RQ 2.3 asked, How was the confidence aspect of learning motivation of UCT undergraduate health science students affected by using the AR mobile application? Based on this

Table 4

	Di Serio et al. [4]	Chiang et al. [11]	This study	Variance with average
A	15%	11%	31%	+18%
R	5%	15%	-3%	-13%
C	7%	11%	11%	+2%
S	13%	11%	13%	+1%

finding, RQ 2.3 was answered: after using the AR mobile application, the confidence aspect of learning motivation of UCT undergraduate health science students showed a significant increase of 11%.

5.5. Satisfaction. The satisfaction factor was used to measure student satisfaction after using the prelearning material, the anatomy notes, and the postlearning material, the Anatomy 4D mobile application [11]. The increase in the mean value of satisfaction indicated that the students felt more satisfied after using the Anatomy 4D mobile application than when using the anatomy notes. Satisfaction may be in the form of a sense of achievement, praise, or entertainment [27]. The increase in satisfaction indicated that students were entertained using the Anatomy 4D mobile application [27]. RQ 2.4 asked, How was the satisfaction aspect of learning motivation of UCT undergraduate health science students affected by using the AR mobile application? Based on this finding, RQ 2.4 was answered: after using the AR mobile application, the satisfaction aspect of learning motivation of UCT undergraduate health science students showed a significant increase of 13%.

5.6. Summary. The use of the AR mobile application increased the motivation of the students by 14%. The attention, confidence, and satisfaction of the students were increased by 31%, 11%, and 13%, respectively, and these increases were found to be significant. The 3% decrease in the mean value of the relevance factor was found to be insignificant. The increase in the mean values of the attention, confidence, and satisfaction factors is an outcome that is consistent with previous studies. However, the decrease in relevance is an outcome that is not consistent with the results of previous studies. Di Serio et al. [4] found that the attention, relevance, confidence, and satisfaction factors were increased by 15%, 5%, 7%, and 13%, respectively. Chiang et al. [11] found that the attention, relevance, confidence, and satisfaction factors showed significant increases of 11%, 15%, 11%, and 11%, respectively. The 13% increase in satisfaction obtained was consistent with the 13% increase found by Di Serio et al. [4] and the 11% increase in confidence obtained was consistent with the 11% increase found by Chiang et al. [11] (see Table 4).

The overall mean values obtained are shown in Table 1. Based on these values and the mean values obtained for each ARCS factor, RQ 1 may be answered. Student learning motivation after using the AR mobile application was 14% higher than student learning motivation before using the Anatomy 4D mobile application. Therefore, using the Anatomy 4D mobile application had a positive impact on student learning motivation. The overall outcome of the research is consistent with previous studies which showed a positive impact on student learning motivation. Students were moderately motivated when using the anatomy notes and slightly more motivated when using the Anatomy 4D mobile application [4].

6. Conclusion

The objective of this research was to understand the impact of an AR mobile application on the learning motivation of undergraduate health science students at UCT. The literature indicated that there is insufficient research on the impact of using mobile AR in education, and there is room to explore the potential of AR to improve student learning motivation and contribute to improved academic achievement [4, 7, 10]. The literature review summarised various concepts which led to developing the research questions that were based on the attention, relevance, confidence, and satisfaction (ARCS) model of motivational design [17]. Augmented reality (AR) was defined as combining real and virtual worlds, supplementing the real world with computer-generated virtual objects in real-time [1, 3, 12, 13, 18], and AR was explained in the context of education. Mobile AR was discussed given that AR may easily be used through mobile devices [3, 5]. The design involved using the Anatomy 4D mobile application as the educational AR tool.

The literature review looked at the use of AR in education followed by an overview of some previous studies which used AR applications [8, 11, 23]. Various advantages and challenges of the use of AR in education were also discussed. Motivation in the context of learning and the intrinsic motivation theory, which was used to explain learning motivation, were then discussed [25]. This led to the main research question (RQ) (RQ 1): What are the differences in student learning motivation before and after using the AR mobile application? The ARCS model was used to answer RQ 1. The ARCS model and each ARCS factor was used to understand the impact of AR technology on student motivation towards learning [4, 8, 11, 13]. The Instructional Materials Motivation Survey (IMMS) was used to develop the instruments for this research [17].

The methodology and design of the research were discussed, as well as the methods of data collection and data analysis. The data analysis was used to interpret the findings to answer the research questions. The outcomes of this research showed that the use of an AR mobile application increased the learning motivation of undergraduate health science students at the University of Cape Town (UCT). The results are consistent with previous studies by Di Serio et al. [4], Chiang et al. [11], Gopalan et al. [8], and Solak and Cakir

[13]. The overall mean value obtained for the current teaching method was 3.05 and the overall mean value for the use of the Anatomy 4D mobile application was 3.49. An increase in the attention, confidence, and satisfaction factors was found after using the Anatomy 4D mobile application, while there was a decrease in the relevance factor.

The results of this study add to previous studies conducted to measure student learning motivation after using an AR educational tool. Similar research studies should be conducted over extended periods of time to reduce the novelty effect which may have acted as a disturbing factor [4]. This study along with many other previous studies has proved the contribution of AR technology in education; however, research on this topic is still in an early stage [13]. Further research should be conducted to determine which learning activities would benefit the most from AR technology [4]. Akçayır et al. [23], Chiang et al. [11], Ibáñez et al. [10], and Solak and Cakir [13] showed that AR tools had a positive impact on academic performance. Further research should be conducted to assess the impact of AR on academic performance, as suggested by Lecturer X who said, "research would need to be conducted as to whether it improves understanding of content, assessment performance etc."

Appendix

A. Instructional Materials Motivation Survey (IMMS [17])

(1) (or A) = not true
(2) (or B) = slightly true
(3) (or C) = moderately true
(4) (or D) = mostly true
(5) (or E) = very true

(1) When I first looked at this lesson, I had the impression that it would be easy for me.
(2) There was something interesting at the beginning of this lesson that got my attention.
(3) This material was more difficult to understand than I would like for it to be.∗
(4) After reading the introductory information, I felt confident that I knew what I was supposed to learn from this lesson.
(5) Completing the exercises in this lesson gave me a satisfying feeling of accomplishment.
(6) It is clear to me how the content of this material is related to things I already know.
(7) Many of the pages had so much information that it was hard to pick out and remember the important points.∗
(8) These materials are eye catching.
(9) There were stories, pictures or examples that showed me how this material could be important to some people.
(10) Completing this lesson successfully was important to me.
(11) The quality of the writing helped to hold my attention.
(12) This lesson is so abstract that it was hard to keep my attention on it.∗
(13) As I worked on this lesson, I was confident that I could learn the content.
(14) I enjoyed this lesson so much that I would like to know more about this topic.
(15) The pages of this lesson look dry and unappealing.∗
(16) The content of this material is relevant to my interests.
(17) The way the information is arranged on the pages helped keep my attention.
(18) There are explanations or examples of how people use the knowledge in this lesson.
(19) The exercises in this lesson were too difficult.∗
(20) This lesson has things that stimulated my curiosity.
(21) I really enjoyed studying this lesson.
(22) The amount of repetition in this lesson caused me to get bored sometimes.∗
(23) The content and style of writing in this lesson convey the impression that its content is worth knowing.
(24) I learned some things that were surprising or unexpected.
(25) After working on this lesson for awhile, I was confident that I would be able to pass a test on it.
(26) This lesson was not relevant to my needs because I already knew most of it.∗
(27) The wording of feedback after the exercises, or of other comments in this lesson, helped me feel rewarded for my effort.
(28) The variety of reading passages, exercises, illustrations, etc., helped keep my attention on the lesson.
(29) The style of writing is boring.∗
(30) I could relate to the content of this lesson to things I have seen, done or thought about in my own life.
(31) There are so many words on each page that it is irritating.∗
(32) It felt good to successfully complete this lesson.
(33) The content of this lesson will be useful to me.
(34) I could not really understand quite a bit of the material in this lesson.∗
(35) The good organization of the content helped me be confident that I would learn this material.
(36) It was a pleasure to work on such a well-designed lesson.

∗Asterisked items should be recoded prior to data analysis (1 = 5, 2 = 4, 4 = 2, and 5 = 1).

Table 5: IMMS scoring guide [17].

Attention	Relevance	Confidence	Satisfaction
2	6	1	5
8	9	3 (reverse)	14
11	10	4	21
12 (reverse)	16	7 (reverse)	27
15 (reverse)	18	13	32
17	23	19 (reverse)	36
20	26 (reverse)	25	
22 (reverse)	30	34 (reverse)	
24	33	35	
28			
29 (reverse)			
31 (reverse)			

Table 6: IMMS reliability estimates [17].

Scale	Reliability estimate (Cronbach α)
Attention	0.89
Relevance	0.81
Confidence	0.90
Satisfaction	0.92
Total scale	0.96

B.

See Table 5.

C.

See Table 6.

D. Preusage Questionnaire

(1) When I first looked at the anatomy notes, I had the impression that studying from them would be easy for me.

(2) There was something interesting in the anatomy notes that got my attention.

(3) The anatomy notes were more difficult to understand than I would like for it to be.

(4) After reading the introductory information, I felt confident that I knew what I was supposed to learn from the anatomy notes.

(5) It is clear to me how the content of the anatomy notes is related to things I already know.

(6) Many of the notes had so much information that it was hard to pick out and remember the important points.

(7) The anatomy notes are eye-catching.

(8) Successfully learning from the anatomy notes is important to me.

(9) The quality of the writing of the anatomy notes helped to hold my attention.

(10) The anatomy notes are so abstract that it was hard to keep my attention on it.

(11) As I read through the anatomy notes, I was confident that I could learn the content.

(12) I enjoyed studying from the anatomy notes so much that I would like to know more about this topic.

(13) The pages of the anatomy notes look dry and unappealing.

(14) The content of the anatomy notes is relevant to my interests.

(15) The way that information is arranged on the pages helped keep my attention.

(16) The exercises in the anatomy notes were too difficult.

(17) The anatomy notes have things that stimulated my curiosity.

(18) I really enjoyed studying the anatomy notes.

(19) The amount of repetition in the anatomy notes caused me to get bored sometimes.

(20) The content and style of writing in the anatomy notes convey the impression that its content is worth knowing.

(21) After working on the anatomy notes for a while, I was confident that I would be able to pass a test on it.

(22) The anatomy notes were not relevant to my needs because I already knew most of it.

(23) The variety of reading passages, exercises, illustrations, etc., helped keep my attention on the anatomy notes.

(24) The style of writing of the anatomy notes is boring.

(25) I could relate the content of the anatomy notes to things I have seen, done, or thought about in my own life.

(26) There are so many words on each page of the anatomy notes that it is irritating.

(27) The content of the anatomy notes will be useful to me.

(28) I could not really understand quite a bit of the material in the anatomy notes.

(29) The good organization of the content helped me be confident that I would learn this material.

(30) It was a pleasure to work on such well-designed notes.

E. Postusage Questionnaire

(1) When I first looked at the Anatomy 4D mobile application, I had the impression that studying from it would be easy for me.

(2) There was something interesting in the Anatomy 4D mobile application that got my attention.

(3) The content of the Anatomy 4D mobile application was more difficult to understand than I would like for it to be.

(4) After downloading the Anatomy 4D mobile application, I felt confident that I knew what I was supposed to learn from the mobile application.

(5) It is clear to me how the content of the Anatomy 4D mobile application is related to things I already know.

(6) The Anatomy 4D mobile application had so much information that it was hard to pick out and remember the important points.

(7) The Anatomy 4D mobile application is eye-catching.

(8) There were stories, pictures, or examples that showed me how the information in the Anatomy 4D mobile application could be important to some people.

(9) Successfully learning from the Anatomy 4D mobile application is important to me.

(10) The quality of the content in the Anatomy 4D mobile application notes helped to hold my attention.

(11) The content in the Anatomy 4D mobile application is so abstract that it was hard to keep my attention on it.

(12) As I used the Anatomy 4D mobile application, I was confident that I could learn the content.

(13) I enjoyed studying from the Anatomy 4D mobile application so much that I would like to know more about this topic.

(14) The Anatomy 4D mobile application looks dry and unappealing.

(15) The content of the Anatomy 4D mobile application is relevant to my interests.

(16) The way that information is presented on the Anatomy 4D mobile application helped keep my attention.

(17) Using the Anatomy 4D mobile application was too difficult.

(18) The Anatomy 4D mobile application has things that stimulated my curiosity.

(19) I really enjoyed using the Anatomy 4D mobile application.

(20) The amount of repetition in the Anatomy 4D mobile application caused me to get bored sometimes.

(21) I learned some things that were surprising or unexpected from the Anatomy 4D mobile application.

(22) After working with the Anatomy 4D mobile application for a while, I was confident that I would be able to pass a test on it.

(23) The Anatomy 4D mobile application was not relevant to my needs because I already knew most of it.

(24) The content of the Anatomy 4D mobile application is boring.

(25) I could relate the content of the Anatomy 4D mobile application to things I have seen, done, or thought about in my own life.

(26) When using the Anatomy 4D mobile application, there is so much information on the screen that it is irritating.

(27) The content of the Anatomy 4D mobile application will be useful to me.

(28) I could not really understand quite a bit of the material in the Anatomy 4D mobile application.

(29) The good organization of the content on the Anatomy 4D mobile application helped me be confident that I would learn this material.

(30) It was a pleasure to work on such a well-designed mobile application.

Data Availability

The empirical data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

References

[1] M. Sirakaya and D. A. Sirakaya, "Trends in educational AR studies: a systematic review," *Malaysian Online Journal of Educational Technology*, vol. 6, no. 2, pp. 60–74, 2018.

[2] J. Martín-Gutiérrez, P. Fabiani, W. Benesova, M. D. Meneses, and C. E. Mora, "AR to promote collaborative and autonomous learning in higher education," *Computers in Human Behavior*, vol. 51, pp. 752–761, 2015.

[3] M. Akçayır and G. Akçayır, "Advantages and challenges associated with AR for education: a systematic review of the literature," *Educational Research Review*, vol. 20, pp. 1–11, 2017.

[4] Á. Di Serio, M. B. Ibáñez, and C. D. Kloos, "Impact of an AR system on students' motivation for a visual art course," *Computers and Education*, vol. 68, pp. 586–596, 2013.

[5] H. Wu, S. W. Lee, H. Chang, and J. Liang, "Current status, opportunities and challenges of AR in education," *Computers and Education*, vol. 62, pp. 41–49, 2013.

[6] J. Pelet, *Mobile Platforms, Design, and Apps for Social Commerce*, Business Science Reference, Pennsylvania, Pa, USA, 2017.

[7] T. Lin, H. B. Duh, N. Li, H. Wang, and C. Tsai, "An investigation of learners' collaborative knowledge construction performances and behavior patterns in an AR simulation system," *Computers and Education*, vol. 68, pp. 314–321, 2013.

[8] V. Gopalan, A. N. Zulkifli, and J. A. A. Abubakar, "A study of students' motivation using the AR science textbook," *AIP Conference Proceedings*, vol. 1761, no. 1, pp. 27–35, 2016.

[9] J. Bacca, S. Baldiris, R. Fabregat et al., "AR trends in education: a systematic review of research and applications," *Journal of Educational Technology and Society*, vol. 17, no. 4, pp. 133–149, 2014.

[10] M. B. Ibáñez, Á. Di Serio, D. Villarán, and K. C. Delgado, "Experimenting with electromagnetism using AR: impact on flow student experience and educational effectiveness," *Computers and Education*, vol. 71, pp. 1–13, 2014.

[11] T. H. C. Chiang, S. J. H. Yang, and G. J. Hwang, "An AR-based mobile learning system to improve students' learning achievements and motivations in natural science inquiry activities," *Journal of Educational Technology and Society*, vol. 17, no. 4, pp. 352–365, 2014.

[12] R. D. A. Budiman, "Developing learning media based on AR (AR) to improve learning motivation," *Journal of Education*, vol. 1, no. 2, pp. 89–94, 2016.

[13] E. Solak and R. Cakir, "Exploring the effect of materials designed with AR on language learners' vocabulary learning," *The Journal of Educators Online*, vol. 12, no. 2, pp. 50–72, 2015.

[14] M. Billinghurst, A. Clark, and G. Lee, "A survey of AR," *Foundations and Trends in Human-Computer Interaction*, vol. 8, pp. 73–272, 2015.

[15] K. Kapp, "Motivation slides from Workshop," DevLearn, 2012.

[16] DAQRI, "Anatomy 4D (Version 2.0.1.110), Mobile application software," 2015, https://play.google.com/store.

[17] J. M. Keller, *Motivational Design for Learning and Performance*, Springer, New York, NY, USA, 2010.

[18] X. Wei, D. Weng, Y. Liu, and Y. Wang, "Teaching based on AR for a technical creative design course," *Computers and Education*, vol. 81, pp. 221–234, 2015.

[19] K. Cheng and C. Tsai, "Affordances of AR in science learning: suggestions for future research," *Journal of Science Education and Technology*, vol. 22, no. 4, pp. 449–462, 2013.

[20] Y. Jain, "8 examples of AR apps and their successful uses," 2017, https://www.newgenapps.com/blog/augmented-reality-apps-ar-examples-success.

[21] M. Popolo, J. Schneider, and P. Hyde, "The 10 best virtual reality headsets," 2018, https://www.lifewire.com/best-virtual-reality-headsets-4060322.

[22] S. Osborne-Walker, "Lenovo Mirage: Jedi Challenge," 2018, http://www.trustedreviews.com/reviews/lenovo-mirage-jedi-challenges.

[23] M. Akçayır, G. Akçayır, H. M. Pektaş, and M. A. Ocak, "AR in science laboratories: the effects of AR on university students' laboratory skills and attitudes toward science laboratories," *Computers in Human Behavior*, vol. 57, pp. 334–342, 2016.

[24] S. Cuendet, Q. Bonnard, S. Do-Lenh, and P. Dillenbourg, "Designing augmented reality for the classroom," *Computers and Education*, vol. 68, pp. 557–569, 2013.

[25] V. Gopalan, J. A. A. Abubakar, A. N. Zulkifli, A. Alwi, and R. C. Mat, "A review of the motivation theories in learning," *AIP Conference Proceedings*, vol. 1891, no. 1, 2017.

[26] I. C. S. da Silva, G. Klein, and D. M. Brandão, "Segmented and detailed visualization of anatomical structures based on AR for health education and knowledge discovery," *Advances in Science*, vol. 2, no. 3, pp. 469–478, 2017.

[27] S. Malik, "Effectiveness of arcs model of motivational design to overcome non completion rate of students in distance education," *Turkish Online Journal of Distance Education*, vol. 15, no. 2, pp. 194–200, 2014.

[28] C. Pappas, "Instructional Design Models and Theories: Keller's ARCS Model of Motivation," 2015, https://elearningindustry.com/arcs-model-of-motivation.

[29] N. Loorbach, O. Peters, J. Karreman, and M. Steehouder, "Validation of the Instructional Materials Motivation Survey (IMMS) in a self-directed instructional setting aimed at working with technology," *British Journal of Educational Technology*, vol. 46, no. 1, pp. 204–218, 2015.

[30] Smart Reality, "DAQRI's anatomy 4D AR app," 2015, http://smartreality.co/daqris-anatomy-4d-augmented-reality-app/.

[31] L. Sullivan, *Hypothesis Testing for Means and Proportions*, Boston University School of Public Health, Massachusetts, Mass, USA, 2013.

[32] S. R. Namdeo and S. D. Rout, "Calculating and interpreting Cronbach's alpha using Rosenberg assessment scale on paediatrician's attitude and perception on self esteem," *International Journal of Community Medicine and Public Health*, vol. 6, pp. 1371–1374, 2016.