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# Soft Transducer for Patient's Vitals Telemonitoring with Deep Learning-Based Personalized Anomaly Detection

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**Abstract:** This work addresses the design, development and implementation of a 4.0-based wearable soft transducer for patient-centered, vitals telemonitoring. In particular, first, the soft transducer measures hypertension-related vitals (heart rate, oxygen saturation and systolic/diastolic pressure), and sends the data to a remote database (which can be easily consulted both by the patient and the physician). In addition to this, a dedicated deep learning algorithm, based on a Long-Short-Term-Memory Autoencoder, was designed, implemented and tested for providing an alert when the patient's vitals exceed certain thresholds, which are automatically personalized for the specific patient. Furthermore, a mobile application (*EcO2u*) was developed to manage the entire data flow and facilitate the data fruition; this application also implements an innovative face-detection algorithm that ensures the identity of the patient. The robustness of the proposed soft transducer was validated experimentally on five individuals, who used the system for 30 days. Experimental results demonstrated an accuracy in anomaly detection greater than 93%, with a true positive rate of more than 94%.

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**Keywords:** wearable systems; wearable sensors; deep learning; LSTM; machine learning; remote health monitoring; vital sign monitoring; telemonitoring; health 4.0

## 1. Introduction

The recent COVID-19 pandemic and the associated transition of patient care outside the hospital have boosted the development of systems for the remote monitoring of patient vitals signs [1–3], a task that has been favored also by the advancement of wearable technologies [4–9] and of the Internet of Things (IoT). These two technologies have contributed to the widespread adoption smart healthcare solutions (soft transducer), deployed either at hospitals or at home [10,11]. In fact, on one hand, the integration of IoT with wearable devices enables the doctor to monitor remotely the patients' health. On the other hand, it also allows patients to gain awareness of their health status, which is particularly important when affected by chronic diseases. This approach facilitates an engaging and responsive patient experience, thus improving the *patient's journey*.

Among chronic diseases, one of the most widespread is certainly hypertension. In fact, the World Health Organization states that one in three adults in the world suffers from hypertension, and this proportion increases with age. Hypertension is frequently referred to as *silent killer*, because often it does not involve disturbing symptoms but still can degenerate suddenly and seriously. Even a moderate increase in blood pressure is associated with reduced life expectancy. In this regard, monitoring patient vitals represents an important aspect of patient care, because these signs usually give first information

34 about abnormal physiology. In practice, this can be accomplished by employing soft  
35 transducers, which are wearable devices able to acquire and process a large amount of  
36 data in real time [12,13]. Indeed, it is crucial for physicians to be able not only to monitor  
37 hypertensive patients regularly, but also to predict the evolution of this condition.

38 In the last few years, the processing of data related to patient vitals has been facili-  
39 tated by the adoption of Artificial intelligence (AI), which is one of the most promising  
40 enabling technologies of the 4.0 paradigm [14]. In fact, AI represents a strategic tool for  
41 supporting clinical decision and improving disease management [15], thus promoting  
42 the correct management, interpretation and use of multiple data collected from the indi-  
43 vidual patient [16]. The incorporation of AI, and in particular Machine Learning (ML)  
44 and Deep Learning (DL), has the potential to improve personalized, patient-centered  
45 care medicine, thus strengthening the effectiveness of therapies [17–19]. AI can be de-  
46 fined as a technology aimed to provide algorithms that learn from data without being  
47 programmed [20–22]. ML and DL are a sub-category of AI and refer to data processing  
48 oriented to (i) identify and design their relevant characteristics, and (ii) perform predic-  
49 tion on the output generated [23]. In Healthcare, the adoption of ML and DL can be  
50 considered as the best practice in designing decision support systems aimed to predict  
51 patients health [24].

52 Starting from these considerations, this work presents the development of a DL-  
53 based soft transducer for the telemonitoring of patient vitals. In addition to the wearable  
54 sensors platform for remote monitoring of the vital signs, a DL algorithm, based on  
55 the Long-Short-Term-Memory (LSTM) Autoencoder, was implemented. This choice is  
56 driven by the potential of the DL to be able to automatically identify complex features  
57 even without having any prior knowledge of the domain. As detailed in the following,  
58 the implemented network allows to anticipate possible onset or worsening of the disease.  
59 The most notable aspect is that, differently from the state of the art (see Sec. 2), the  
60 proposed algorithm is trained to identify patient-specific alert thresholds. In fact, the  
61 definition of personalized threshold values reduces false positives occurrence during  
62 normal operating conditions. Finally, to manage data flow and to facilitate data fruition,  
63 a dedicated mobile application was developed which also provides an alert to patients  
64 and physicians in case of aggravating conditions. The application also includes a face-  
65 recognition feature that allows to verify the patient's identity. It is important to point out  
66 that, while the proposed system was developed and validated in case-study related to  
67 healthcare, the obtained results have broader generality and may be declined for other  
68 application contexts.

69 The paper is organized as follows. In Sec. 2, several approaches similar with the one  
70 proposed in this work are discussed, showing strong and weak points. Then, in Sec. 3, a  
71 conceptual description of the proposed soft transducer is provided, and the design of  
72 the proposed soft transducer is presented. Section 4 addresses its implementation of the  
73 soft transducer, while in Section 5, the experimental results are reported and discussed.  
74 Finally, in Section 6, conclusions are drawn and future work is outlined.

## 75 2. Related Work

76 As mentioned in the Introduction, AI has been widely used as a solution for predict-  
77 ing patients' health [24]. For example, in [25], 21 different ML algorithms were applied  
78 and compared in the field of hypertension. In [26], a prediction system characterized by  
79 the use of an artificial neural network was described to evaluate the risk of hypertension  
80 in rural residents over the age of 35 years in a Chinese area. In [27], the authors proposed  
81 a hybrid machine learning algorithm of *k*-Nearest Neighbor (*k*-NN) and *Least-Square*  
82 *Support Vector Machine* (LS-SVM) for predicting future values of monitored vital signs  
83 using wearable technologies. In [28], it was found that (i) predictive observation and  
84 real-time analysis of values of biomedical signals, and (ii) automatic detection of epileptic  
85 seizures before onset are beneficial for the development of warning systems for patients  
86 as they, once informed that an epilepsy seizure is about to start, can take safety measures

87 in useful time. In [29], a system based on LSTM network was used in order to monitor  
 88 vital parameters and ensure an intelligent rehabilitation process. In [30], a novel DL-  
 89 based anomaly detection approach, called *DeepAnT*, was presented for time series data.  
 90 It consists of both a time series prediction module and an anomaly detection module.  
 91 The time series prediction module uses a deep convolution neural network (CNN) to  
 92 predict the next timestamp on the defined horizon. The expected value is then passed  
 93 to the anomaly detector module, which is responsible for marking the corresponding  
 94 timestamp as normal or abnormal. In [31], DL was applied to provide early prediction  
 95 for type 2 diabetes and hypertension. To perform this analysis, the *Isolation Forest* al-  
 96 gorithm was used to detect abnormal data from the data set, while *SMOTETomek* was  
 97 used to balance the unbalanced data set. Finally, in [32], a forecasting system capable  
 98 of predicting systolic blood pressure in real time, by means of a *Bidirectional Short-Term*  
 99 *Memory* (BI-LSTM) algorithm, was described.

100 All these aforementioned works have demonstrated to be a suitable solution to  
 101 improve real-time patients' health monitoring. However, a training phase of the al-  
 102 gorithms was always required on generalized sets of data. Hence, the resulting alert  
 103 values are not personalized for the specific patient. As a result, the development of  
 104 a processing strategy to identify patient-specific features can represent an interesting  
 105 solution to enhance the patient's vitals monitoring and the accuracy of the alert provided  
 106 in case of worsening of health status.

### 107 3. Design and Overall Architecture

108 This section addresses the conceptual description of the proposed soft transducer.  
 109 In particular, the overall architecture and the development of the mobile application are  
 110 described. Basically, the proposed soft transducer works as follows.

- 111 1. The patient uses wearable sensors to measure the vitals.
- 112 2. The measured data are sent to a cloud database and are made available, through a  
 113 mobile application, for the patient and the remote physician.
- 114 3. The data on the cloud are processed by means of a DL algorithm, which is trained  
 115 on the basis of preliminary measurements of the patient vitals.
- 116 4. If the patient vitals exceeds a certain threshold, an alert is sent to the physician and  
 117 to the patient.

118 The overall architecture of the proposed soft transducer is shown in Fig. 1. One  
 119 or more *Wearable Sensors* are used to measure a set of the patient's vitals. Then, the  
 120 measurement results are sent to a *Cloud Database*. The obtained data are saved in the  
 121 database and processed by an *AI Processing* algorithm. The system returns a *Score*, which  
 122 is sent to the user *Mobile App* along with all the information regarding the data acquired;  
 123 if the vitals exceed a pre-established threshold, evaluated after a training on preliminary  
 124 measurements of the patient, an alert is sent both to the physician and the patient.

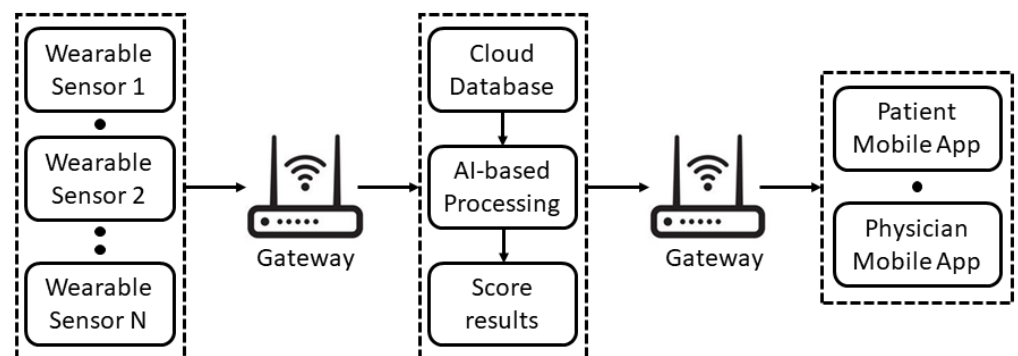


Figure 1. General architecture of the proposed soft transducer.

125 The *mobile application* was developed considering the essential requirements of  
 126 the healthcare context, including the description of the services offered by the system,  
 127 the sensor connection, the vital parameter reading, the parameter processing, and the  
 128 activation of emergency alarms. Overall, the application was designed with a six-level  
 129 structure, dedicated to:

- 130 1. *Patient registration.*
- 131 2. *Vitals measurements.*
- 132 3. *Management of the patient's Medical History.*
- 133 4. *Remote Vitals visualization.*
- 134 5. *AI processing.*
- 135 6. *Delivery of the Score results to the patient and the physician.*

136 The design of the user interface was carried out taking into account the principles of  
 137 good system design as reported in [33]: guaranteeing a minimalist design to prevent  
 138 cognitive overload, using large and readable icons to facilitate user interaction, and,  
 139 finally, using a clear, concise and intuitive language to help users identify their clinical  
 140 status.

#### 141 4. Implementation

##### 142 4.1. Wearable Sensing Platform

143 Fig. 3 shows the schematization of the wearable sensing platform as implemented  
 in this work.

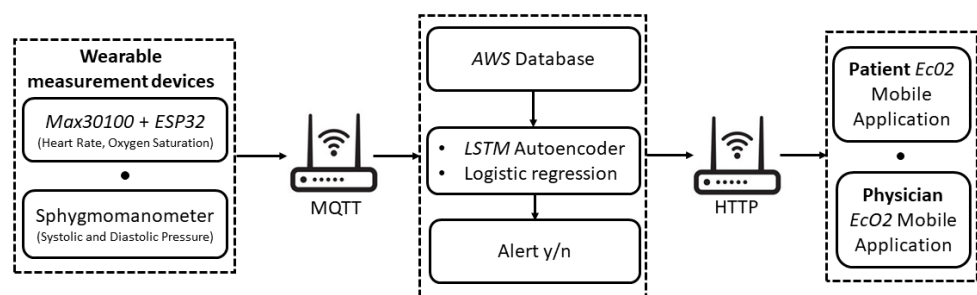


Figure 2. Implementation of the proposed telemonitoring system

144 Heart rate (HR), oxygen saturation (SpO<sub>2</sub>), and systolic and diastolic pressure (SP,  
 145 DP) were considered as vitals-to-be-monitored. To this aim, for the monitoring task, the  
 146 MAX30100, a low-cost SpO<sub>2</sub> and HR monitor sensor was used [34].

147 In order to retrieve the diastolic and systolic pressure values, the patient is also  
 148 required to measure his/her blood pressure through a sphygmomanometer. As detailed  
 149 in the following section, it is used only once for calibrating the sensor for the successive  
 150 automated evaluation of the blood pressure starting from HR values.

151 The wearable sensing platform also includes a low-cost microcontroller with inte-  
 152 grated Wi-Fi and dual-mode Bluetooth, namely the ESP32 [35], to allow the wireless  
 153 transmission of the measured patient data.

154 The patient vitals are transmitted via Wi-Fi to the database by MQTT protocol. Such  
 155 database was created and managed in *Node-RED* and works on the AWS (Amazon Web  
 156 Services) cloud platform.

157 The vitals monitoring and the real-time anomaly detection is carried out by means of  
 158 the developed AI-based algorithm. First, a *Multivariate Linear Regression* (MLR) algorithm  
 159 is used to estimate the value of SP and DP starting from the HR and SpO<sub>2</sub> values coming  
 160 from the MAX30100, and taking into account the age and the presence of diabetes for  
 161 each patient. The MLR was chosen since it is one of the most consolidated approaches  
 162 adopted at the state of the art [36–38]. However, also other algorithms, based on Support  
 163 Vector Machine, Support Vector Regression [39], and Regression Tree [40] can be suitably  
 164

165 used to estimate systolic and diastolic pressure values. Then, an *LSTM Autoencoder* is  
 166 implemented to process the entire set of obtained data (HR, SpO<sub>2</sub>, SP, DP).

167 Once the measured data are classified, the result is sent in real time to the mobile  
 168 application (available to the user and to the physician). In case of hypertension risk, an  
 169 alert is also sent to the physician to allow his/her prompt intervention. As shown in  
 170 Fig. 3, the interactions between the mobile application and Node-RED are managed as  
 171 HTTP calls.

#### 172 4.2. Mobile application

173 The mobile application (which was called *Eco2u*) was developed in Java, and it is  
 174 compatible with Android (from version 4.4 onward). As aforementioned, the application  
 is structured in six levels, as shown in Fig. 3.

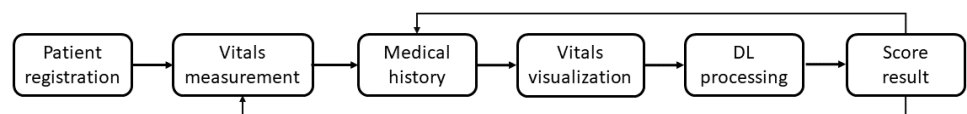


Figure 3. Application level of the proposed telemonitoring system.

175

- 176 1. *Patient registration*: Fig. 4(a) shows the window for registration and/or log in.  
 177 During registration, the patient inserts his/her tax code (which is automatically  
 178 verified) and the patient is associated to the reference physician. The user also  
 179 enters additional personal information (such as name, surnames, date of birth).  
 180 The association to the *wearable measurement devices* is carried out by scanning a QR  
 181 code generated specifically for a single device. These sensitive data are treated  
 182 in full compliance with anonymity requirements. In fact, only when an anomaly  
 183 is detected the doctor is warned and is able to trace the patient identity. Fig. 4(b)  
 184 shows the window that summarizes the user's data, before they are sent to the *cloud*  
 185 *database*, which checks the data and sends a feedback on the correct registration.  
 186 Once the registration phase is completed, the patient is brought back to the log-in  
 187 window to make the first log in. Also at this stage, there is a check with the database  
 to verify that the password and tax code entered are correct.

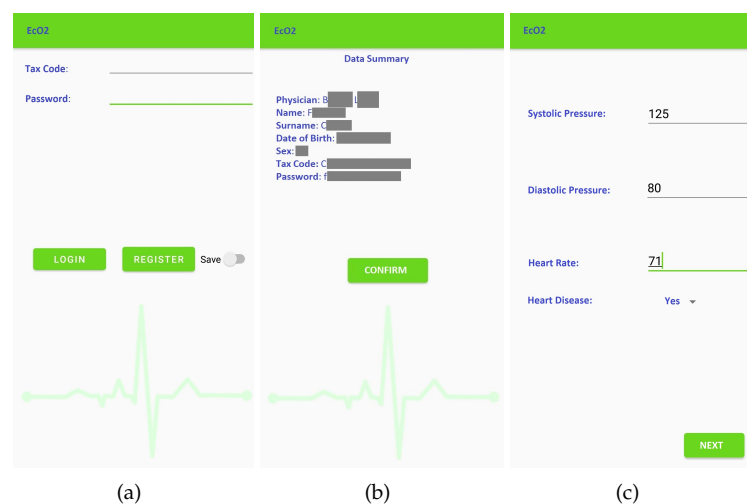
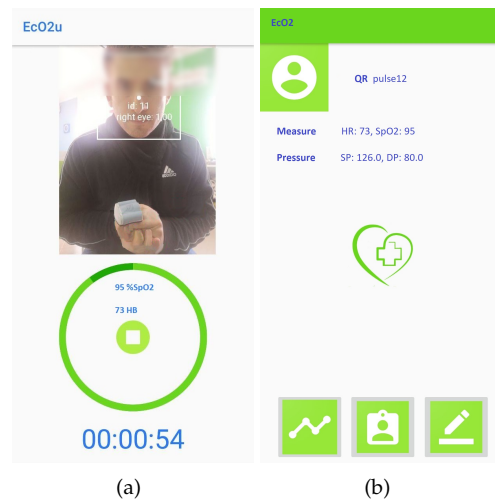


Figure 4. Window of the Eco2u mobile application: Main menu of the application (a); Patient registration (sensitive data are hidden) (b); Data calibration (c).

188

- 189 2. *Vitals measurement*: to allow the successive automated estimation of the systolic  
 190 and diastolic pressure, a preliminary calibration procedure has to be carried out.





**Figure 5.** Vitals monitoring with face recognition (a); Vitals visualization after completing the measurement (b).

- 191 In particular, the patient use a sphygmomanometer to measure the systolic and  
 192 diastolic pressure values, while the wearable sensing platform sensor is measuring  
 193 HR and SpO2. Then, the patient manually enters these data in the application (Fig.  
 194 4(c)). This phase, which has to be carried out only once, is necessary to identify  
 195 the parameters that will subsequently allow the soft transducer to estimate the  
 196 pressure. After the calibration, the patient can start using the soft transducer.  
 197 The mobile application was also endowed with an important identification feature  
 198 that allows to associate (and later verify) the patient's identity acquired through  
 199 the smartphone camera, as shown in Figure 5(a). Finally, the monitored vitals are  
 200 displayed to the patient, as shown in Fig. 5(b).
- 201 3. *Management of the patient's Medical History:* The management of the patient medical  
 202 history is conducted by: (a) showing the daily progress by a graph of the mea-  
 203 surements made, (b) reporting the symptoms during the day, (c) indicating any  
 204 symptoms not present to study a certain correspondence. The cloud database is  
 205 updated in real time after each measurement session.
- 206 4. *Remote Vitals Visualization:* The physician can access the *EcO2u* mobile application  
 207 with the *master* credentials to view his/her patient list; after selecting the specific  
 208 patient, the physician can display the most recent medical parameters, the graph of  
 209 past trends and the list of notes, which can be also entered by the patient, in order  
 210 to see if there is an onset of new symptoms that require a change in therapy (see  
 211 Fig. 5(b)).
- 212 5. *AI processing:* the AI-based processing of the acquired vitals provides a diagnostics  
 213 tool to detect anomalies in real time. In particular, as detailed in the following  
 214 section, a multivariate linear regression is used to estimate the value of SP and DP  
 215 starting from the HR and SpO2 values coming from the MAX30100, and taking into  
 216 account the age and the presence of diabetes for each patient, while a DL algorithm,  
 217 based on a LSTM Autoencoder, is used to process the entire set of obtained data  
 218 (HR, SpO2, SP, DP).
- 219 6. *Delivery of the Score result:* The Score result is a synthetic quantity which indicates  
 220 if an anomaly is detected, on the basis of the patient history and current data. In  
 221 that case, the physician and the patient are immediately warned about the patient  
 222 condition.

### 223 4.3. Deep-learning Algorithm for Anomaly Detection

224 The approach used in this work is the Semi-supervised learning; in fact, most of  
225 the originally available data imported from [41] were not labeled, but described the  
226 patients normal health conditions. However, with such data it was possible to train a  
227 robust model and evaluate its performance in the validation and test phase using a small  
228 amount of labeled data including normal and abnormal data.

229 The operating steps of the procedure were the following.

- 230 1. *Data Set Creation*: first, the reference data set for the anomaly detection was im-  
231 ported from [41]. The 50 subjects included are 80% men (40) and 20% women (10)  
232 with an age range ranging from 26 to 35 years. Oxygen saturation, heart rate, and  
233 identification are indicated for each user.
- 234 2. *Model Identification and Training*: the second phase consisted in the construction of  
235 a normal behavior model using the 80% of the imported data set as training data.  
236 The identification of this model is necessary to allow the subsequent classification  
237 of anomalies when they occur. The model chosen was the LSTM Autoencoder.  
238 This structure is characterized by an Encoder, which learns to generate an internal,  
239 compressed representation of input data, and a Decoder, which tries to reconstruct  
240 the original input on the basis of this internal representation. The Autoencoder  
241 was developed with a LSTM neural network. This choice was dictated by the  
242 fact that LSTM is the most suitable approach to process data when effects from  
243 past events need to be taken into account, differently from CNN which does  
244 not depend on any previous information for prediction, since it uses only the  
245 current window [42]. The LSTM requires a pre-processing of the data based on  
246 a three-dimensional array which contains the number of observations, the time  
247 window, and the relevant information. To determine the LSTM architecture, it was  
248 considered that the number of layers, and the corresponding number of neurons  
249 should be high enough to avoid underfitting but, at the same time, should be as low  
250 as possible to avoid both overfitting and high computational complexity. Therefore,  
251 an input level with 16 nodes, two hidden layers with 4 nodes each, and an output  
252 level with 16 nodes was chosen. The number of epochs was set to 100 and the batch  
253 size to 10. The model was trained by minimizing the reconstruction error, defined  
254 as the average absolute difference between the original input and the rebuilt output  
255 produced by the decoder.
- 256 3. *Alarm Value Identification*: the third phase consisted in the identification of threshold  
257 values to allow to mark the data as standard or anomalous. These thresholds were  
258 determined by the reconstruction errors that the Autoencoder performs in the  
259 training phase. An anomaly occurs if the obtained reconstruction error exceeds  
260 that threshold; in that case, the corresponding data is marked as anomalous.
- 261 4. *Test Validation*: the fourth phase allowed the validation of the threshold identified  
262 in the previous step. At this stage, the Autoencoder was provided with labeled  
263 data containing two anomalies to be identified. This test data is constituted by  
264 remaining 20% of the imported data set. The identification of an anomaly can be  
265 seen as a binary classification problem that provides as output a prediction score.  
266 The score indicates the certainty of the system that a given observation belongs to  
267 the standard class or that there is an anomaly.  
268 To this aim, the assessment of the obtained model was carried out using three  
269 figures of merit: the *Area Under Curve-Receiving Operating Characteristic* (AUC-ROC)  
270 curve; the *F1 score*; and the *Binary Accuracy*.
  - 271 • The ROC curve is plotted following two metrics: *True Positive Rate* (also known  
272 as *Sensitivity*) and *False Positive Rate*. The True Positive Rate is defined as the  
273 number of true positive results divided by the number of all samples that  
274 should have been identified as positive. On the other hand, the False Positive  
275 Rate is defined as ratio between the number of negative results wrongly  
276 categorized as positive (false positives) and the total number of actual negative



277 results. The ROC curve shows the relationship between the *True Positive Rate*  
 278 and the *False Positive Rate*. The closer Area Under Curve (AUC) is to 1, the  
 279 more accurate is the model.

280 • The *F1* score is calculated based on two metrics: *Precision* and *Recall* (also  
 281 known as *Sensitivity* or *True Positive Rate*, and already defined in the previous  
 282 item). The *Precision* is defined as the number of true positive results divided  
 283 by the number of all positive results, including those not identified correctly.  
 284 The *F1* score is obtained as the harmonic mean of the *Precision* and *Recall* and  
 285 it is a indication of test's accuracy.

286 • The *Binary Accuracy* represents how well a classification test correctly identi-  
 287 fies or excludes a condition. Then, it is defined as the proportion of correct  
 288 predictions among the total number of cases examined.

289 5. *Readjustment*: Once the model was validated, it was readjusted after 30 days with  
 290 further measurements provided by the user. The readjustment was aimed to  
 291 identify customized threshold values for the personalized patient care.

## 292 5. Experimental Results and Discussion

293 In this Section, the obtained experimental results are presented and discussed. More  
 294 specifically, a metrological characterization of the soft transducer, in terms of validation  
 295 of (i) the telemonitoring system, and (ii) the DL algorithm performance, was conducted.

### 296 5.1. Experimental Validation of the Telemonitoring System

297 The telemonitoring application *EcO2U* was tested on five volunteers. Firstly, a func-  
 298 tional testing was carried out to ensure each block worked properly. In particular, during  
 299 this phase it was possible to verify 1) the correctness of *Wearable Sensing Platform*/Subject  
 300 association within the database; and 2) the calls inserted in the database application to  
 301 correctly use the information.

302 Then, the correct estimation of systolic and diastolic pressure, obtained by means of  
 303 the multivariate linear regression algorithm, was verified after inserting the parameters  
 304 required during the calibration phase. Throughout the measurement, the mobile phone  
 305 focused on the user and on the sensor in order to validate the procedure. Automatically  
 306 the data is sent to the database and made visible to the user. If the measurement result,  
 307 after appropriate processing, indicates a risk for the patient, then the application itself  
 308 will manage this alarm by informing the doctor and the patient himself.

309 For each subject, 30 HR and SP/DP values were recorded. Two different sessions were  
 310 conducted. Table 1 summarizes the obtained results in terms of mean value and related  
 311  $1-\sigma$  repeatability. Results confirmed the proper functioning of the telemonitoring section  
 312 of the soft transducer.

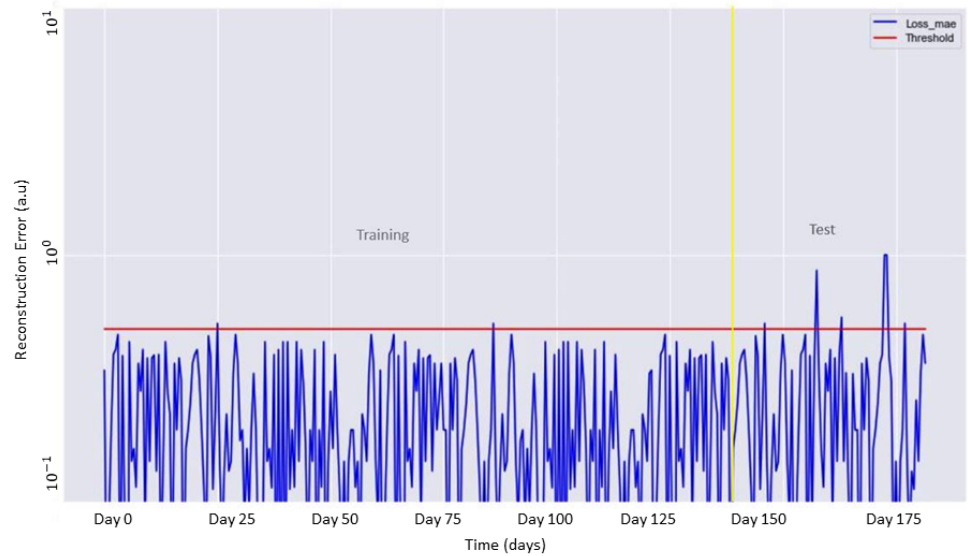
**Table 1.** Average values of vitals acquired in two sessions with related  $1-\sigma$  repeatability.

| Subject | HR [Bpm]    | HR [Bpm]    | SP/DP [mmHg] | SP/DP [mmHg] |
|---------|-------------|-------------|--------------|--------------|
|         | 1st session | 2nd session | 1st session  | 2nd session  |
| #1      | 85 ± 3      | 82 ± 2      | 112/80 ± 2   | 112/79 ± 2   |
| #2      | 71 ± 2      | 68 ± 2      | 130/82 ± 1   | 128/82 ± 2   |
| #3      | 88 ± 4      | 85 ± 4      | 125/85 ± 2   | 124/84 ± 1   |
| #4      | 75 ± 1      | 73 ± 2      | 126/84 ± 2   | 125/84 ± 1   |
| #5      | 70 ± 2      | 67 ± 1      | 136/82 ± 1   | 134/82 ± 2   |

### 313 5.2. Experimental Validation of the Developed DL Algorithm

314 As mentioned in Section 4.3, the training of the LSTM Autoencoder was carried out  
 315 for 100 epochs and allowed the identification of the appropriate threshold value. Fig.  
 316 6 shows the behavior of the Autoencoder on the complete dataset, including the data

317 used for training and for test. These data were indexed day by day. As visible, during  
 318 the observation period the score of the reconstruction error occasionally exceeded the  
 319 threshold value, indicating an anomaly in the measured data.



**Figure 6.** Reconstruction error (blue line) as a function of the training and test data. The identified threshold for the anomaly detection is shown in red.

320 Table 2 summarizes the results of the binary classification (anomalous/standard  
 321 data) on the test set in terms of True Positive Rate, False Positive Rate, and Precision.

**Table 2.** Results of data classification.

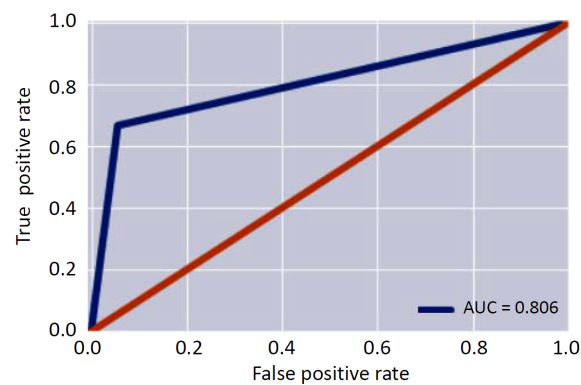
| Metric              | Result |
|---------------------|--------|
| True Positive       | 68     |
| False Positive      | 1      |
| False Negative      | 4      |
| True Negative       | 2      |
| True Positive Rate  | 0.94   |
| False Positive Rate | 0.33   |
| Precision           | 0.99   |
| Area Under Curve    | 0.81   |
| F1 Score            | 0.96   |
| Binary Accuracy     | 0.93   |

322 Starting from these metrics, the three figures of merit (AUC, F1 score, and Binary  
 323 Accuracy) were evaluated. In particular, the AUC was equal to 0.81, while the F1 score  
 324 was equal to 0.96, and the binary accuracy equal to 0.93. Figure 7 shows the resulting  
 325 AUC. The obtained results confirmed the capability of the system to successfully identify  
 326 the anomalies which can occur during the monitoring phase.

#### 327 5.2.1. Patient-specific Customization and Validation of The Soft Transducer

328 The patient-specific customization of the proposed soft transducer (*Readjustment*)  
 329 was carried on the five volunteers. The operative steps, conducted separately for each  
 330 volunteer, were the following:

- 331 1. The user employed the soft transducer for 30 days. The acquisition of his/her vitals  
 332 (twice a day) included also abnormal values, which were emulated by placing  
 333 him/her under stress conditions (e.g., a short run).



**Figure 7.** Area under the curve

334 2. The obtained data set (60 samples) was splitted in 80 % training (48 samples) and  
335 20 % test (12 samples). Therefore, the LSTM Autoencoder was re-trained in order  
336 to identify the patient specific threshold value

337 During the test phase, it was observed that the algorithm successfully identified all  
338 the labelled anomalies.

339 After this 30-days phase, further tests were conducted in order to determine the  
340 optimal number of days to wait to update the model still keeping adequate performance.  
341 Results showed that 15 days is the optimal calibration interval necessary to personalize  
342 and update the model. In fact, this choice allowed to obtain a value of AUC equal to  
343 0.831 in the test phase, while after 30 days this value slightly increased to 0.836.

## 344 6. Conclusion

345 In this work, a soft-transducer for remote monitoring of patient's health was de-  
346 signed, implemented and experimentally validated. The soft transducer measures in  
347 real time the patient's heart rate, oxygen saturation and systolic/diastolic pressure, and  
348 sends the data to a remote database; this can be easily consulted both by the patient and  
349 the physician. To endow the soft transducers with predictive features, a DL algorithm  
350 (based on LSTM Autoencoder) was developed and implemented: the algorithm pro-  
351 vides an alert when the vitals exceed certain thresholds, personalized for the specific  
352 patient. Also, a dedicated application (named *EcO2u*) was developed (i) to manage the  
353 remote collection of the patient vitals and the communication with the physician, and  
354 (ii) to automatically detect anomalies by means of a patient-personalized, DL-based  
355 processing. After a validation on a public data set, the obtained experimental results  
356 on five volunteers showed an accuracy in anomaly detection greater 93% with a true  
357 positive rate higher than 94%, thus confirming the robustness of the proposed strategy.

358 In practical applications, the proposed soft transducer can facilitate the monitoring  
359 of patients outside clinical facilities by providing advantages to the hospital in terms  
360 of resource management. Moreover, the proposed system manages to improve the  
361 quality of the patients life by allowing them to stay in their own family environment, in  
362 contact with family and friends. Such benefit is particularly important for children or  
363 elderly patients, for whom hospitalisation may have a severe emotional impact. Finally,  
364 it is worth mentioning that, although in this work a healthcare-related case-study was  
365 considered, the obtained results have broader generality and may be declined for other  
366 application scenarios.

367 Future work will be addressed to integrate the developed soft transducer with an  
368 Augmented Reality-based interface, which has proven effective in the medical field  
369 [43–46], in order to further improve patient's engagement and his/her *journey*.

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372 P.A.; data curation, F.C.; writing—original draft preparation, F.C.; writing—review and editing,  
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