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Longitudinal observation of psychophysiological data as a novel approach to personalised postural defect rehabilitation

Patrycja Romaniszyn-Kania[1]✉, Anita Pollak[2], Damian Kania[3] & Andrzej W. Mitas[1]

Postural defects are one of the main diseases reported to be at the top of the list of diseases of civilisation. The present study aimed to develop a novel approach to defining a set of measurable physiological biomarkers and psychological characteristics with identifiable information content and data analysis, enabling the determination of the adaptation period and conditioning the effectiveness of the treatment in personalised rehabilitation. During the rehabilitation, multimodal physiological signals (electrodermal activity, blood volume pulse) and psychological data (anxiety as a state and as a trait, temperament) were recorded on a group of 20 subjects over a period of three months (120 measurement sessions). Preprocessing of the physiological signals and psychological data was performed. A stepwise forward regression method was used to determine a set of successive statistically significant predictors of the model. For each group, a matrix of coefficients for fitting a linear regression of changes in the value of a given predictor in subsequent measurement was determined. Adaptive Boosting was chosen to develop a mathematical model of the patient. The analysis of the results of the psychological tests enabled the participants to be divided into five new, previously undefined subgroups, which were both labels for the classifier. Using the dimensionality reduction method, 8 significant, statistically important features were extracted. AdaBoost classifier allowed the creation of a prediction model for therapy parameters with 84% accuracy, and the Pseudo-Random Number Generator was used to check the validity of it. The AdaBoost algorithm was used again to check the dynamics of changes in regression coefficients for individual groups—a set of psychophysiological characteristics identified as the basis for personalised therapeutic interventions. Each individual requires time to adapt to a new situation, conditioned by their characteristics. An appropriate interdisciplinary approach to professional rehabilitation influences the therapeutic process's quality, duration, and effectiveness. Physiological features determine the patient's involvement in the rehabilitation process, allowing robust personalisation of therapy in a closed feedback loop. The fusion of psychophysiological data and multimodal measurements enables the development of a unique behavioral-physiological profile of the patient undergoing rehabilitation.

Keywords Signal preprocessing, Psychophysiological state analysis, Machine learning, AdaBoost, Emotion analysis, Computer-assisted physiotherapy

Postural defects are increasingly recognized as a significant health concern in our contemporary society among children[1]. Alarmingly, it is estimated that approximately 60% of children, ranging from ages 3 to 18, are afflicted with some form of postural disorder[2]. Scoliosis, characterised by an abnormal, often lateral, curvature of the spine, is particularly noteworthy due to its complex aetiology and prevalence.

The complexity of idiopathic scoliosis and its multifaceted contributing factors present a substantial and unresolved challenge in medical practice. Due to the intricate nature of its diagnosis and treatment, its management requires a comprehensive and interdisciplinary approach. Patients, particularly during these phases, often experience apprehension, tension, and unease[3]. These emotional states can significantly impact

[1]Faculty of Biomedical Engineering, Silesian University of Technology, Roosevelta 40, 41-800 Zabrze, Poland. [2]Institute of Psychology, University of Silesia in Katowice, Grażyńskiego 53, 40-126 Katowice, Poland. [3]Institute of Physiotherapy and Health Sciences, The Jerzy Kukuczka Academy of Physical Education in Katowice, Mikołowska 72A, 40-065 Katowice, Poland. ✉email: patrycja.romaniszyn-kania@polsl.pl

various aspects of their lives and well-being. They can intensify pain, negatively affect self-perception, hinder functional abilities, and damage mental health, decreasing overall life satisfaction[4].

A comprehensive therapeutic approach is necessary to address this matter, encompassing motor control, biomechanical, and behavioural analyses. Additionally, it is imperative to develop a comprehensive strategy to address the individual's undesirable behaviour and emotional reactions during exercise as part of the response to treatment. Integrating psychophysiological dimensions into the treatment strategy is a pivotal aspect that enables continuous and long-term validation and proper selection of therapeutic parameters. This comprehensive approach enhances our understanding of this condition and improves patient outcomes, ultimately contributing to the broader goal of advancing human health.

Integrating novel technologies, such as sensors and artificial intelligence methodologies, into health research is progressively transforming the field. This technological shift is not only expanding capabilities, but it's also fostering an unprecedented level of collaboration between biologists and computer scientists. Thanks to these advancements, more accurate measurement and understanding of health indicators can be achieved, providing a more comprehensive picture of human health.

The evolution of health understanding has fostered the development of a model that accentuates the role of psychological and socio-environmental aspects in deciphering the illness process[5]. This approach, known as the biopsychosocial or holistic-functional model, interprets illness as a disruption of the multifaceted relationships that characterise a patient as a human being[6]. Comprehensive approach is vital in enhancing patient care, promoting improved treatment adherence, and fostering increased patient satisfaction[7].

LeDoux presented the physiological basis for developing emotional reactions to external stimuli in his work[8]. The amygdala, responsible for the body's defensive reactions, including reactions to emotions, stimulates the sympathetic nervous system, activating the eccrine sweat glands, whose primary role is thermoregulation[9]. The significant activity of these glands is associated with sweating, and sweat, a salt solution, contributes to changes in skin conductivity and the generation of higher values of electrodermal activity (EDA)[10]. EDA is one of the most frequently used signals for behavioral-physiological analysis, as it reflects normative and pathological states[11]. The sympathetic nervous system activity directs cognitive and affective states. Therefore the EDA signal directly analyses the autonomic regulation of emotions[12].

Stimulation of the sympathetic nervous system also affects the heart. This is the primary mechanism for short-term regulation of blood pressure, which is reflected in signals such as blood volume pulse (BVP) or heart rate (HR), the second most frequently analysed group of physiological data characterising emotional states[13]. Other physiological data like electromyography or electroencephalography and behaviours such as gestures and movements are non-verbal creations of the human body, which often reveal valuable and reliable information about what people are thinking and feeling[14]. The combination of behavior and physiological signals makes it possible to describe human behavior. In addition, using computer-aided diagnosis, mathematical models, and artificial intelligence algorithms will make it likely to develop objective emotion recognition systems[15].

A frequently encountered problem in the literature many researchers pose is the objectification of the results obtained. Many papers focus on analysing physiological data based on the results of quantitative measurements. Signals recorded from the patient's body are independent data - the participants cannot change their fundamental values by their expectations[16]. Therefore, multimodal analysis of the effects of spontaneous emotions on autonomic nervous system excitations used physiological signals like electrodermal activity, electrocardiogram (ECG), or skin temperature[17]. This and the support vector machine made a system for assessing emotions[18]. The effectiveness of machine learning methods in combination with physiological signals in the context of comparing the results obtained to the quantitative evaluation derived from the Hamilton Depression Rating Scale questionnaire has also been the subject of other studies[19]. A recent literature report presents a method for differentiating subclinical patients with anxiety and depression based on a comprehensive battery of behavioral tests and machine learning methods[20]. Due to the multitude of physiological signals dedicated to measuring emotions, it was necessary to define a data set for analysing affective states. For this purpose, the EDA and BVP signals were selected, and emotion classification models were developed based on them - the patient's response to a stressful stimulus validated under laboratory conditions and then verified on real data[21]. Detecting stress and its correlated events is another step to counteracting its negative effects on health and well-being. The three-hour recording of physiological signals using the Empatica E4 wristband allowed to hypothesise that monitoring physiology to assess emotions is a key aspect of maintaining a satisfactory level of health[22]. Assessing mental well-being through the valence-arousal model of emotion, using ECG signals, EDA, and HRV parameters combined with AI algorithms, is also a current research focus[23–25]. Utilising EDA and BVP signals, a machine learning-based system has been developed for quick stress symptom identification and differentiation between stressful and non-stressful scenarios during the execution of simple tasks[26]. The importance of this research facet is highlighted in multiple studies[27]. In developing models of mental health, it is important to have reference data recorded during controlled situations that evoke a given emotion. Emotional experiences reflected in physiological data (EEG, BVP, and EDA signals) may have been triggered by visual or auditory stimuli, additionally amplified by the regulation of ambient temperature[28]. Understanding the informational value of different physiological signals and their combinations has led to the development of cost-effective and objective systems for detecting, processing, and interpreting emotions, with ECG emerging as an effective signal[29–32].

Developing computer-aided systems using artificial intelligence to identify stressful situations is being pursued. The results would enable more objective, consistent diagnosis and decision-making based on physiological signals[33]. A quality data recording system was also proposed for subjective recognition of emotions evoked by video recordings, based on EDA signals[34]. Artificial intelligence methods combined with physiological signals, representing the organism's most authentic reactions, allow the development of methods to accurately distinguish individual emotions in real-time[35]. Fuzzy logic methods were used to understand a patient's psychophysiological state during robot-assisted rehabilitation[36]. Detecting emotional states associated with the valence-arousal model of emotion is also at the core of scientific research. Using ECG signals, EDA, and HRV parameters, combined with artificial intelligence algorithms, makes it possible to assess the mental well-being of patients[23–25]. The relevance of neuroticism and negative affectivity to the severity of stress experienced during physiotherapy interventions in a non-clinical group was also identified[37]. Obtaining information about emotional reactions perceived during physiotherapy becomes immensely important in the context of understanding the patient's affective state. However, using both HRV parameters and EEG signals for this purpose hinders the simplicity of the study[38,39]. However, ensuring measurement objectivity is crucial, possibly by cross-verifying physiological signal parameters (ECG, EEG, HRV, EDA) with cortisol levels[27] or blood-derived biochemical variables[40]. The results from comprehensive methodologies enable more objective and consistent diagnoses and decision-making based on physiological signals[41].

Based on the literature review undertaken, to the best of the author's knowledge, there are no comprehensive systems for analysing the psychophysiological data of a patient undergoing therapy. Therefore, this study aimed to define a set of measurable physiological biomarkers and psychological characteristics with identifiable information content, enabling the determination of the adaptation period and optimising the treatment protocol for individual needs during the physiotherapy process.

Materials and methods

Study group

The study group consisted of 20 children (16 girls and 4 boys) who were patients of a private physiotherapy practice. Table 1 detailed characteristics of the study group, including sex (F—female, M—male), age, number of rehabilitation sessions, how the actuator module was set up during exercise (head positioning, RU—right-up, RD—right-down, LU—left-up, LD—left-down).

In total, more than 120 measurement sessions were recorded. Figure 1 presents the distribution of the number of rehabilitation sessions.

The criteria for inclusion in the study included a referral from a physiotherapist and diagnosed scoliosis, the age range of the patient from 8 to 13 years old, written consent from the legal guardian to participate in the study, and no impairment in understanding and following instructions. The age range of the participants was from 10 to 13 years. The Bioethics Committee of the Jerzy Kukuczka Academy of Physical Education in Katowice approved the study protocol (No. 3/2019), and it was conducted according to the Declaration of Helsinki.

Research protocol

The presented research protocol was carried out over a long-term period of three months. A total of 120 measurement samples were collected (the number of rehabilitation sessions for all patients).

During the patient's first visit to the rehabilitation facility, the research protocol included more components. The following figure (Fig. 2) illustrates the different stages of the research protocol. Throughout each phase, optimal research conditions repeatable for each successive measurement and the necessary equipment were provided.

ID	Sex	Age	Number of rehabilitation sessions	Module positioning
101	F	13	7	LU
102	F	13	6	RU, LD
103	F	13	7	RU
104	F	12	8	RU, LD
105	F	13	6	RU, LD
106	F	12	6	LD
107	F	13	8	LD
108	F	12	7	RU
109	M	12	6	RU
110	F	12	6	LU
111	F	12	6	LU
112	F	11	5	RU, LD
113	F	11	7	LU
114	F	12	5	RU, LD
115	F	10	5	RU
116	M	11	6	LD
117	F	13	5	RU, LD
118	M	10	7	RD
119	M	10	4	RU
120	F	13	4	RU

Table 1. Characteristics of the study group.

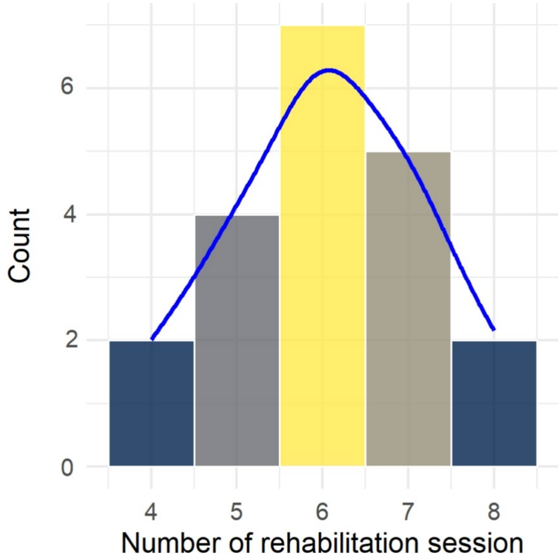


Figure 1. Distribution of the number of therapy sessions during the presented study.

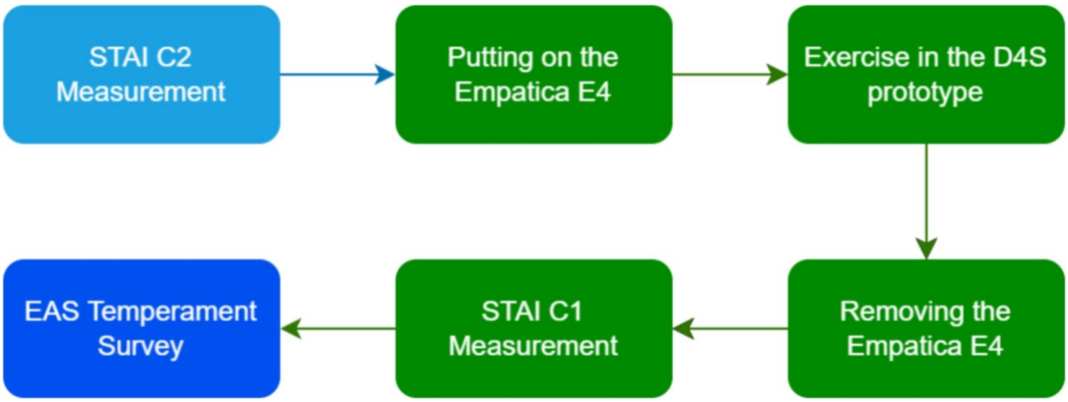


Figure 2. Components of the protocol highlighting the elements carried out during successful examinations; light blue—additional element of the first visit, dark blue—additional element of the last visit, green—elements of each examination.

At the first visit, the patient was asked to complete the State-Trait Anxiety Inventory psychological questionnaire defining anxiety as a trait (STAI-C2) in paper-pencil version, consisting of 20 statements[42]. The main part of the examination began with the application of the Empatica E4 wristband (E4), a certified medical device, to the patient's non-dominant hand two fingers below the wrist line, according to the manufacturer's guidelines[43]. The E4 enabled the recording of real-time physiological signals, such as electrodermal activity, temperature, blood volume pulse signal, and accelerometer (Acc) signal. The EDA signal and temperature sampling frequency were 4 Hz, the BVP signal—64 Hz, and the Acc signal—32 Hz.

The patient was then instructed to enter the D4S device (Fig. 3, which was a comprehensive diagnostic and therapeutic system to support the rehabilitation of postural defects and scoliosis[44].

The D4S physiotherapy module is a workstation for advanced exercises based on the Pressio concept, performed in the kneeling-supported position. It allows conservative treatment and prevention of scoliosis through the active involvement of the patient's strength[44]. Once the participant was positioned correctly and secured in the exercise cage, the patient was asked to perform a series of approximately 8-second-long "cat-backs" while applying maximum self-pressure to the resistance elements during a 4-minute session. A 2-second pause separated each series. Each child had a different, customised setting of the resistive elements.

Upon exiting the D4S device, the patient immediately removed the Empatica E4 device. Subsequently, the participant was asked to complete the STAI-C1, a paper-pencil questionnaire designed to measure anxiety as a state[42]. It consists of 20 questions and relates to the frequency of occurrence of emotions i.e. anger, irritation, anxiety, doubt, and feelings of insecurity, directly during exercise in the prototype device. At the end of the research, the therapist was asked to complete a teacher-assessed version of the Emotionality Activity Sociability (EAS) Temperament Survey that measures the four dimensions of temperament i.e. emotionality, activity,

Figure 3. D4S system with distinguished modules, red—physiotherapy module, green—actuator module, orange—diagnostic-monitoring module.

sociability, and shyness of children[45]. It encompasses 20 questions regarding the evaluation of children on a scale of 1 to 4 from a teacher's perspective (in our study—a physiotherapist).

Independent division of the study group

Five variables (emotionality, activity, sociability, shyness from EAS and anxiety from STAI-C2) were obtained based on the collected psychological data. In the next step, the distribution of scores for each psychological characteristic was checked. The results were then verified whether the results obtained allowed the creation of coherent groups. For this purpose, to objectively verify the obtained class divisions, an unsupervised machine learning algorithm was used—cluster trees with median weighted center-of-mass distance for all psychological characteristics of the patients[46,47].

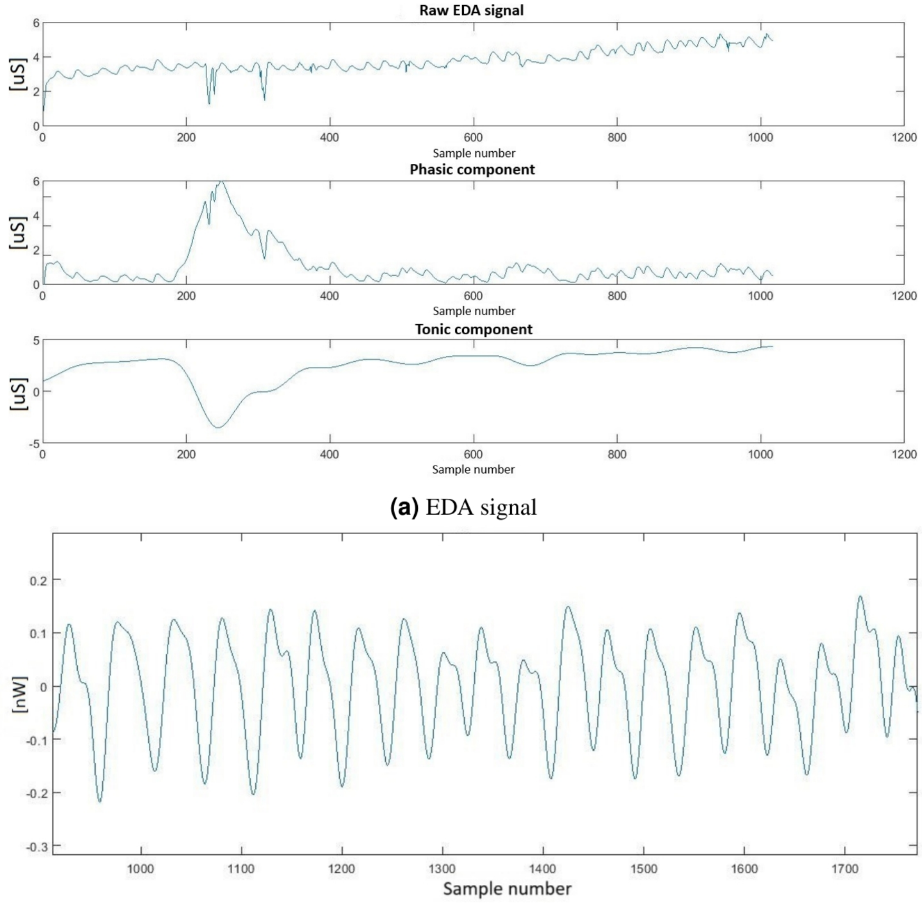
The cluster tree algorithm allowed the division into new, previously undefined groups, which were carried forward in detail by a psychologist named and described.

Physiological signal processing

In the presented approach, 76 signal features and 1 psychological trait - the value of the anxiety test as a state (STAI-C1) - were determined from all recorded data (for each patient).

The first step for each signal discussed below (EDA, BVP, Acc) was to extract the fragment recorded during the exercise based on the timestamps marked each time on the E4 device at the beginning and end of the activity. Filtering was then carried out, using a different method for each of the signals presented, and in the final step, the features were determined. Figure 4 presents raw physiological signals acquired during rehabilitation session.

The convex optimisation to the EDA model was used to determine the basic components of the EDA signal—tonicity, phase and ϵ error[48]. The basic unit representing the EDA signal, including its components, is μS. After the removal of the additive error from EDA, the signal was further analysed. The most relevant set of features from the EDA signal is based on the Skin Conductance Level (SCL) and the Galvanic Skin Response (GSR), which is defined as the change in electrical skin resistance in response to temporary emotional stimulation, increasing the activity of the sympathetic nervous system[10]. Based on the results, the values of the following parameters were estimated: *rpm*—denoting the number of GSRs per minute, the number and value of GSRs, and the number and value of significant GSRs (amplitude value above 1.5 μS), as well as the quadratic measure of the discrepancy between predicted and observed signal data (obj). For the four-minute signal fragment, the number of statistical indicators was additionally estimated[37]. Additional parameters for fitting the hyperbolic tangent model were determined to analyse the EDA signal due to the analogy of this function with the EDA wave. The sum of the tonic and phase components (tr_{EDA}) was smoothed using a moving average filter with a fixed window length, directly dependent on the input signal, of 10% of its length by default and then normalised from 0 to 1 to transfer the EDA function to a set of values of the hyperbolic tangent function. A fit of the input function *tr* of EDA to the hyperbolic tangent model $tanh(x)$ was created. Values of the model coefficients a and b were sought to achieve the smallest possible matching errors between the input signal and the modeled signal. Based on the developed model, it was decided to determine the time point T_{EDA} for the received wave. According to the hypothesis, this point is significant as it marks the point at which the patient has warmed up sufficiently, i.e., their skin perspiration has stabilised, indicating readiness to reach maximum self-effort.



(a) EDA signal

(b) BVP signal

Figure 4. Raw signals from Empatica E4.

In the next step of cardiac signal processing, the de-noised BVP signal was used to determine the inter-beat-interval (IBI) vector, i.e., the consecutive time intervals (d_t) between individual heartbeats - local maxima or minima. Based on the IBI vector, a series of time-dependent coefficients describing heart rate variabilities, such as standard deviation of successive differences (SDSD) between two adjacent IBI intervals [ms], standard deviation of normal-to-normal intervals (SDNN) [ms], root mean square of successive differences (RMSSD) between two consecutive IBI values [ms], probability of intervals greater than 50ms (pNN50), Triangular Interpolation of NN Interval Histogram (TINN) and Heart Rate Variability Triangular Index (TRI). In addition, the heart rate variability parameters were also determined in the frequency domain: Low Frequency (LF)—the power of the low-frequency spectrum in the range of 0.04 to 0.15 Hz, High Frequency (HF)—the power of the high-frequency spectrum in the range 0.15 to 0.4 Hz, and the LF/HF index—the quotient of the power of the low (LF) to high (HF) frequency spectrum.

The Table 2 shows all analysed features by data type, modalities, and purpose (labels for further analysis or features for classification).

Features dimensionality reduction

From a total of 77 features recorded during each of all 120 rehabilitation sessions, after removing 8 features by applying the False Discovery Rate (FDR) correction, the algorithm determined the most significant ones that best model the dependent variable.

A stepwise forward regression (SFR) method was used to determine a set of successive statistically significant predictors ($p < 0.05$) of the model that directly impact the prediction of the dependent variable[49]. The FDR correction was introduced, conceptualising Type I errors in null hypothesis testing when conducting multiple comparisons. In other words, the FDR represents the expected percentage of Type I errors. It was necessary to perform Pearson correlation analysis between variables in the dataset. Based on the results, 8 physiological traits highly correlated with each other were rejected ($r = 1$).

The fusion of physiological and psychological data allowed the patient's condition to be analysed over time. A matrix of coefficients for fitting a linear regression of changes in the value of a given predictor in subsequent measurement (all patients independently) was determined. It allows for verification of the rate and character of changes in each variable.

Type	Modality and purpose	Features
Psychological	STAI C2—label	Anxiety as a trait (STAI-C2)
	STAI C1—classifier features	Anxiety as a state (STAI-C1)
	EAS—label	Emotionality, activity, sociability, shyness
Physiological	BVP—classifier features	mean frequency, passband, centre of gravity
	EDA—classifier features	Skin conductance level, galvanic skin response, response per minute, number of rpm, the amplitude of rpm, number of significant rpm, value of significant rpm, obj, mean value, standard deviation, median, variance, 25th and 75 percentile, minimum and maximum value, signal range, 4th and 5th order moment, skewness, kurtosis, mean squared error, entropy, parameters of fitted regression line: sum of squared error, R^2, root mean squared error, slope and shift coefficients, the distance between EDA and regression line, T_{EDA}, sum, mean value and median of energy
	HRV—classifier features	SDSD, SDNN, RMSSD, pNN50, TINN, TRI, HR, LF, HF, LF/HF ratio

Table 2. Features determined from all modalities at each stage of the presented analysis.

Prediction model for therapy parameters

For linear regression coefficients, the Adaptive Boosting (AdaBoost) method, which, as an iterative algorithm, creates a strong classifier based on many weak classifiers, was chosen to develop a mathematical model for therapy parameters[50]. For the AdaBoost method, the support vector machine (SVM) algorithm was chosen as the weak classifier because this classifier is very efficient and simple to implement[51]. The input data of the classifier was the matrix of correlation coefficients defined above, and labels were information about each record belonging to one of the new, previously undefined groups.

Subsequently, using the Grid Search method, an experiment was performed to verify the optimal hyperparameters for the developed model. More than 1,000 trials were performed, in which different combinations of parameters were checked in all possible options. For the SVM, there were:

- kernel function—linear, polynomial, sigmoid, and radial basis function,
- for polynomial functions, the degrees of the polynomial from 2 to 6,
- regularization parameter—1, 10, 20, 50, 100, 150, 200, 250,
- γ—$\frac{1}{n}$ or $\frac{1}{n*\sigma^2}$
- shape of decision function—one vs. rest (OVR) or one vs. one (OVO).

For the AdaBoost classifier, these were tested:

- the number of estimators with values of 1, 10, 20, 50, 100, 150, 200, 250, 500, and 1000,
- learning rate from 0.1 to 1, with step 0.1,
- calculation of class probabilities algorithm—SAMME and SAMME.R.

Subsequently, the data were divided into a training and a test set with 5-fold cross-validation in a ratio of 1:4 (i.e., 80% of the data were assigned to the training set and the remaining 20% to the test set).

For classification, the most important parameters describing its performance are the accuracy (ACC), precision, (PPV) sensitivity or true positive rate (TPR), specificity or true negative rate (TNR), F_1, which is the harmonic mean between precision (PPV) and sensitivity (TPR). Macro parameters refer directly to the average value of a given indicator for all cases analysed, micro parameters are quotients of the sum of true positive indicators for all classes and the number of all cases considered (x), weighted parameters are calculated as the sum of the products of the values of a given indicator and its weight, determined as the number of cases classified as true positive for a given class divided by all cases.

Validation and testing of the model

Pseudo-random number sequences using the Pseudo-Random Number Generator (PRNG) were used to check the validity of the proposed approach for predicting therapy parameters to determine the values of input variables corresponding to differentiating psychological characteristics, such as emotionality, activity, sociability, shyness, and anxiety. All simulated values were randomised, scaled, and rounded according to a psychological test score key of 5 to 25 (for temperamental traits) and 20 to 60 for anxiety. The algorithm used 5 PRNG generators in parallel for each trait independently.

Once the classification results into 5 groups were obtained, a specialist psychologist evaluated the simulated data independently. This stage aimed to test the model and verify that the class labels assigned by the unsupervised learning method, based on the proposed author's division of the study group and the expert evaluation, were consistent.

The next step in testing was to check the dynamics of change of the most relevant characteristics. For this purpose, it was verified how the regression coefficients changed from therapy to therapy for each patient in the group. A limitation was the number of treatment sessions carried out. Therefore, it was decided to analyse the dynamics of change in 5 consecutive sessions (Fig. 7) to compare the results obtained and the subsequent classification of the regression coefficients obtained using the AdaBoost algorithm described earlier.

Results

Independent division of the study group

The results of the division using the cluster tree are shown in Fig. 5. Based on this, five subgroups were identified. The patient groups obtained were consistent, except ID 106.

Based on the results and the description of the research group, the individual emotions and their intensity, it was decided to give each of five group authoritative names directly related to their characteristics, such as:

1. *Sociable*—is characterized by very low emotionality and shyness but high values of qualities such as activity, sociability, and anxiety; they are people open to others and new situations in which they engage, willing to establish contacts without experiencing anxiety,
2. *Calm*—is distinguished by low emotionality, high activity, average anxiety, sociability, and shyness, tolerating high sensitivity to external stimuli, including social,
3. *Distanced*—are people with low emotionality and sociability, high activity, medium intensity of shyness and anxiety, showing optimal reactions to activity despite experiencing anxiety while trying to act and maintain contact,
4. *Inhibited*—are characterized by very low activity and sociability, average emotionality and fear, and high shyness; they are withdrawn from social contacts, manifesting a lack of need for deep relationships with others, more distanced from others,
5. *Shy*—similar to group No. 4, are those showing low sociability, moderate emotionality, activity, and drug, as well as high shyness, are characterized by low acceptance of the situation at hand, feeling a sense of the situation of lack of understanding of action, negatively referring to the past.

Based on the differences between the patients, it should be noted that the individual groups differ from the theoretical model and individually from each other. The theoretical model was based on two assumptions. The first derives from a statistical approach, in which the average intensity of a trait (median value) was taken as a reference point between individual measurements. The second assumption was based on the importance of a trait to functioning. Research suggests that a lack or excess of a trait results in a lack of fit with the environment. Hence, the centre of the dimension was taken as the optimal result. A comparison of the mean scores between the groups and the theoretical model is shown in Fig. 6.

Features dimensionality reduction

Table 3 shows the step-by-step results of the stepwise forward regression using the dimensionality reduction algorithm and the regression fit coefficients determined at each subsequent step.

From the total features, the algorithm determined the 8 most significant (statistically important) for which the p-value was less than 0.05. These were the following parameters:

1. STAI-C1 test result (C1),
2. the upper limit of the BVP signal bandwidth ($Bandpass\_H_{BVP}$),
3. time to reach T-point based on EDA (T_{EDA}),
4. skin conductance level (SCL_{EDA}),
5. the quadratic measure of the discrepancy between predicted and observed data of an EDA signal (Obj_{EDA}),
6. the amplitude of galvanic-skin responses (Amp_{EDA}),
7. mean heart rate of the patient (HR_{HRV}),
8. minimum EDA signal value (Min_{EDA}).

Prediction model

The general characteristics of the change in the regression coefficients of the relevant study groups according to the proposed author's division—the increase (*nearrow*) or decrease (*searrow*) of the selected parameters in the context of successive treatment sessions—are shown in the Table 4.

Table 5 shows the accuracy of the AdaBoost classifier prepared according to the methodology shown above for averaged results from all attempts.

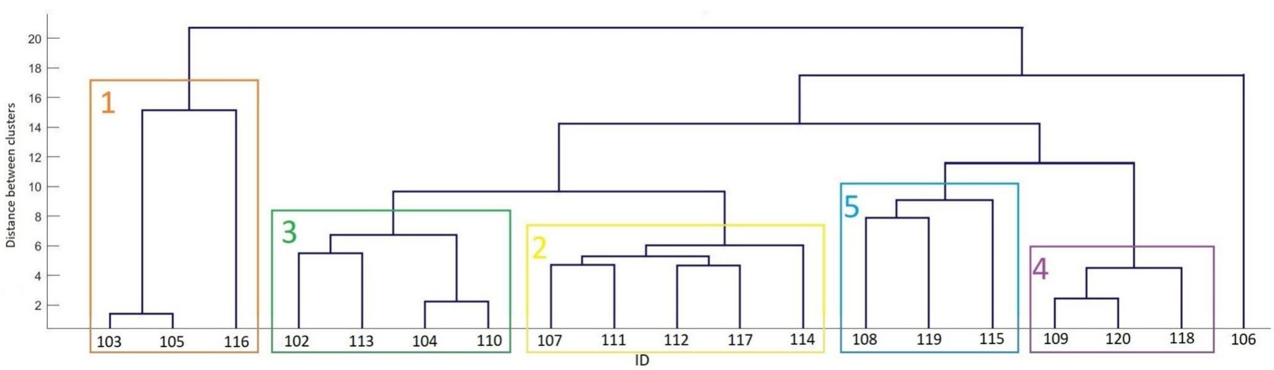


Figure 5. Division of the participants into groups according to the cluster tree division.

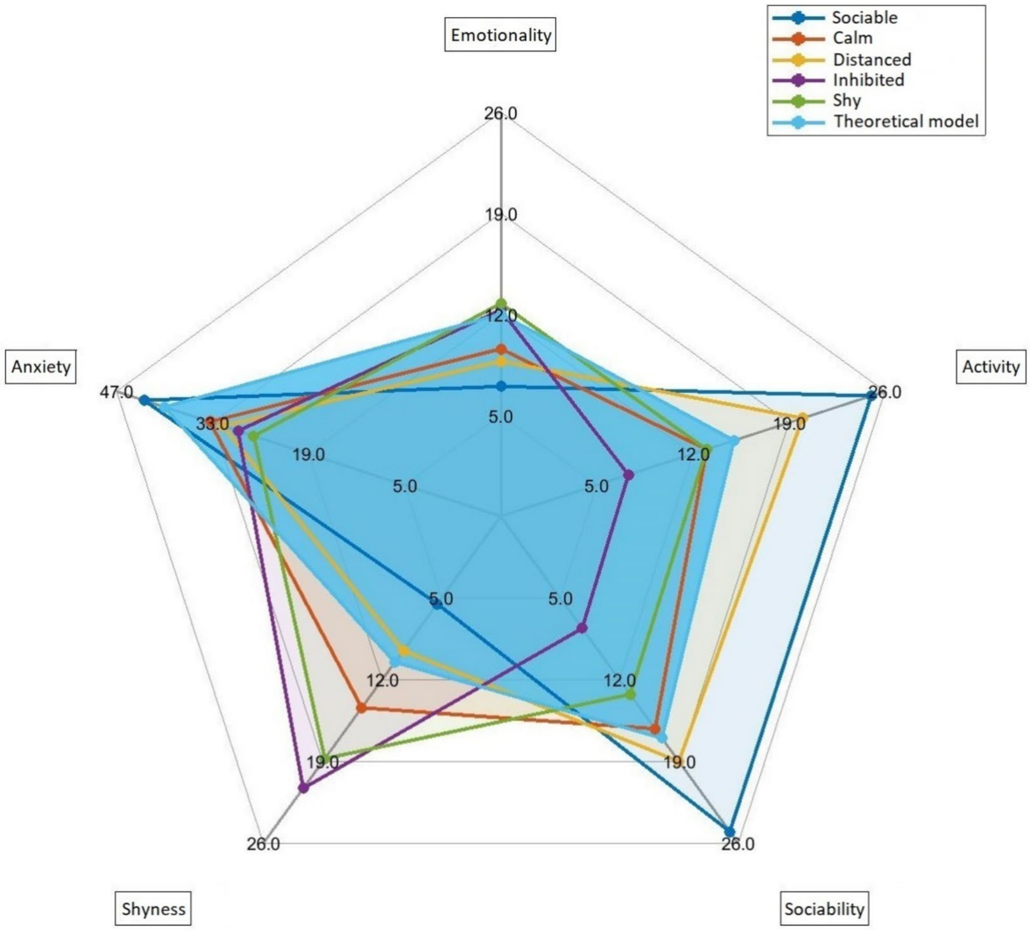


Figure 6. Distribution of characteristics in different groups relative to the theoretical model.

Step	Selected feature	R^2	$adjR^2$	RMSE	C_p	AIC
1	C1	0,123	0,105	1,242	38,639	286,763
2	$Bandpass\_H_{BVP}$	0,186	0,171	1,195	28,173	378,726
3	T_{EDA}	0,214	0,194	1,179	25,258	376,520
4	SCL_{EDA}	0,245	0,218	1,161	22,057	373,897
5	Obj_{EDA}	0,281	0,249	1,138	17,844	370,125
6	Amp_{EDA}	0,320	0,283	1,112	13,175	365,593
7	HR_{HRV}	0,366	0,325	1,078	7,428	359,519
8	Min_{EDA}	0,389	0,344	1,063	5,352	357,037

Table 3. Results of the stepwise forward regression algorithm. R^2—Coefficient of determination, adjR^2—adjusted R-squared, RMSE—Root mean square error, C(p)—Mallows' Cp coefficient, AIC—The Akaike information criterion

Validation and testing

In validation, in the case of classification using the decision tree algorithm, the concordance of the assignment of a simulated case to a class by the expert and by the PRNG algorithm was 82% (41 simulated patients).

In testing the developed model of predicting therapy parameters, the dynamics of change of the most relevant characteristics for the next 5 therapeutic sessions were shown in Fig. 7.

The AdaBoost algorithm was used again to check the dynamics of changes in regression coefficients for individual groups (Table 6). The input data in each case were regression coefficients, after including in the analysis the parameters determined in subsequent treatment sessions, and the labels of these data were membership in one of five new classes (sociable, calm, distanced, inhibited, shy). To better visualize the results, the analysis was restricted to analysis after 2, 3, 4, 5, and the maximum number of sessions for a given patient group.

	Sociable	Calm	Distanced	Inhibited	Shy
C1	↘	↗	↗	↗	↘
$Bandpass\_H_{BVP}$	↗	↘	↘	↗	↗
T_{EDA}	↘	↘	↘	↘	↘
SCL_{EDA}	↗	↗	↘	↗	↘
Obj_{EDA}	↘	↗	↘	↘	↘
Amp_{EDA}	↘	↗	↘	↘	↘
HR_{HRV}	↘	↘	↗	↘	↘
Min_{EDA}	↘	↘	↘	↘	↘

Table 4. Generalised characteristics of changes in selected features for individual groups.

	PPV	TNR	TPR	F_1	ACC
macro	0.72	0.68	0.91	0.65	0.84
micro	0.65	0.69	0.90	0.79	
weighted	0.58	0.62	0.72	0.53	

Table 5. Accuracy of the AdaBoost classifier.

Discussion

The continuous development of many scientific fields, particularly medical and technical sciences, has contributed to the knowledge of increasingly complex interrelations within the human body[52]. In the biopsychosocial model of health, the multidimensional approach and understanding of health indicate a key problem: the level of health is determined by biological, social, and psychological factors, as a whole, in interaction with each other[7]. This provides a theoretical basis for the analysis of the behavioral-physiological profile of the patient in the context of increasing or restoring health potentials during illness and the personalisation of therapy.

The results obtained in the present study allow to substantiate the assumptions made concerning the health model. The previously mentioned multidimensional approach to health, particularly for the patient with scoliosis, in the context of monitoring their physiological and psychological reactions, will contribute to achieving maximum but controlled effort and faster recovery. A key element presented was the independent division of the study group based on psychological data. Variables such as anxiety level or temperamental traits determined the patient's belonging to a strictly defined class, demonstrating the importance of psychological factors. Physiological characteristics selected based on objective algorithms formed the basis for building a model for determining the adaptation period and optimising the treatment protocol for individual needs during physiotherapy.

Based on the methodology for the overall processing of the collected data, it is possible to define the biomarkers which can determine the progress of the conducted therapy with 84% accuracy and the belonging of the person examined to a given group of patients, according to the proposed division to personality types.

At the validation stage using the PRNG algorithm, the accuracy was 82%. The results obtained are satisfactory, as they confirm the validity of the author's classification. The discrepancy with a highly accurate classification (100%) may be due to the fact that there is a high probability of a previously undescribed individual presenting a completely different combination of behavioral characteristics. It is important to remember that every patient is different, and the therapy provided will require an individualised approach, both in the psychological analysis and the rehabilitation provided, especially when the main goal is personalising therapy.

Subsequently, it was noted that different groups of patients were characterised by different changes in regression coefficients for the appropriate biomarker. It was also verified how the regression coefficients changed from therapy to therapy for each patient in the group. This indicates a particular analogy with biological processes occurring in the environment. Each individual requires a certain amount of time to adapt to a new situation, determined by personal characteristics (in this case, temperament and anxiety, which formed the basis for the division into five new groups). A more extended period of observation of the patient allows one to get to know him better and to adapt therapy sessions to current conditions based on knowledge of the value of physiological characteristics closely dependent on psychological traits. The obtained accuracy of the model shows that the more measurement sessions the more accurately the patient's behavior can be predicted. It points directly to the need and importance of observing the patient before proceeding to the appropriate part of the therapy. All patients, however, had one thing in common: within each group, there was a turning point at which the stabilisation of the values of individual parameters was noticeable. This moment occurred after the third meeting for individuals belonging to the sociable group. After the fourth therapeutic session, patients classified as calm show the greatest changes and stabilisation of selected parameters. The distanced group also required a longer adaptation time to the therapy—a key moment for these patients occurred after the 4th meeting. Inhibited are those showing low activity and great shyness. The description reflects the results this group's patients achieved in successive treatment cycles. An important stage of rehabilitation for the patients in this group is the time between

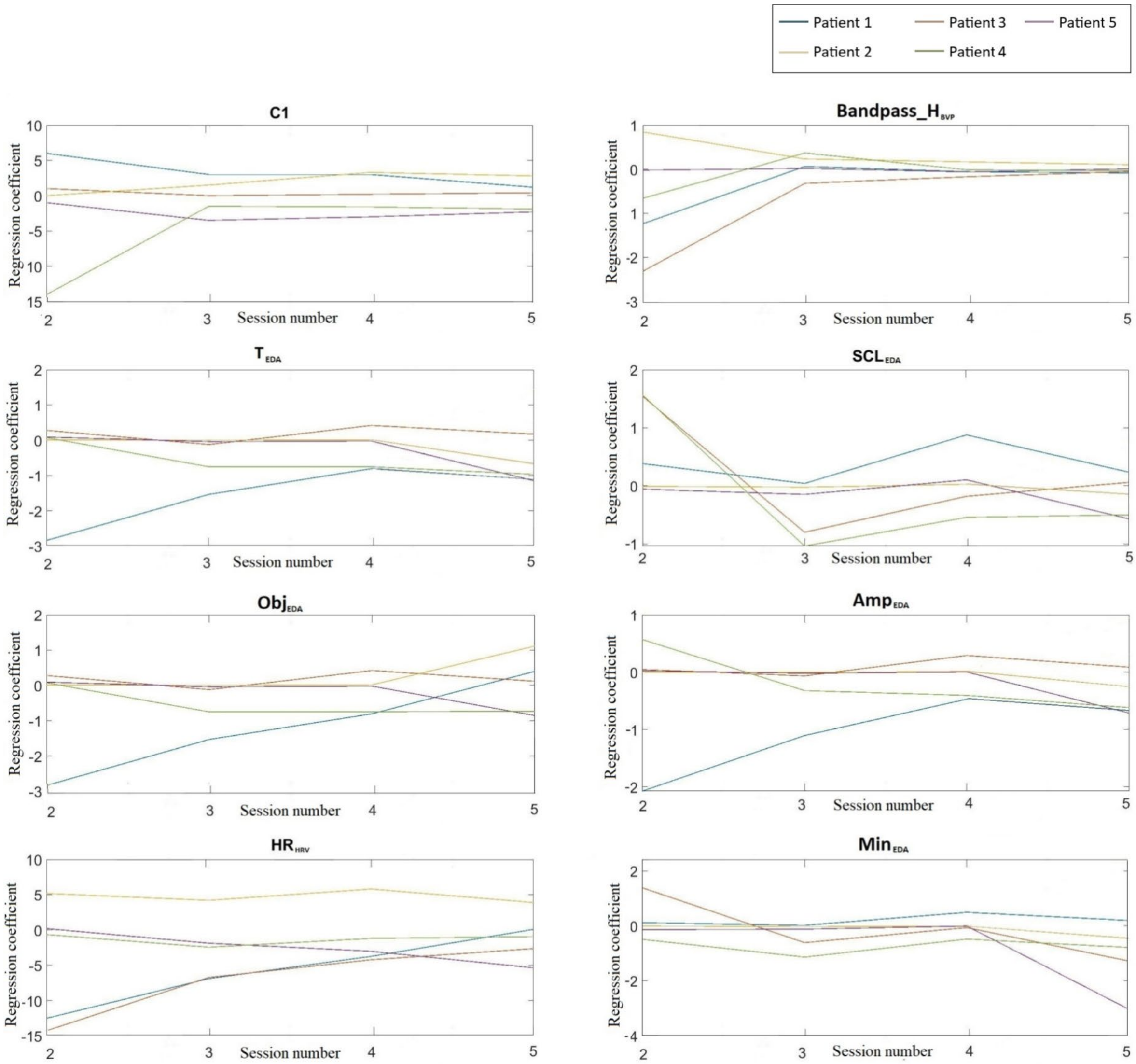


Figure 7. Dynamics of parameter changes between sessions for the group sociable.

	2	3	4	5	max
PPV	0.04	0.20	0.25	0.60	0.80
TPR	0.20	0.40	0.50	0.60	0.80
TNR	0.20	0.40	0.40	0.60	0.80
F1	0.07	0.27	0.33	0.53	0.80
ACC	0.20	0.40	0.50	0.60	0.80

Table 6. Classification accuracy for the different number of included therapies in the regression analysis.

the 3rd and 4th sessions. A turning point in the rehabilitation was between the second and third sessions for the shy group. A decrease in the regression coefficient value for most of the analysed parameters is then noticeable.

Based on the above characteristics, it is important to note a certain analogy with biological phenomena occurring in the natural environment[53]. Each individual requires a certain amount of time to adapt to a new situation, conditioned by their characteristics (in this case, temperamental). A longer period of patient observation allows one to get to know them better and adapt therapeutic sessions to current conditions based on the knowledge of values of physiological characteristics closely related to psychological characteristics.

It is challenging to relate the results obtained to other available publications. To the best of the authors' knowledge, there are no published reports on measurement systems that analyse multimodal data to personalise ongoing postural defect rehabilitation. The only point of reference is other subjective emotion assessment systems based on analysis of physiological data. Romaniszyn et al. obtained the highest accuracy of 80.49% for unsupervised classification using k-means to assess emotion evaluation during physiotherapeutic procedures[37]. In contrast, in an attempt to objectify the assessment of affective states using the kNN method, 85.71% accuracy was obtained[54]. Another system for assessing emotional states in terms of the Valence-Arousal plane, based on the EDA signal, was developed by Dutta et al.[16]. Using different classifiers (kNN or SVM), they obtained relatively low f1-score results—44% for kNN and 53% for the SVM classifier. In the paper by Raheel et al., it was proven that the BVP signal gives the highest accuracy for emotion recognition, while the fusion of EDA, EEG and BVP physiological signals allows for an improvement in classification accuracy of up to 79.76%.[28]. The multimodal approach presented by Kuman et al. used EDA, ECG signals and various deep-learning networks to detect moments of stress and affect[55]. Combining physiological data with DL methods, 86.66% accuracy was achieved. Attempts to objectify the emotional state (level of depression) were also made by the team of Ghandeharioun et al. using the Empatica E4 and ML methods[19]. The given RMSE error of 4.5 is a low value, indicating the high accuracy of the system's performance. The combination of emotional states and physiological data assessments has allowed the development of other classification methods that work at a maximum level of 71%[56]. The recognition of sadness, happiness and a neutral state allowed to the preparation of the system by Domínguez-Jiménez et al.[35]. Based on physiological data, the SVM classifier detected individual emotional states with an accuracy of 100%. Fuzzy logic algorithm allows to constructions patients perception model of state during robot-assisted rehabilitation based on the physiological parameters (galvanic skin response, heart rate, and respiration rate),[36]. High values of statistically significant correlation coefficients were achieved, indicating acceptable accuracy of the presented model. Other multimodal systems based on ECG, EDA, and EMG signals enabled the classification of emotional states at levels above 80%.[29–31]. The combination of EEG and HRV signals made it possible to propose a method for recognising emotions in two dimensions, according to Russel's model of emotions, in real-time[38].

All suggestions for emotion recognition systems cited above are primarily subjective, depending on the patient's declaration, which performs at a similar level to the system proposed in the present work, achieving an accuracy of 80%. However, none of the above applies to assessing a person's behavior during rehabilitation. Not to mention the attempt to objectives the measurements made or to personalise the postural defects therapy, which, in an age of an ageing population and civilisation diseases affecting increasingly younger people, is extremely important. The key role in the actions is attributed to a convergent interaction in physiological and psychological areas. In the case of idiopathic scoliosis, the first involves the musculoskeletal activation of the patient (movement or deliberate exertion of pressure). In contrast, the second includes a set of factors influencing willingness to cooperate in therapy. It has been noted that the combined study of mental state and changes in longitudinal observation of physical condition makes it possible to assess the degree of engagement in the physiotherapeutic process, usually requiring considerable patient activity, optimising the choice of measures.

This leads to the conclusion that an appropriate interdisciplinary approach to professional rehabilitation influences the therapeutic process's quality, duration, and effectiveness. The knowledge deficits observed in this area are natural, given the specificity of working with preschool and early school-aged children, if only because of the difficulty of establishing a typical conceptual apparatus and the axiomatic-deductive reasoning necessary for interactive activity therapy.

From the above analysis, it can also be concluded that the probability of therapeutic success (in terms of duration and quality of results) can be increased using a decision support system. Above all, a set of metrics for assessing changes in the patient's physical and mental state, both at baseline (e.g., personality type) and in terms of rapid change (e.g., mood).

The paradigm established in this work allows the development of a concept for selecting the type and range of therapeutic measures to minimise the risk to the patient, with an increase in a therapeutic effect, provided that the patient's participation in therapy is controlled. It is worth emphasising that the author's proposal of a measuring system can be used in real situations in the therapy room, as it incorporates sensors and measuring systems that are becoming widely available. Of course, as a non-trivial solution, it requires appropriate hardware and software.

Based on the results presented above, it was concluded that it is essential for the patient to have a breakthrough moment, after which the patient can undertake exercises independently. Therapeutic practice indicates that even when the patient has expressed an understanding of the tasks and is ready to work individually, the patient needs to be controlled by a physiotherapist, as otherwise, the activities may be counterproductive. In biology, such a time of adaptation and stabilisation is commonly observed, which is worth establishing in the therapeutic process for the patient's benefit. The development of methodologies to analyse the rate of change in the patient's condition in such a process is fully justified, particularly in the context of personalising the therapy provided and objectifying the measurement methodology.

Conclusion

The proposed measurement method and data processing methodology are key elements in developing an intervention to achieve maximum therapeutic effects in the shortest possible time with minimal patient effort. The combination of psychological and physiological data allows for a holistic, innovative view of the overall rehabilitation process, thus making it possible to answer the question that troubles many specialists and patients: why does the same therapy produce the expected results at different times? Based on the results, it can be assumed that this is not only a psychological condition but also a physiological one. Combining both modalities will optimise the therapeutic process and conduct fully personalised therapy. The adaptation time to the therapy provided is strongly dependent on specific temperamental characteristics and perceived anxiety as a trait. Physiological characteristics (EDA signal parameters and HRV) condition the patient's involvement in the rehabilitation process while allowing for personal adaptation dependent on the patient's current condition.

The fusion of psychophysiological data and multimodal measurements allows the development of a unique behavioral-physiological profile of a patient undergoing rehabilitation.

Data availability

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

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References

1. Vámossy, Z. & Kocsis, M. Status analysis system of scoliosis. In *2013 IEEE 11th International Symposium on Applied Machine Intelligence and Informatics (SAMI)*, 181–185, https://doi.org/10.1109/SAMI.2013.6480971 (IEEE, 2013).
2. Golalizadeh, D. et al. Faulty posture: Prevalence and its relationship with body mass index and physical activity among female adolescents. *Biomed. Hum. Kinetics* **12**, 25–33. https://doi.org/10.2478/bhk-2020-0004 (2020).
3. Kotwicki, T., Kinel, E., Stryła, W. & Szulc, A. Estimation of the stress related to conservative scoliosis therapy: an analysis based on bssq questionnaires. *Scoliosis* **2**, 1–6. https://doi.org/10.1186/1748-7161-2-1 (2007).
4. Weiss, H.-R., Karavidas, N., Moramarco, M. & Moramarco, K. Long-term effects of untreated adolescent idiopathic scoliosis: A review of the literature. *Asian Spine J.* **10**, 1163 (2016).
5. Frazier, L. D. The past, present, and future of the biopsychosocial model: A review of the biopsychosocial model of health and disease: New philosophical and scientific developments by derek bolton and grant gillett. *New Ideas Psychol.* **57**, 100755 (2020).
6. Wrona-Polańska, H. *Zdrowie jako funkcja twórczego radzenia sobie ze stresem: Psychologiczne mechanizmy i uwarunkowania zdrowia w zawodzie nauczyciela* (Wydawnictwo Naukowe Akademii Pedagogicznej, Kraków, 2003).
7. Syed, S., Syed, S. & Bhardwaj, K. The role of the bio-psychosocial model in public health. *J. Med. Res.* **6**, 252–254 (2020).
8. LeDoux, J. *The Emotional Brain: The Mysterious Underpinnings of Emotional Life* (Simon and Schuster, 1998).
9. Buijs, R. M. & Van Eden, C. G. The integration of stress by the hypothalamus, amygdala and prefrontal cortex: Balance between the autonomic nervous system and the neuroendocrine system. *Prog. Brain Res.* **126**, 117–132. https://doi.org/10.1016/S0079-6123(00)26011-1 (2000).
10. Boucsein, W. *Electrodermal activity* (Springer, 2012).
11. Posada-Quintero, H. F. & Chon, K. H. Innovations in electrodermal activity data collection and signal processing: A systematic review. *Sensors* **20**, 479. https://doi.org/10.3390/s20020479 (2020).
12. Carlson, N. R. & Carlson, N. R. *Physiology of behavior* (Pearson Boston, 2007).
13. Benarroch, E. E. The central autonomic network: functional organization, dysfunction, and perspective. In *Mayo Clinic Proceedings***68**, 988–1001. https://doi.org/10.1016/S0025-6196(12)62272-1 (Elsevier, 1993).
14. Nourbakhsh, N., Chen, F., Wang, Y. & Calvo, R. A. Detecting users' cognitive load by galvanic skin response with affective interference. *ACM Trans. Interact. Intell. Syst.* **7**, 1–20. https://doi.org/10.1145/2960413 (2017).
15. Bhavan, A. et al. Bagged support vector machines for emotion recognition from speech. *Knowl.-Based Syst.* **184**, 104886. https://doi.org/10.1016/j.knosys.2019.104886 (2019).
16. Dutta, S., Mishra, B. K., Mitra, A. & Chakraborty, A. An analysis of emotion recognition based on gsr signal. *ECS Trans.* **107**, 12535. https://doi.org/10.1149/10701.12535ecst (2022).
17. Kumar, P., Garg, S. & Garg, A. Assessment of anxiety, depression and stress using machine learning models. *Procedia Comput. Sci.* **171**, 1989–1998. https://doi.org/10.1016/j.procs.2020.04.213 (2020).
18. Kim, K. H., Bang, S. W. & Kim, S. R. Emotion recognition system using short-term monitoring of physiological signals. *Med. Biol. Eng. Comput.* **42**, 419–427. https://doi.org/10.1007/BF02344719 (2004).
19. Ghandeharioun, A. *et al.* Objective assessment of depressive symptoms with machine learning and wearable sensors data. In *2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII)*, 325–332, https://doi.org/10.1109/ACII.2017.8273620. (IEEE, 2017).
20. Richter, T., Fishbain, B., Markus, A., Richter-Levin, G. & Okon-Singer, H. Using machine learning-based analysis for behavioral differentiation between anxiety and depression. *Sci. Rep.* **10**, 1–12. https://doi.org/10.1038/s41598-020-72289-9 (2020).
21. Gjoreski, M., Luštrek, M., Gams, M. & Gjoreski, H. Monitoring stress with a wrist device using context. *J. Biomed. Inform.* **73**, 159–170. https://doi.org/10.1016/j.jbi.2017.08.006 (2017).
22. Gouverneur, P. *et al.* Classification of physiological data for emotion recognition. In *International Conference on Artificial Intelligence and Soft Computing*, 619–627, https://doi.org/10.1007/978-3-319-59063-9_55 (Springer, 2017).
23. Oğuz, F. E., Alkan, A. & Schöler, T. Emotion detection from ecg signals with different learning algorithms and automated feature engineering. *Signal, Image and Video Processing* 1–9, https://doi.org/10.1007/s11760-023-02606-y (2023).
24. Bota, P. et al. Group synchrony for emotion recognition using physiological signals. *IEEE Trans. Affect. Comput.* https://doi.org/10.1109/TAFFC.2023.3265433 (2023).
25. Moin, A., Aadil, F., Ali, Z. & Kang, D. Emotion recognition framework using multiple modalities for an effective human–computer interaction. *J. Supercomput.* **79**, 9320–9349. https://doi.org/10.1007/s11227-022-05026-w (2023).
26. Campanella, S., Altaleb, A., Belli, A., Pierleoni, P. & Palma, L. A method for stress detection using empatica e4 bracelet and machine-learning techniques. *Sensors* **23**, 3565. https://doi.org/10.3390/s23073565 (2023).
27. Benchekroun, M. et al. Cross dataset analysis for generalizability of hrv-based stress detection models. *Sensors* **23**, 1807. https://doi.org/10.3390/s23041807 (2023).
28. Raheel, A., Majid, M., Alnowami, M. & Anwar, S. M. Physiological sensors based emotion recognition while experiencing tactile enhanced multimedia. *Sensors* **20**, 4037. https://doi.org/10.3390/s20144037 (2020).
29. Pinto, G. et al. Multimodal emotion evaluation: A physiological model for cost-effective emotion classification. *Sensors* **20**, 3510. https://doi.org/10.3390/s20123510 (2020).
30. Vaz, M., Summavielle, T., Sebastião, R. & Ribeiro, R. P. Multimodal classification of anxiety based on physiological signals. *Appl. Sci.* **13**, 6368. https://doi.org/10.3390/app13116368 (2023).
31. Castro-García, J. A., Molina-Cantero, A. J., Merino-Monge, M., Lebrato-Vázquez, C. & Gómez-Gónzalez, I. M. The effect of demanding mental tasks on electrodermal activity and heart rate during physical activity: A pilot study. *IEEE Access* https://doi.org/10.1109/ACCESS.2023.3273303 (2023).
32. Liu, H. et al. Eeg-based multimodal emotion recognition: A machine learning perspective. *IEEE Trans. Instrum. Meas.* https://doi.org/10.1109/TIM.2024.3369130 (2024).
33. Madhuri, V., Mohan, M. R. & Kaavya, R. Stress management using artificial intelligence. In *2013 Third International Conference on Advances in Computing and Communications*, 54–57, https://doi.org/10.1109/ICACC.2013.97. (IEEE, 2013).
34. Chen, S. et al. Emotion recognition based on skin potential signals with a portable wireless device. *Sensors* **21**, 1018. https://doi.org/10.3390/s21031018 (2021).

35. Domínguez-Jiménez, J. A., Campo-Landines, K. C., Martínez-Santos, J. C., Delahoz, E. J. & Contreras-Ortiz, S. H. A machine learning model for emotion recognition from physiological signals. *Biomed. Signal Process. Control* **55**, 101646. https://doi.org/10.1016/j.bspc.2019.101646 (2020).
36. Tamantini, C. et al. A fuzzy-logic approach for longitudinal assessment of patients' psychophysiological state: An application to upper-limb orthopedic robot-aided rehabilitation. *J. Neuroeng. Rehabil.* **21**, 202. https://doi.org/10.1186/s12984-024-01501-y (2024).
37. Romaniszyn-Kania, P. et al. Hybrid system of emotion evaluation in physiotherapeutic procedures. *Sensors* **20**, 6343. https://doi.org/10.3390/s20216343 (2020).
38. Wei, Y. *et al.* A real-time and two-dimensional emotion recognition system based on eeg and hrv using machine learning. In *2023 IEEE/SICE International Symposium on System Integration (SII)*, 1–6 (IEEE, 2023).
39. Dar, M. N., Akram, M. U., Yuvaraj, R., Khawaja, S. G. & Murugappan, M. Eeg-based emotion charting for Parkinson's disease patients using convolutional recurrent neural networks and cross dataset learning. *Comput. Biol. Med.* **144**, 105327. https://doi.org/10.1016/j.compbiomed.2022.105327 (2022).
40. García Pagès, E. et al. Psychosomatic response to acute emotional stress in healthy students. *Front. Physiol.* **13**, 2605. https://doi.org/10.3389/fphys.2022.960118 (2023).
41. Haque, Y. et al. State-of-the-art of stress prediction from heart rate variability using artificial intelligence. *Cognit. Comput.* **16**, 455–481. https://doi.org/10.1007/s12559-023-10200-0 (2024).
42. Spielberger, C. D., Gonzalez-Reigosa, F., Martinez-Urrutia, A., Natalicio, L. F. & Natalicio, D. S. The state-trait anxiety inventory. *Rev. Interamericana de Psicologia/Interamerican J. Psychol.* **5**. https://doi.org/10.30849/rip/ijp.v5i3&4.620
43. Empatica, S. E4 wristband user's manual (2015).
44. Szurmik, T., Bibrowicz, K., Lipowicz, A. & Mitas, A. W. Methods of therapy of scoliosis and technical functionalities of disc4spine (d4s) diagnostic and therapeutic system. In *Information Technology in Biomedicine*, 201–212, https://doi.org/10.1007/978-3-030-49666-1_16 (Springer, 2021).
45. Buss, A. H. The eas theory of temperament. In *Explorations in temperament*, 43–60, https://doi.org/10.1007/978-1-4899-0643-4_4 (Springer, 1991).
46. Charbuty, B. & Abdulazeez, A. Classification based on decision tree algorithm for machine learning. *J. Appl. Sci. Technol. Trends* **2**, 20–28, https://doi.org/10.38094/jastt20165 (2021).
47. Hubert, L., Köhn, H.-F. & Steinley, D. Cluster analysis: A toolbox for matlab. *Handbook of Quantitative Methods in Psychology*, 444–512 (2009).
48. Greco, A., Valenza, G., Lanata, A., Scilingo, E. P. & Citi, L. cvxeda: A convex optimization approach to electrodermal activity processing. *IEEE Trans. Biomed. Eng.* **63**, 797–804. https://doi.org/10.1109/TBME.2015.2474131 (2015).
49. Bendel, R. B. & Afifi, A. Comparison of stopping rules in forward stepwise regression. *J. Am. Stat. Assoc.* **72**, 46–53. https://doi.org/10.1080/01621459.1977.10479905 (1977).
50. Freund, Y., Schapire, R. & Abe, N. A short introduction to boosting. *J.-Japanese Soc. Artif. Intell.* **14**, 1612 (1999).
51. Suthaharan, S. Support vector machine. In *Machine learning models and algorithms for big data classification*, 207–235, https://doi.org/10.1007/978-1-4899-7641-3_9 (Springer, 2016).
52. Sadeghi Milani, A., Cecil-Xavier, A., Gupta, A., Cecil, J. & Kennison, S. A systematic review of human–computer interaction (hci) research in medical and other engineering fields. *International Journal of Human–Computer Interaction***40**, 515–536,https://doi.org/10.1080/10447318.2022.2116530 (2024).
53. Masuda, Y. Meta-model of human recognition-behavioral adaptation system. *Integr. Psychol. Behav. Sci.* **58**, 149–159. https://doi.org/10.1007/s12124-023-09781-0 (2024).
54. Romaniszyn, P., Kania, D., Bugdol, M. N., Pollak, A. & Mitas, A. W. Behavioral and physiological profile analysis while exercising–case study. In *Information Technology in Biomedicine*, 161–173. https://doi.org/10.1007/978-3-030-49666-1_13 (Springer, 2021).
55. Kumar, P. S., Govarthan, P. K., Gadda, A. A. S., Ganapathy, N. & Ronickom, J. F. A. Deep learning-based automated emotion recognition using multimodal physiological signals and time-frequency methods. *IEEE Trans. Instrum. Meas.* https://doi.org/10.1109/TIM.2024.3420349 (2024).
56. Lima, R. et al. Multimodal emotion classification using machine learning in immersive and non-immersive virtual reality. *Virtual Reality* **28**, 107. https://doi.org/10.1007/s10055-024-00989-y (2024).

Author contributions

PRK: conceptualization, methodology, investigation, data curation, formal analysis, resources, writing-drafting the initial manuscript, writing-review or editing of the manuscript. AP: conceptualization, methodology, formal analysis, writing-drafting the initial manuscript, writing-review or editing of the manuscript. DK: methodology, formal analysis, writing-drafting the initial manuscript. AWM: conceptualization, methodology, supervision, writing-review or editing of the manuscript. All authors approved the final manuscript as submitted and agreed to be accountable for all aspects of the work.

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Declarations

Ethics approval and consent to participate

The Bioethics Committee of the Jerzy Kukuczka Academy of Physical Education in Katowice approved the study protocol (No. 3/2019), and it was conducted according to the Declaration of Helsinki.

Consent for publication

The participants of the presented study were underage, and the parents or guardians gave written permission to participate in the research and to use the collected data for further analysis and publication.

Competing interests
The authors declare that they have no competing interests.

Additional information
Correspondence and requests for materials should be addressed to P.R.-K.

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