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# A semi-automatic mHealth system using wearable devices for identifying pain-related parameters in elderly individuals

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A R T I C L E I N F O

*Keywords:*
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Semi-automatic systems
Mobile health systems
Wearable devices
Chronic pain
Stress

A B S T R A C T

*Background:* Mobile health systems integrating wearable devices are emerging as promising tools for registering pain-related factors. However, their application in populations with chronic conditions has been underexplored.
*Objective:* To design a semi-automatic mobile health system with wearable devices for evaluating the potential predictive relationship of pain qualities and thresholds with heart rate variability, skin conductance, perceived stress, and stress vulnerability in individuals with preclinical chronic pain conditions such as suspected rheumatic disease.
*Methods:* A multicenter, observational, cross-sectional study was conducted with 67 elderly participants. Predicted variables were pain qualities and pain thresholds, assessed with the McGill Pain Questionnaire and a pressure algometer, respectively. Predictor variables were heart rate variability, skin conductance, perceived stress, and stress vulnerability. Multiple linear regression analyses were conducted to examine the influence of the predictor variables on the pain dimensions.
*Results:* The multiple linear regression analysis revealed that the predictor variables significantly accounted for 27% of the variability in the affective domain, 14% in the miscellaneous domain, 15% in the total pain rating index, 10% in the number of words chosen, 14% in the present pain intensity, and 16% in the Visual Analog Scale scores.
*Conclusion:* The study found significant predictive values of heart rate variability, skin conductance, perceived stress, and stress vulnerability in relation to pain qualities and thresholds in the elderly population with suspected rheumatic disease. The comprehensive integration of physiological and psychological stress measures into pain assessment of elderly individuals with preclinical chronic pain conditions could be promising for developing new preventive strategies.

## 1. Introduction

Chronic pain is one of the most prevalent and debilitating symptoms experienced during the aging process [1,2]. Rheumatic diseases are found to be observed in almost half of the elderly individuals (41–53%), resulting in chronic pain conditions [3]. To better comprehend the multifaceted nature of chronic pain in rheumatic diseases, it is becoming increasingly important to understand the role of physiological and psychological biomarkers. Mobile health (mHealth) systems, which integrate wearable devices, are emerging as promising tools for continuously registering pain-related physiological biomarkers in real-world settings, such as heart rate variability (HRV) and skin conductance (SC) [4–7]. Data on these biomarkers, gathered through wearables, have shown significant positive associations with pain intensity [8]. Wristbands, in particular, have demonstrated potential for precise data collection on the HRV and SC, yielding outcomes comparable to those from clinical monitoring equipment [9,10]. For instance, the Empatica E4 wristband enables the capture of end-user physiological or

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behavioral data that correlate with various health conditions or pathologies [11–13].

Research on employing wearables for pain tracking, to date, has focused primarily on symptomatic aspects of pain such as its intensity [14]. However, the development of complex predictive models that address the underlying pain mechanisms remains unexplored. Moreover, it would be innovative to improve mHealth systems with the capability to establish early detection models in everyday environments. This enhancement could potentially enable the identification of initial alterations in pain mechanisms before the clinical diagnosis of chronic pathologies typically associated with such disruptions. Thus, a model incorporating different potential pain-related parameters in an mHealth system would contribute to a more profound understanding of pain mechanisms.

Physiological stress has been identified as a pain-related parameter in chronic pain conditions [15]. Experiencing pain is known to stimulate the sympathetic nervous system, evoking a stress response that leads to an increased heart rate and SC [16,17]. The HRV and SC are recognized as useful biomarkers for evaluating responses to experimentally induced pain [18,19]. On the other hand, another pain-related parameter is psychological stress, which plays a crucial role in chronic pain. It causes a cumulative physiological burden on various bodily systems, which can potentially induce allodynia [20,21] and predispose individuals to chronic pain. Although numerous studies have examined the impact of perceived psychological stress, its influence is shown to vary among individuals due to several factors [22]. One of these factors is the stress vulnerability—a dynamic process reflecting the result of previous stress exposure and changes in adaptive capacity—that determines an individual's ability to cope with stressful situations [23]. The elderly population is more commonly subjected to uncontrollable circumstances that can lead to greater vulnerability [24]. Despite this, there is limited research on how these stress mechanisms integratively affect pain symptoms in elderly individuals with preclinical chronic pain conditions [25]. Incorporating stress indicators into mHealth systems presents an opportunity to better understand the relationship of physiological and psychological stressors with pain mechanisms in this population.

In healthcare research, mHealth systems are used not only for assessing pain but also for enhancing its management and treatment. These systems have proven effective in controlling pain intensity [26] and supporting self-management across various pain conditions [27,28]. However, literature on this topic lacks several elements that could be needed in both clinical and research areas. These elements include: (i) the development of a semi-automatic system to collect both manual and automatic data in the same setting, which would facilitate integrating elements from clinical assessments that currently lack automated technologies but are necessary for creating more comprehensive predictive models; (ii) the early detection of alterations in pain mechanisms before the diagnosis of conditions associated with chronic pain symptoms; and (iii) the identification of alternative predictive models that are capable of detecting various types of pain without the need for direct evaluation, by integrating wearable data that are more accessible to healthcare professionals. These considerations align with the perspective of the European Alliance of Associations for Rheumatology (EULAR), which recognizes mHealth systems as a potential strategy for chronic pain monitoring [23].

Given this background, the present study aims to: (i) design an mHealth system based on wearable devices and mobile platforms, and (ii) establish a predictive model incorporating physiological and psychological stress indicators in chronic pain.

## 2. Methods

### 2.1. Study design

An mHealth system utilizing smartwatches, smartphones, and a microservices software architecture has been designed and implemented (Fig. 1).

This system was used to monitor the performance of individuals during "shopping," an Activity of Daily Living (ADL) chosen for its comprehensive nature, encompassing cognitive, musculoskeletal, and social aspects. It was devised to assess the health status of elderly adults in an ecological way [29,30]. The ADL of shopping encompasses several components that typically require significant physical exertion for the elderly, including starting in a sitting position, standing up, walking to and from the supermarket, and shopping inside it [31]. Throughout this ADL, the mHealth system was collecting the HRV and SC data via the E4 wristband worn by the elderly participants. This allowed for accurate and precise acquisition of the HRV and SC data unobtrusively [11,12], which is further elaborated below.

The empirical part of the study was based on a multicenter, observational, cross-sectional design, conducted in Granada, Spain. The research adhered to the Declaration of Helsinki and was approved by the Ethics Committee on Human Research (CEIH) of the University of Granada with reference number: 3364.

### 2.2. Participants

Sixty-seven elderly adults with suspected rheumatic disease were enrolled in the study. Recruitment was performed in several randomly selected community day centers from the province of Granada, Spain. Potential participants were contacted through these centers, where they received an information sheet detailing the study and its objectives, along with an informed consent form. Clarifications were made to assure participants that the study outcomes were based on information from the entire data sample, aiming to address any concerns about confidentiality. Those interested reviewed the information sheet and signed the informed consent before undergoing the evaluation. The evaluation process was structured in a specific sequence, beginning with the collection of sociodemographic, anthropometric, and clinical descriptive data, followed by pain assessments and psychological evaluations.

The inclusion criteria for participants were as follows: (i) adults aged 65–90 years; (ii) without a confirmed diagnosis but suspected of having a rheumatic disease, based on the manifestation of arthralgia in joints lasting less than one year [32]; and (iii) experiencing at least moderate pain intensity (Visual Analog Scale $\geq$ 3.5) persisting beyond 3 months [33]. The exclusion criteria included: (i) diagnosis of dementia or severe cognitive impairment; (ii) severe auditory, visual, or tactile impairments; (iii) unstable medical conditions; (iv) any other acute pathology; (v) hospitalization; and (vi) severe behavioral disturbances or motor disabilities.

### 2.3. Measures of pain and pain-related physiological and psychological parameters

The McGill Pain Questionnaire was employed to evaluate both qualitative and quantitative aspects of pain, including sensory, affective, and evaluative dimensions [34,35].

Pressure algometry, a common and reliable method, was utilized to quantify the pressure pain threshold, which is regarded as the minimum pressure force that induces pain sensation [36]. In the present study, a hand-held dial pressure algometer (0.5 $cm^2$ circular flat probe) was

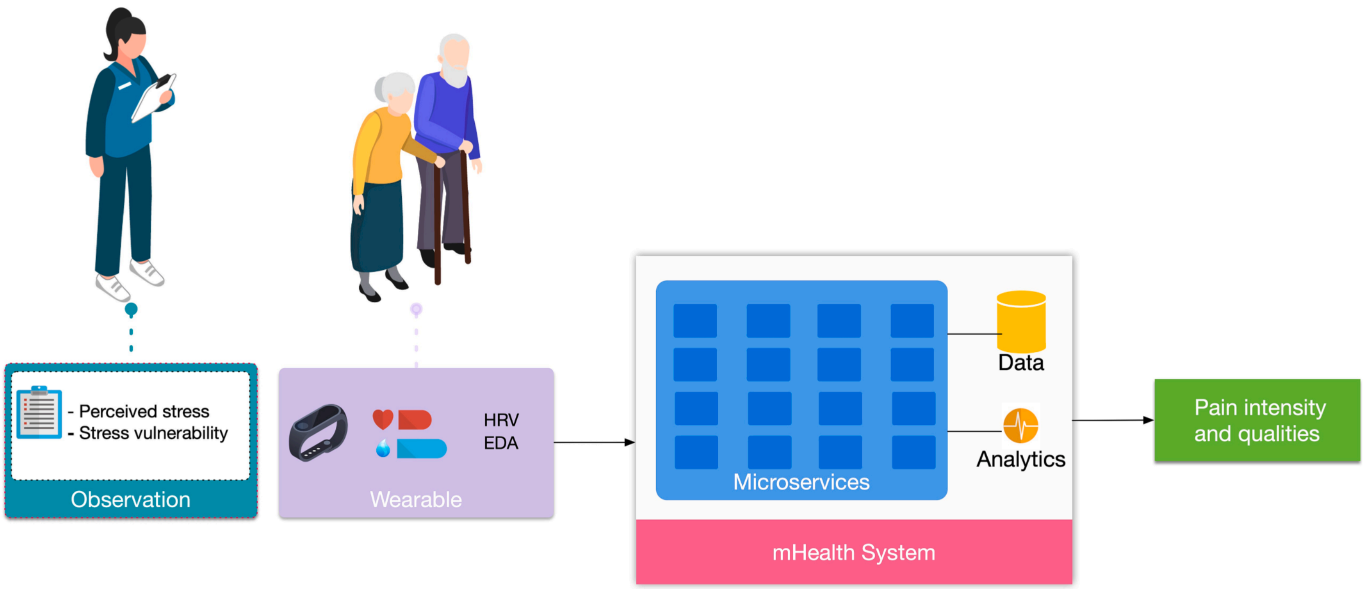


**Fig. 1.** Representation of the mHealth System. This system includes wearable devices worn by the elderly for health data collection. Observers annotate the behaviors of the elderly while integrating other evaluation instruments to enrich the collected data. The system employs microservices for data processing, which enables assessments of pain intensity and perceived stress to be incorporated into data analysis. This approach facilitates detailed healthcare monitoring and personalized support for the elderly.

applied to the midpoint of the upper border of the trapezius muscles on both the dominant and non-dominant sides of the body, respectively [37].

The HRV reflects the variations in time intervals between successive heartbeats, serving as a physiological stress marker that captures the dynamism of autonomic nervous system activity. During the ADL of shopping, blood volume pulse was measured by the Empatica E4 at a sampling rate of 1 Hz. The HRV was computed using the root-mean-square of successive R-R (or beat-to-beat) Interval Differences (RMSSD) derived from the blood volume pulse. The formula for RMSSD was: $$\sqrt{\frac{1}{N-1}\left(\sum_{i = 1}^{N-1}\Big((R - R)_{i + 1}-(R - R)_i\Big)^2\right)}$$. The average HRV value was calculated for each component of the ADL.

The SC is a measure that serves as a physiological index of autonomic nervous system activity, which fluctuates in response to varying stress levels. The SC data were gathered by the Empatica E4 during the ADL of shopping, with the raw signal captured at a sampling rate of 4 Hz. The average SC value for each component of the ADL was calculated from this raw data.

The Perceived Stress Scale-10 was employed to assess "the degree to which individuals appraise situations in their lives as stressful" over the past month [38].

**Table 1**
Sociodemographic, anthropometric, and clinical descriptive data of the study sample.

| Sociodemographic, Anthropometric, and Clinical Data | M ± SD or n (%) |
|---|---|
| **Education** | |
| Unschooled | 12 (17.9) |
| Incomplete primary education | 20 (29.9) |
| Primary | 31 (46.3) |
| Secondary | 1 (1.5) |
| Tertiary | 3 (4.5) |
| **Literacy** | |
| Illiterate | 7 (10.4) |
| Non-fluent reading and writing | 15 (22.4) |
| Fluent reading and writing | 45 (67.2) |
| **Number of children** | 2.51 ± 1.17 |
| **Weight, kg** | 70.69 ± 11.14 |
| **Height, cm** | 151.68 ± 6.40 |
| **Body mass index, kg/m$^2$** | 30.72 ± 4.35 |
| Healthy weight (18.5–24.9 kg/m$^2$) | 4 (6.0) |
| Overweight (25–29.9 kg/m$^2$) | 26 (38.8) |
| Obese (≥ 30 kg/m$^2$) | 37 (52.2) |
| **Waist circumference, cm** | 97.57 ± 10.89 |
| **Hip circumference, cm** | 109.19 ± 9.61 |
| **Waist-to-hip ratio** | 0.86 ± 0.20 |
| **Waist-to-height ratio** | 0.62 ± 0.15 |
| **Oxygen saturation, %** | 95.28 ± 3.68 |
| **Number of pathologies** | 3.43 ± 2.26 |
| **Number of medications used** | 4.90 ± 3.56 |
| **Handedness, right** | 58 (86.6) |

*Abbreviations.* M, mean; SD, standard deviation; n, sample size.

**Table 2**
Descriptive data on pain symptoms, perceived stress, and stress vulnerability.

| Outcome Measures | M ± SD or n (%) |
|---|---|
| **McGill Pain Questionnaire** | |
| Sensory (0–42) | 7.84 ± 3.28 |
| Affective (0–14) | 2.55 ± 2.05 |
| Evaluative (0–5) | 2.76 ± 1.33 |
| Miscellaneous (0–17) | 2.13 ± 1.77 |
| Total Pain Rating Index (0–78) | 15.28 ± 6.32 |
| Number of words chosen (0–20) | 6.91 ± 2.17 |
| Present Pain Intensity (1–5) | 2.93 ± 1.25 |
| Visual Analog Scale (0–10) | 7.54 ± 1.84 |
| **Pressure pain thresholds right** | 7.60 ± 2.16 |
| **Pressure pain thresholds left** | 7.67 ± 2.12 |
| **Perceived Stress Scale (0–40)** | 14.30 ± 8.03 |
| **Stress Vulnerability Scale (0–80)** | 25.22 ± 17.22 |

*Abbreviations.* M, mean; SD, standard deviation; n, sample size.

A scale derived from the original Stress Vulnerability Scale [39] was used to assess individuals' vulnerability to stress [40,41].

### 2.4. Statistical analysis

All data were analyzed using SPSS v26.0 for Windows (IBM Corp., Armonk, NY, USA). An overview of the data was provided through descriptive analyses, with continuous variables reported as mean ± standard deviation, and categorical variables as absolute frequencies and percentages. All outcome variables were statistically analyzed based on data type, and the relevant assumptions were considered, including normality, homoscedasticity, and independence of the data. To explore the relationships among the variables, a multiple linear regression analysis (stepwise method) was conducted. In this analysis, the dependent variables (predicted variables) were the scores obtained from the McGill Pain Questionnaire's subscales—sensory, affective, evaluative, and miscellaneous—along with their total, the number of words chosen, Visual Analog Scale scores, and pressure pain thresholds. The independent variables (predictor variables) consisted of the HRV and SC data collected during the performance of shopping activity—encompassing its components of sitting, standing, walking, and shopping—as well as the scores from the Perceived Stress Scale and Stress Vulnerability Scale. Effect sizes in the regression analyses were calculated using Cohen's $f^2$, categorized as "small" ($\geq$ 0.02), "medium" ($\geq$ 0.15), and "large" ($\geq$ 0.35) [42].

## 3. Results

A total of 67 elderly adults met the eligibility criteria for the study. The participants were 75.58 ± 5.79 years old, 91% of whom were female. Detailed sociodemographic, anthropometric, and clinical data are presented in Table 1.

Descriptive data on pain symptoms, perceived stress, and stress vulnerability are provided in Table 2. Regarding the pain intensity, the Visual Analog Scale assessments revealed that 47.8% of the participants experienced moderate pain, while the remaining 52.2% suffered from severe pain, according to the previously published cutoff points for the population with chronic musculoskeletal pain [33].

### 3.1. Multiple linear regression analysis

The multiple linear regression analysis resulted in significant overall models for various pain indices. These included the PRI-Sensory [$F$(1, 65) = 5.926, $p$ = 0.018, adjusted $R^2$ = 0.069], PRI-Affective [$F$(2, 64) = 9.767, $p$ < 0.001, adjusted $R^2$ = 0.210], PRI-Miscellaneous [$F$(1, 65) = 10.447, $p$ = 0.002, adjusted $R^2$ = 0.125], PRI-Total [$F$(1, 65) = 13.003, $p$ = 0.001, adjusted $R^2$ = 0.154], number of words chosen [$F$(1, 65) = 8.169, $p$ = 0.006, adjusted $R^2$ = 0.098], present pain intensity [$F$(1, 65) = 11.949, $p$ = 0.001, adjusted $R^2$ = 0.142], Visual Analog Scale [$F$(2, 64) = 7.072, $p$ = 0.002, adjusted $R^2$ = 0.155], and pressure pain thresholds of the left trapezius [$F$(1, 65) = 5.153, $p$ = 0.027, adjusted $R^2$ = 0.059]. Among the predictors, the variances in the PRI-Sensory were explained by the Perceived Stress Scale ($t$ = 2.434, $p$ = 0.018); PRI-Affective by SC-walking ($t$ = −2.012, $p$ = 0.048) and Stress Vulnerability Scale ($t$ = 4.206, $p$ < 0.001); PRI-Miscellaneous by HRV-shopping ($t$ = −3.232, $p$ = 0.002); PRI-T by Stress Vulnerability Scale ($t$ = 3.606, $p$ = 0.001); the number of words chosen by Stress Vulnerability Scale ($t$ = 2.858, $p$ = 0.006); present pain intensity by Perceived Stress Scale ($t$ = 3.457, $p$ = 0.001); Visual Analog Scale by HRV-sitting ($t$ = 2.435, $p$ = 0.018) and Stress Vulnerability Scale ($t$ = 3.284, $p$ = 0.002); and pressure pain thresholds by Stress Vulnerability Scale ($t$ = −2.270, $p$ = 0.027). No collinearity was found among the variables in the regression models. The multiple linear regression models are shown in Table 3.

## 4. Discussion

The mHealth system designed for this study facilitates the creation of a predictive model for pain qualities and thresholds by organizing information collected from potentially relevant health parameters. This system enables the automatic integration of data collected both automatically through wearable devices and manually through clinical evaluations. The resulting predictive model provides evidence regarding the influence of physiological and psychological stress on chronic pain mechanisms. The findings identified the HRV and SC as physiological indicators of various pain dimensions. Notably, the SC was associated with affective pain qualities only during the walking stage. On the other hand, perceived stress and stress vulnerability emerged as significant psychological determinants of sensory and affective pain qualities, as well as the overall pain experience. These findings highlight the importance of effectively integrating psychological data alongside physiological data into mHealth systems when aiming to use it as a complementary tool in the early identification of chronic pain conditions.

The results of this study align with existing literature. The HRV has been linked to pain perception, with studies showing that a decrease in the HRV is associated with higher levels of clinical pain [43,44]. Similarly, the SC responses have been observed to increase in response to painful stimuli, indicating heightened sympathetic arousal during painful events [45]. Perceived stress has been recognized as a significant factor influencing various dimensions of pain, such as pain intensity and its interference with daily living [46]. Additionally, previous findings also indicate a consistent relationship between stress vulnerability and pain experience [47].

Regarding the clinical implications of the findings, this research underscores the potential for collaborative efforts across various healthcare disciplines. To establish a complementary assessment tool in primary care, future studies could build on the incipient findings of the current study to validate the use of wearable devices in clinical settings

**Table 3**
Multiple linear regression models for predictive factors associated with the qualitative and quantitative aspects of clinical pain and pressure pain thresholds.

| Independent Variables | Unstandardized B | Unstandardized SE | Standardized $\beta$ | $p$ | 95% CI LB | 95% CI UB | Cohen's $f^2$ |
|---|---|---|---|---|---|---|---|
| **McGill Subscale PRI-Sensory (Adjusted $R^2 = 0.069$, Cohen's $f^2 = 0.074$)** | | | | | | | |
| Perceived Stress Scale | 0.118 | 0.048 | 0.289 | 0.018 | 0.021 | 0.215 | 0.074 |
| **McGill Subscale PRI-Affective (Adjusted $R^2 = 0.210$, Cohen's $f^2 = 0.\ 266$)** | | | | | | | |
| Stress Vulnerability Scale | 0.055 | 0.013 | 0.466 | < 0.001 | 0.029 | 0.082 | 0.219 |
| SC-walking | −0.054 | 0.027 | −0.223 | 0.048 | −0.107 | 0.000 | 0.009 |
| **McGill Subscale PRI-Miscellaneous (Adjusted $R^2 = 0.125$, Cohen's $f^2 = 0.143$)** | | | | | | | |
| HRV-shopping | −0.011 | 0.003 | −0.372 | 0.002 | −0.018 | −0.004 | 0.143 |
| **McGill Subscale PRI-Total (Adjusted $R^2 = 0.154$, Cohen's $f^2 = 0.182$)** | | | | | | | |
| Stress Vulnerability Scale | 0.150 | 0.042 | 0.408 | 0.001 | 0.067 | 0.233 | 0.182 |
| **McGill - Number of Words Chosen (Adjusted $R^2 = 0.098$, Cohen's $f^2 = 0.109$)** | | | | | | | |
| Stress Vulnerability Scale | 0.042 | 0.015 | 0.334 | 0.006 | 0.013 | 0.071 | 0.109 |
| **McGill - Present Pain Intensity (Adjusted $R^2 = 0.142$, Cohen's $f^2 = 0.166$)** | | | | | | | |
| Perceived Stress Scale | 0.061 | 0.018 | 0.394 | 0.001 | 0.026 | 0.097 | 0.166 |
| **McGill - Visual Analog Scale (Adjusted $R^2 = 0.155$, Cohen's $f^2 = 0.183$)** | | | | | | | |
| Stress Vulnerability Scale | 0.041 | 0.012 | 0.379 | 0.002 | 0.016 | 0.065 | 0.108 |
| HRV-sitting | 0.004 | 0.002 | 0.281 | 0.018 | 0.001 | 0.008 | 0.033 |
| **Pressure Pain Thresholds - Left (Adjusted $R^2 = 0.059$, Cohen's $f^2 = 0.063$)** | | | | | | | |
| Stress Vulnerability Scale | −0.033 | 0.015 | −0.271 | 0.027 | −0.063 | −0.004 | 0.063 |

*Abbreviations.* PRI, Pain Rating Index; HRV, heart rate variability; SC, skin conductance; $R^2$, regression coefficient of determination; $B$, regression coefficient; CI, confidence interval; LB, lower bound; UB, upper bound; $\beta$, adjusted coefficient from multiple linear regression analysis; *SE,* coefficient standard error.

among populations susceptible to developing chronic pain, particularly in elderly individuals with suspected rheumatic disease. To develop ongoing monitoring and preventive care strategies, it appears to be promising to explore the potential of the mHealth systems that integrate such devices as a complementary tool in medical practice.

## 5. Conclusions

The study found significant predictive values of heart rate variability, skin conductance, perceived stress, and stress vulnerability in relation to pain qualities and thresholds in the elderly population with a preclinical chronic pain condition. The application of mHealth systems, integrating wearable data on physiological stress measures, holds promise for assessing various pain dimensions in real-life scenarios.

## 6. Summary Table

What was already known on the topic:

- Wearable devices in mobile health (mHealth) systems serve as promising tools for data acquisition, enabling the continuous monitoring of pain-related physiological biomarkers in everyday environments.
- Understanding the complexity of chronic pain conditions during the aging process requires an integrative consideration of both physiological biomarkers and psychological factors.
- Heart rate variability and skin conductance serve as quantifiable indicators for evaluating physiological stress responses in chronic pain conditions.
- Psychological stress and stress vulnerability are key contributing factors to chronic pain by playing a significant role in coping with stress.

What this study added to our knowledge:

- The potential of the mHealth system devised for this study in facilitating a comprehensive assessment of pain by automatically

collecting data from multiple sources and integrating objective outcome measures via wearable devices.
- The impact of the combination of both physiological and psychological stress on chronic pain.
- Identification of specific pain dimensions associated with heart rate variability and skin conductance.
- The influence of psychological stress and stress vulnerability on sensory and affective qualities of pain, as well as on pain experience.

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## CRediT authorship contribution statement

**Dogukan Baran Gungormus:** Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Francisco M. Garcia-Moreno:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – review & editing, Visualization. **María Bermudez-Edo:** Conceptualization, Methodology, Software, Investigation, Resources, Writing – review & editing, Project administration, Funding acquisition. **Laura Sánchez-Bermejo:** Formal analysis, Investigation, Data curation, Writing – review & editing. **José Luis Garrido:** Conceptualization, Methodology, Software, Investigation, Resources, Writing – review & editing, Funding acquisition. **María José Rodríguez-Fórtiz:** Conceptualization, Methodology, Software, Investigation, Resources, Writing – review & editing, Funding acquisition. **José Manuel Pérez-Mármol:** Conceptualization, Methodology, Formal analysis, Investigation, Resources, Writing – review & editing, Visualization, Supervision, Funding acquisition.

## Declaration of competing interest

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

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