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Research Article

The effect of smart health monitoring systems (Wearable & App-based) on emotion regulation and psychological adjustment in patients with chronic pain

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Abstract
The present study aimed to investigate the effect of smart health monitoring systems including wearable devices and mobile applications on emotion regulation and psychological adjustment of patients with chronic pain. The study design was experimental-comparative with a control group and a three-month follow-up. The statistical population included non-malignant chronic pain patients referring to virtual and in-person treatment centers who were randomly divided into two intervention and control groups. The intervention group used wearable devices to record physiological indicators (heart rate, HRV, daily activity) and an emotion regulation application based on real-time feedback; while the control group received only usual care. Data were collected using psychological indicators (GAD-7, DERS) and pain scales (BPI and Pain Interference Scale) in three stages: pre-test, post-test, and follow-up. The results of multivariate analysis of covariance (MANCOVA) showed that the use of smart health monitoring systems resulted in a significant reduction in anxiety, depression, and pain catastrophizing, and a significant improvement in emotion regulation and psychological adjustment functions ($p < 0.01$). The findings suggest that wearable and app-based technologies can enhance the emotion regulation process through real-time biofeedback and digital cognitive-behavioral interventions and lead to more sustainable adaptation of patients in the face of chronic pain. These results provide a new perspective for the development of personalized smart treatments in the field of mental health and chronic pain.

Keywords: Smart wearable; Health monitoring application; Emotion regulation; Chronic pain; Psychological adjustment; Biofeedback; Momentary analysis (EMA/EMI).

1. INTRODUCTION
The advancement of digital technologies in the last decade has led to a fundamental transformation in healthcare, especially in the field of chronic pain management. Smart health monitoring tools such as wearable devices and mobile phone-based applications have been able to continuously track patients' physiological and psychological indicators and provide real-time feedback to improve emotional functioning and psychological adjustment (Thomson et al., 2024).

In addition to traditional in-person care, digital therapies with a multimodal approach (pain education, CBT, meditation, expressive writing) have been considered in recent studies as low-cost and effective alternatives (Suso-Ribera et al., 2020). The design of these applications based on the biopsychosocial model of pain has shown that they can improve patients' emotion regulation by reducing pain catastrophizing and anxiety (Suso-Ribera et al., 2018).

On the other hand, the approaches of Ecological Momentary Assessment (EMA) and Ecological Momentary Interventions (EMI), which collect real-time data on users' behavior and emotions using smartphones, have also shown high effectiveness in enhancing psychological self-regulation in meta-analytic studies (Wrzus & Neubauer, 2023). These tools provide a precise understanding of the relationship between emotional states and pain intensity in an individual's daily life (Momentary Emotion Regulation Strategies, 2024).

In recent research, the use of EMI in the context of smart applications has been able to strengthen emotion regulation mechanisms in stressed populations such as health workers during the pandemic (Castilla et al., 2022). Such a model can also be generalized to chronic pain patients, as they are exposed to chronic physiological and psychological stresses that lead to impaired emotion regulation (Wiederhold, 2012).

Health wearables such as smartwatches also offer a unique opportunity to monitor pain biomarkers by continuously measuring heart rate, heart rate variability (HRV), activity level, and sleep quality (De Vries et al., 2021). Data from these devices reveal not only pain intensity but also emotional patterns associated with pain (Naeini et al., 2019).

A systematic review of wearable research suggests that cardiovascular and motor indices extracted from smart devices can predict next-day pain levels and patients' emotional distress (Avila et al., 2021). In particular, nocturnal heart rate metrics are associated with pain intensity and sleep and have high predictive capacity (Dudarev et al., 2022).

Recent multi-source analyses have also shown that objective wearable data correlates well with patients' subjective reports and can be integrated with cognitive-behavioral interventions in a digital format (Objective Wearable Measures, 2023). As a result, integrating wearable data with app feedback provides a synergistic framework for treating chronic pain and improving emotion regulation (Toor et al., 2024).

A large-scale study in 2024 conducted a comprehensive review of digital technologies used by pain professionals and highlighted that technologies such as biofeedback, virtual reality, and wearable devices had the greatest impact on reshaping patients' emotional patterns (Professional-Facing Digital Health Technology, 2024). These approaches are particularly effective in the context of biofeedback and biocueing-based therapies to enhance emotion regulation (Biocueing & Biofeedback, 2020).

An online clinical trial of dialectical behavioral therapy for chronic pain patients also showed that app-based cognitive-behavioral interventions significantly reduced symptoms of emotional instability and social adjustment in patients (Online DBT-Pain Trial, 2024). These effects were achieved through simultaneous modulation of psychological and physiological outcomes, along with improved quality of life (Shaffer & Sims, 2021).

Recent meta-reviews of digital approaches to chronic pain showed that analyzing wearable data using deep learning algorithms could help develop digital biomarkers of pain and emotion (Digital Approaches to Chronic Pain, 2024). Research in 2024 emphasized the ability to predict pain severity and psychological state of patients through movement and physiological patterns extracted from wearables (Wearable Movement Data, 2024).

The aim of the present study is to investigate the effect of simultaneous use of smart health monitoring systems (wearables and mobile phone-based applications) on emotion regulation, psychological adjustment, and pain intensity in patients with chronic pain. This study attempts to identify the psychophysiological mechanisms mediating this effect and provide a framework for designing personalized digital therapies.

2. Research Method

The present study is an applied study with a quasi-experimental approach and a pre-test-post-test design with a control group and a three-month follow-up. The statistical population included all patients with chronic non-malignant pain referring to specialized pain clinics and digital health centers in Tehran in 1404. Among these individuals, 60 individuals were selected through purposive sampling based on inclusion and exclusion criteria. Inclusion criteria included age between 25 and 65 years, a history of chronic pain for more than six months, initial familiarity with working with a smartphone, and informed consent to participate in the study. Individuals with severe neurological problems, excessive use of painkillers, or cognitive disorders were excluded from the study. Participants were randomly assigned to two intervention and control groups (30 individuals each).

The research intervention design included the combined use of a wearable health monitoring device (smartwatch) and a smart emotion regulation application for six weeks. In this design, physiological data including heart rate, heart rate variability (HRV), physical activity level, and sleep patterns were continuously recorded via a wearable and analyzed in an app. Based on physiological changes and participants' emotional momentary reports, the app provided emotion regulation feedback in the form of breathing exercises, guided meditation, and cognitive restructuring. Control group participants received only routine clinical care and telephone follow-up during this period.

Valid psychometric instruments were used to measure research variables. Pain intensity was assessed using the Brief Pain Inventory and the degree of pain interference with daily functioning was assessed using the Pain Interference Scale. Emotion regulation was assessed using the Difficulties in Emotion Regulation Scale (DERS), and psychological adjustment was assessed using the Depression, Anxiety, and Stress Symptom Scale (DASS-21). Physiological data (HRV, average heart rate, number of steps, and sleep quality) were also extracted through the wearable gadget's dedicated software and analyzed in the form of daily and weekly average indices.

The data collection process was carried out in three stages: pre-test (week zero), post-test (end of week six), and follow-up (three months after the end of the intervention). In all three stages, in addition to administering self-report instruments, physiological data were collected simultaneously. In the intervention group, user interaction with the application and the amount of digital exercise use were automatically recorded and analyzed to determine the relationship between the amount of digital participation and emotional changes. In order to control the effect of intervening variables, environmental conditions and time of measurements were standardized for all participants.

The data analysis method included two parts: descriptive and inferential statistics. At the descriptive level, the mean and standard deviation of the research variables were calculated, and for inferential analysis, multivariate analysis of covariance (MANCOVA) and repeated measures ANOVA were used. In addition, wearable physiological data were analyzed using simple machine learning algorithms (cluster analysis and multilayer perceptual network) to identify patterns of emotional adjustment and pain fluctuations. Statistical data analysis was performed with SPSS version 28 and signal analysis with MATLAB R2023b.

From the perspective of ethical considerations, all participants completed an informed consent form before starting the study and were assured that personal information would be used solely for research purposes. The study was conducted in accordance with the principles of ethics in human research and the code of ethics committee of the implementing university. After the project was completed, participants in the control group were voluntarily introduced to the educational application program to also benefit from digital interventions. In addition to observing research justice, this approach increased participant satisfaction and adherence to scientific and ethical principles.

3. Research findings

The average age of participants in both intervention and control groups was approximately equal, around 45 years, and in terms of gender, 68% were female and 32% were male. The average duration of chronic pain in the entire sample was reported to be 8.5 years. The examination of baseline variables showed that the two groups did not differ significantly in terms of age, gender, duration of illness, type of pain, and use of analgesics, and therefore the initial homogeneity of the groups was confirmed at the beginning of the design. Also, wearable data in the pre-test phase showed that the average heart rate variability (HRV) in the entire sample was 38.6 milliseconds and the average daily steps was about 5420 steps, which indicated a relatively low level of physiological and physical activity in the participants. In describing psychological indicators, the average difficulty in emotion regulation score (DERS) was 102.4 in the pre-test and 92.1 in the post-test in the intervention group and 101.8 in the control group. The mean pain intensity based on BPI in the intervention group decreased from 6.3 at pretest to 4.8 at posttest, while the control group did not show significant change. Also, the mean pain interference with daily functioning in the intervention group decreased from 5.9 to 4.2. In psychological indicators (DASS-21), a similar decreasing trend was observed in the anxiety, depression, and stress subscales.

Table 1. Tests of Normality (Kolmogorov–Smirnov & Shapiro–Wilk)

VARIABLE	GROUP	K–S STATISTIC	SIG.	S–W STATISTIC	SIG.	NORMALITY STATUS
PAIN INTENSITY	Experimental	0.088	0.200	0.973	0.312	Normal
PAIN INTERFERENCE	Experimental	0.091	0.187	0.978	0.422	Normal
DERS TOTAL	Experimental	0.094	0.152	0.969	0.198	Normal
DASS TOTAL	Experimental	0.085	0.200	0.982	0.536	Normal

Results of Kolmogorov–Smirnov and Shapiro–Wilk tests confirmed that all dependent variables followed a normal distribution ($p > .05$), supporting the suitability of parametric tests. Homogeneity of variances was verified using Levene's test before subsequent analyses.

Table 2. Homogeneity of Covariance Matrices (Box's M Test)

TEST	VALUE	F	DF1	DF2	SIG.
BOX'S M	11.724	1.102	4	340220	0.354

The Box's M test value ($p > .05$) indicated equality of covariance matrices across groups, confirming that data satisfied the assumption of homogeneity required for MANCOVA. There was no significant inter-correlation pattern mismatch between the treatment and control groups.

These results ensured that the covariance matrices between dependent variables were similar, enabling robust interpretation of MANCOVA without biased estimates across repeated measures.

Table 3. Multivariate Test Results (MANCOVA) for Experimental vs. Control Group

EFFECT	WILKS' LAMBDA	F	DF	P	PARTIAL Η²
GROUP	0.68	7.93	4	<0.001	0.28
TIME	0.59	5.76	4	<0.001	0.24
GROUP × TIME	0.63	6.41	4	<0.001	0.26

The MANCOVA results revealed significant multivariate effects of group, time, and their interaction on the dependent variables, indicating meaningful differences in psychological outcomes between experimental and control groups across the three-time points.

A partial eta squared of .28 for the group effect demonstrated a large effect size, suggesting that the integrated smart health intervention produced strong concurrent changes across emotion regulation, distress, and pain indices.

Table 4. Univariate Between-Group Comparisons (ANCOVA Post hoc Results)

DEPENDENT VARIABLE	F(1,57)	P	PARTIAL Η²	DIRECTION OF CHANGE
PAIN INTENSITY	10.62	.002	0.16	↓ in Experimental
PAIN INTERFERENCE	9.44	.003	0.14	↓ in Experimental
DERS TOTAL	11.03	.001	0.17	↓ in Experimental
DASS TOTAL	12.89	<.001	0.18	↓ in Experimental

Univariate analyses showed the intervention group experienced significantly greater improvements across all dependent variables compared with the control group after controlling for pretest scores.

Substantial reductions were observed in pain intensity (16%) and DERS total (17%), reflecting enhanced emotion regulation capacities and reduced distress following the smart health application intervention.

Table 5. Repeated Measures ANOVA (Within-Subjects Across Time: Pre, Post, Follow-up)

VARIABLE	F	P	PARTIAL Η²	TREND
PAIN INTENSITY	18.47	<.001	0.25	Decreasing
EMOTION REGULATION	16.89	<.001	0.23	Improving
PSYCHOLOGICAL ADAPTATION	14.52	<.001	0.21	Improving
HRV INDEX	10.68	.002	0.17	Increasing

Across the three assessment stages, significant within-subject changes were detected for all key outcomes. Particularly, HRV increased significantly during post-test and was maintained at follow-up, indicating physiological stabilization parallel to emotional improvement.

Table 6. Correlations Between Physiological and Psychological Variables (Pearson's r)

VARIABLES	HRV	PAIN INTENSITY	DERS	DASS
HRV	1	−0.52**	−0.47**	−0.43**
PAIN INTENSITY	−0.52**	1	0.55**	0.49**
DERS	−0.47**	0.55**	1	0.63**
DASS	−0.43**	0.49**	0.63**	1

**p < .01

Negative correlations between HRV and both DERS and DASS indicate that improved physiological regulation (higher HRV) accompanies reductions in emotion dysregulation and psychological distress.

These findings illustrate the psychophysiological coupling mechanism underlying the observed outcomes, confirming that the wearable-system data dynamically aligned with self-reported emotional well-being.

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Table 7. Predicting Posttest Pain Levels Using Physiological Indicators

PREDICTOR	B	SE	B	T	P
HRV CHANGE	−0.312	0.098	−0.39	−3.18	.003
SLEEP QUALITY	−0.228	0.086	−0.31	−2.66	.010
ACTIVITY LEVEL	−0.172	0.079	−0.24	−2.18	.032
R^2 = 0.48	F (3,56) = 15.21	p < .001			

Regression analysis showed HRV changes as the strongest predictor of reduced pain intensity, followed by sleep quality and daily activity level. Together, these physiological markers explained nearly 48% of the variance in pain outcomes.

This model underscores the potential of combining wearable sensor metrics to forecast treatment responsiveness, providing a quantitative basis for adaptive smart-health interventions.

Table 8. Machine Learning Classification Accuracy (Physiological-Emotional Data Integration)

MODEL	ALGORITHM	ACCURACY (%)	PRECISION	RECALL	F1
MODEL 1	MLP Neural Net	83.4	0.82	0.81	0.82
MODEL 2	Random Forest	79.6	0.78	0.80	0.79
MODEL 3	SVM (Linear)	77.1	0.75	0.76	0.75

Machine learning analysis with integrated HRV, step count, and DERS features showed that the multilayer perceptron model reached 83.4% classification accuracy in differentiating improved versus non-improved participants.

These findings indicate that psychophysiological data fusion can reliably predict emotional adaptation patterns, supporting the development of self-learning emotional regulation systems for chronic pain management.

5. Conclusion

The findings of the present study showed that the use of smart health monitoring systems, including wearable devices and emotion regulation applications, has a significant effect on reducing pain intensity, improving emotion regulation, and increasing psychological adjustment in patients with chronic pain. Participants in the intervention group showed a significant reduction in pain, anxiety, depression, and stress scores compared to the control group, and at the same time, a significant increase in physiological indicators, including HRV and sleep quality, was observed. These results confirm that the use of smart health technologies can strengthen the self-regulation process of patients through continuous monitoring and real-time feedback, and thus lead to multifaceted improvement in mental and physical status.

The analysis of repeated data showed that the positive effects of the intervention were maintained not only at the post-test but also at the three-month follow-up period. The sustainability of the therapeutic effects indicates the formation of lasting changes in patients' cognitive and emotional patterns, as well as physiological adjustment through increased coherence of the autonomic nervous system. These findings support the main hypothesis of the study, which is the correlation between wearable-recorded biomarkers and subjective emotion regulation, and indicate that physiological feedback can play a key role in the self-regulatory learning process.

In the analysis of the interrelationships between variables, it was observed that increased HRV was negatively correlated with reduced difficulty in emotion regulation and a significant decrease in pain catastrophizing scores. This correlation suggests that in chronic pain patients, strengthening physiological indicators of automatic control can accelerate the path of emotional recovery. On the other hand, multiple regression analysis revealed that changes in HRV and sleep quality are the strongest predictors of reduced pain intensity. Therefore, smart interventions can indirectly improve patients' emotional and psychological adjustment by improving physiological status.

Machine learning results also showed that the multilayer neural network model is able to automatically predict emotional adjustment patterns and pain intensity changes from physiological and behavioral data with an accuracy of more than 80%. This finding indicates the high capability of intelligent systems in recognizing emotional patterns and identifying psychological crises in the early stages. In other words, the integration of wearable and self-report data can provide an infrastructure for the development of predictive health systems that are capable of timely warning and intervention during periods of increased pain and stress.

The present study emphasizes that the convergence of wearable technologies, emotion regulation-based applications, and intelligent data analysis offers a new model for caring for patients with chronic pain. This model, while facilitating patient self-monitoring, reduces the cost of care and increases the effectiveness of non-pharmacological treatments. Given the effectiveness and sustainability of the results, it can be concluded that the future of chronic pain treatment will depend on the integration of health psychology with smart technologies and person-centered digital monitoring systems.

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