Research Square

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Smartwatch-derived heart rate and activity distinguish episodic pain subgroups in chronic low back pain

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Abstract

Purpose

To determine whether temporal features of six-month smartwatch-derived resting heart rate (RHR), heart rate variability (HRV), and step count trajectories discriminate episodic from non-episodic pain trajectories in chronic low back pain (cLBP).

Methods

Adults with cLBP (n = 261) from a multicenter observational cohort classified their pain over the preceding six months as episodic or non-episodic using the Visual Trajectories Questionnaire for Pain. Daily smartwatch RHR, HRV, and step count for the same period were retrieved retrospectively. Summary statistics were compared between groups, and between-patient trajectory heterogeneity was quantified with functional principal component analysis. Six hundred time-series features per signal were extracted. Stability selection and elastic-net logistic regression with nested cross-validation were used to evaluate four feature sets: RHR, HRV, RHR + HRV, and RHR + HRV+steps. SHAP values quantified feature importance.

Results

Of the 261 participants, 195 (74.7%) reported episodic and 66 (25.3%) non-episodic pain. No summary statistic differed between groups for any signal. Explaining 90% of trajectory variance required 6, 12, and 34 functional components for RHR, HRV, and step count, respectively. Nested AUCs were 0.72 (RHR), 0.67 (HRV), 0.78 (RHR + HRV), and 0.82 (RHR + HRV+steps). Frequency-domain coefficients and local variability measures, including day-to-day RHR change and weekly HRV autocorrelation, were the most important features.

Conclusion

Temporal features of consumer smartwatch data discriminate episodic from non-episodic cLBP, whereas summary statistics of the same signals do not. Combining heart rate and activity features yields the highest discrimination. These findings highlight the potential of biophysical monitoring to better understand and predict recurrent cLBP episodes.

INTRODUCTION

Chronic low back pain (cLBP) is the leading cause of disability worldwide [1], yet clinical phenotyping of cLBP patients remains challenging due to its multifactorial etiology and heterogeneous presentation [2]. While cLBP is often defined as “the persistence of pain beyond 3 months of symptoms” [3], its temporal

dynamics vary substantially between patients [4], [5], [6]. Some experience relatively stable pain, while others exhibit episodic patterns with distinct flare-ups [5], [7]. Individuals' pain trajectories tend to remain stable over years and are associated with patient-reported outcomes [8]. As a result, pain trajectories may represent clinically meaningful subgroups for guiding personalized treatment [4]. Understanding a patient's pain trajectory can additionally advise practitioners on how to best counsel patients, as the episodic nature of pain has been correlated with different types of pathology [9], [10].

Patient trajectories are currently captured through recall-based self-report. The Visual Trajectories Questionnaire for Pain (VTQ-Pain) is a validated and efficient instrument [11], but it is retrospective and subjective. Other patient-reported outcomes such as pain intensity, disability, and quality of life, are administered infrequently at discrete clinical encounters. This represents a fundamental gap: the temporal variability that defines episodic pain is precisely what standard assessment is least equipped to measure.

Wearable devices such as smartwatches are increasingly recognized for their potential to transform chronic pain management through continuous recording of physiological and behavioral signals in everyday life. Resting heart rate (RHR) and heart rate variability (HRV) are associated with chronic pain and pain intensity [12], [13], [14], and physical activity exhibits complex, non-linear relationships with cLBP [15]. However, these studies have largely relied on aggregate measures (e.g., daily averages of step count, sedentary time, resting HRV). These measures discard the temporal structure that distinguishes episodic from persistent pain. That structure appears to be informative: day-to-day variability in activity is associated with cLBP flares [16], and nocturnal RHR can predict next-day pain in chronic pain conditions [17]. Because flares are complex events with both autonomic and behavioral manifestations, temporally resolved heart rate and activity signals in combination may capture episodic pain more completely than either signal alone.

To investigate how biophysical signals for heart rate and activity may relate to episodic pain fluctuations, we first characterized the complexity of smartwatch data trajectories across patients, anticipating that conventional summary measures would be insufficient for pain subgroup discrimination, motivating a richer, feature extraction-based approach. We then evaluated whether temporal trajectory features could discriminate between episodic and non-episodic pain subgroups in cLBP patients using six months of smartwatch data from a cohort of 261 cLBP patients. We hypothesized that temporal features of six-month smartwatch-derived RHR, HRV, and step count trajectories would discriminate episodic from non-episodic pain trajectories in cLBP. We further hypothesized that a model combining heart rate and activity features would outperform models using heart rate features alone. This work seeks to identify biophysical factors associated with cLBP episodes and build toward earlier detection of flare-ups and support personalized pain management.

METHODS

Participants

Participants were drawn from BACKHOME [18], a multicenter longitudinal observational cohort of adults with cLBP recruited between July 2021 and September 2025. Eligibility required cLBP as defined by the NIH Task Force on Research Standards [18], requiring pain between the lower posterior margin of the rib cage and the horizontal gluteal fold that has persisted for at least 3 months and was present for at least 50% of days in the preceding 6 moths. Low back pain also had to be worse than any other bodily pain. Participants who granted access to their Apple HealthKit data and had at least 120 of 180 days of wearable data were included. The study was approved by the responsible institutional review boards, and all participants provided written informed consent.

Pain trajectory classification

Participants completed the VTQ-Pain [11], selecting the visual trajectory that best described the course of their pain over the preceding six months. Responses depicting fluctuating pain with flare-ups were classified as episodic, and responses depicting pain at a relatively constant or monotonically changing level were classified as non-episodic (Fig. 2).

Wearable data

Daily RHR, HRV, and step count for the six months covered by the VTQ-Pain were retrieved retrospectively from Apple HealthKit. Apple Watch estimates RHR from heart rate samples recorded during inactivity. It reports HRV as the standard deviation of normal-to-normal intervals (SDNN), measured from short photoplethysmography recordings taken periodically in the background. Raw samples were aggregated into daily mean RHR, daily median HRV, and daily step count, forming a 180-day trajectory per modality and participant.

Trajectory characterization

For each modality, eight summary statistics were compared between groups using independent t-tests or Mann-Whitney U tests according to distribution: mean, standard deviation, median, minimum, maximum, range, interquartile range, and coefficient of variation. Within-patient Pearson correlations between daily values of each pair of modalities were computed and summarized across participants. To quantify between-patient trajectory heterogeneity, functional principal component analysis (fPCA) was applied to each modality using scikit-fda. The number of functional principal components (fPCs) required to explain more than 90% of variance was recorded.

Feature engineering

Six hundred time-series features per modality were extracted with tsfresh [19], including summary statistics, distribution properties, linear trends, autocorrelation and partial autocorrelation functions, fast

Fourier transform (FFT) coefficients, entropy and complexity measures, and change quantifications. Features with missing or zero variance were removed. For each feature pair correlated above r = 0.90, one feature was removed at random to address multicollinearity, leaving 300 candidate features. Stability selection [20] was then applied. In each of 100 subsamples of 50% of participants, stratified by outcome, features were ranked by univariate ANOVA F-statistic, and those with $p < 0.05$ were selected. Features selected in at least 70% of subsamples were retained. Four feature sets were constructed: RHR only, HEV only, Heart (RHR + HRV), and Heart + Steps.

Model development and evaluation

Elastic-net logistic regression models (scikit-learn) were trained on each feature set to classify episodic versus non-episodic pain. Performance was estimated with nested cross-validation using three outer and three inner folds, repeated 25 times, with stratification by outcome in all folds. The regularization strength and L1 ratio were tuned by grid search in the inner loop, and the nested AUC is the mean across outer folds. Each model was then refit on the full dataset with the selected hyperparameters, and the final AUC and Nagelkerke pseudo-R^2 were calculated from the refit model. SHapley Additive exPlanations (SHAP) values [21] were computed for the final models to quantify the magnitude and direction of each feature's contribution (Fig. 1).

RESULTS

Cohort characteristics

Of 261 cLBP patients (108 male, 153 female), 195 (74.7%) reported 'episodic' pain trajectories and 66 (25.3%) reported 'non-episodic' pain trajectories. Age, sex distribution, and BMI did not differ between groups. Population mean RHR was 64 ± 8.3 bpm and the mean HRV was 29.1 ± 10.4 ms. Step count data were available for 199 participants, with a mean of 5,472 ± 2,653 steps.

Summary statistics and trajectory heterogeneity

None of the eight summary statistics (mean, SD, median, minimum, maximum, range, IQR, and coefficient of variation) differed between groups for RHR, HRV, or step count. Within-patient correlations between modalities were weak with high relative error (RHR-HRV: r = − 0.255 ± 0.191, RHR-Steps: r = 0.109 ± 0.173, HRV-Steps: r = − 0.077 ± 0.123), indicating that each signal carried largely non-redundant information. Trajectories were heterogeneous across patients. Explaining more than 90% of between-patient variance required 6 fPCs for RHR, 12 for HRV, and 34 for step count (Fig. 3).

Discrimination of pain trajectory groups

Stability selection retained 18 RHR, 14 HRV, 30 Heart, and 31 Heart + Steps features. The RHR model achieved a nested AUC of 0.718 ± 0.012 and the HRV model 0.668 ± 00.024. Combining both signals in the Heart model increased the nested AUC to 0.781 ± 0.019. Adding step count features in the Heart +

Steps model yielded the highest discrimination, with a nested AUC of 0.816 ± 0.029, final AUC of 0.820 ± 0.024 and Nagelkerke R^2 of 0.48 (Table 1).

Table 1
Model performance metrics

Model	Features (n)	Nested AUC (mean ± SD)	Final AUC (mean ± SD)	Nagelkerke R^2
RHR	18	0.718 ± 0.012	0.718 ± 0.012	0.045
HRV	14	0.668 ± 0.024	0.671 ± 0.020	-0.070
Heart	30	0.781 ± 0.019	0.780 ± 0.019	0.280
Heart+Steps	31	0.816 ± 0.029	0.820 ± 0.024	0.480

Feature importance

FFT coefficients had the highest mean absolute SHAP values across all models (Fig. 4). In the RHR model, a smaller mean day-to-day change in RHR was associated with non-episodic pain. In the HRV model, higher weekly autocorrelation and partial autocorrelation were associated with non-episodic pain. BMI ranked among the important features in both single-signal models, with higher BMI associated with non-episodic pain. The heart model's most important features included FFT coefficients from both RHR and HRV, and the Heart + Steps model's most important features included features from all three constituent signals.

DISCUSSION

We demonstrate that temporal features extracted from smartwatch data can discriminate between episodic and non-episodic pain subgroups in cLBP patients. Crucially, this discriminative signal is not detectable using conventional summary statistics: mean, standard deviation, and related summary measures did not differ between pain groups across any modality (RHR, HRV, step count). It is only when the temporal structure of the trajectories is characterized through features capturing frequency content, day-to-day variability, and autocorrelation that meaningful group differences emerge. This finding has important methodological implications for future wearable-based pain research, suggesting that trajectory-level analyses may be necessary to detect associations that summary-based approaches miss.

The combination of RHR, HRV, and activity trajectory features in the Heart + Steps model achieved the best discrimination (AUC = 0.820, R^2 = 0.48). While overall model performance for the RHR- and HRV-only models was modest, combining these with step count trajectory features substantially improved model performance, and within-patient correlations between modalities were weak, suggesting that each signal contributed largely non-redundant information and may explain different variances in pain classification. Heart rate metrics may reflect autonomic responses and stress-related processes [13], [14], while activity patterns may reflect functional capacity and pain-related movement avoidance [22]. However, these

signals are also sensitive to other stressors: the multimodal approach may have therefore provided robustness against such confounding factors, offering a more comprehensive picture of a patient's chronic pain trajectory.

The prominence of frequency-domain and local variability features (FFT coefficients, day-to-day RHR change, weekly HRV autocorrelations) over global summary measures in SHAP analyses aligns with the fPCA findings and supports a coherent mechanistic interpretation: fluctuations at shorter timescales may better reflect the episodic nature of pain experience. Non-episodic pain patients exhibited lower day-to-day variability in RHR and higher weekly regularity in HRV, potentially suggesting a more stable autonomic state, while episodic patients showed more irregular physiological patterns, potentially reflecting the fluctuating physiological demands of intermittent pain episodes. These results corroborate prior findings that day-to-day variability in activity associates with flare-up incidence in cLBP and that nighttime heart rate predicts next-day pain in chronic pain conditions, extending these observations to the level of trajectory grouping [16], [17].

Previous study has sought to link episodic and non-episodic pain to distinct underlying pathologies [9], [10], raising the possibility that the differences in RHR- and HRV-derived features observed here reflect different biological processes. Discogenic pain is one candidate. The lumbar intervertebral disc is innervated by sympathetic nerve fibers and sinuvertebral nerves, while many other lumbar pathologies are related to somatic spinal nerves [23], [24]. Discogenic pain has also been described as episodic [9], but that characterization relies on self-reporting. If discogenic pain is accompanied by altered autonomic activity, digital tracking could provide an objective means of testing this association and eventually, of supporting the identification of discogenic pain.

Inflammatory pain generators, which tend to wax and wane, may also produce greater autonomic variability than mechanical generators such as degenerative osteoarthritis, whose course is more constant and progressive. Autonomic measures may also reflect a patient's affective response to pain such as fear-avoidance behavior. Because the relationship between pain and autonomic function is bidirectional [25], the present data cannot distinguish whether autonomic changes reflect the pain generator, the patient's response, or both. Separating these explanations would require pairing wearable data with imaging-defined pain generators and psychological measures.

These findings have implications for digital health approaches to chronic pain management. Passively collected trajectory features could complement or partially substitute self-reported outcomes, reducing recall bias and patient burden. Real-time monitoring could enable earlier detection of impending flare-ups, facilitating timely clinical intervention. The use of consumer smartwatches enhances scalability and real-world applicability. However, this study is not without limitations. First, self-reported pain trajectories using the VTQ-Pain, while validated [11], remain susceptible to recall bias and do not allow for identification of specific flare-up incidences, instead relying on the assumption that patients reporting an episodic trajectory type are more likely to experience a higher frequency of flare-ups. Second, the class imbalance in our cohort (74.7% episodic) reflects the underlying clinical distribution but may limit model

sensitivity for non-episodic classification; stratified sampling during feature selection and cross-validation was employed to mitigate this as much as possible. Third, while subjects with large portions of missing data were excluded, missing data persisted in the final dataset, as is inherent to passive wearable data collection, and this may have attenuated our ability to identify associations between features. Fourth, the retrospective nature of wearable data collection prevents causal inference about the relationship between trajectory features and pain experience. In addition, decreases in model performance may be related to the subjectivity and potential for bias in the VTQ-Pain rather than a lack of prediction power in the activity features. This further emphasizes the importance of objective measures for patient pain tracking and classification.

Future work will incorporate daily pain assessments, which would allow validation against specific flare-up events and enable trajectory features to be used for real-time prediction rather than retrospective classification. Integration of additional wearable-derived metrics (sleep quality, gait parameters, other activity metrics) may further improve subgrouping accuracy. Extension of these methods to other chronic pain conditions would clarify whether observed patterns are specific to cLBP or generalizable across pain syndromes.

In conclusion, we demonstrate that temporal features extracted from RHR, HRV, and step count trajectories discriminate cLBP patients presenting with episodic and non-episodic pain. This could facilitate mechanistic insight into the variability in biophysical responses to pain among patients. Our results support that heart rate and activity tracking, especially in combination, may provide an opportunity for objective monitoring of patient pain, fluctuations, and response to interventions. This study also illustrates the temporal complexity of smartwatch data trajectories, and the failure of summary statistics to capture pain-relevant variation, highlighting the importance of trajectory-level analysis in wearable-based pain research. This work illuminates the potential for tracking changes in biophysical factors to better understand the episodic nature of cLBP and perhaps eventually predict and mitigate risk for recurrent episodes.

DECLARATIONS

Author Contribution

AP and KK wrote the main manuscript text and prepared all figures. All authors reviewed the manuscript.

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Data Availability

The data that support the findings of this study are not openly available due to reasons of sensitivity and are available from the corresponding author upon reasonable request. Data are located in controlled access data storage at the University of California, San Francisco. De-identified data can be accessed at: https://doi.org/10.25934/PR00010819

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Figures

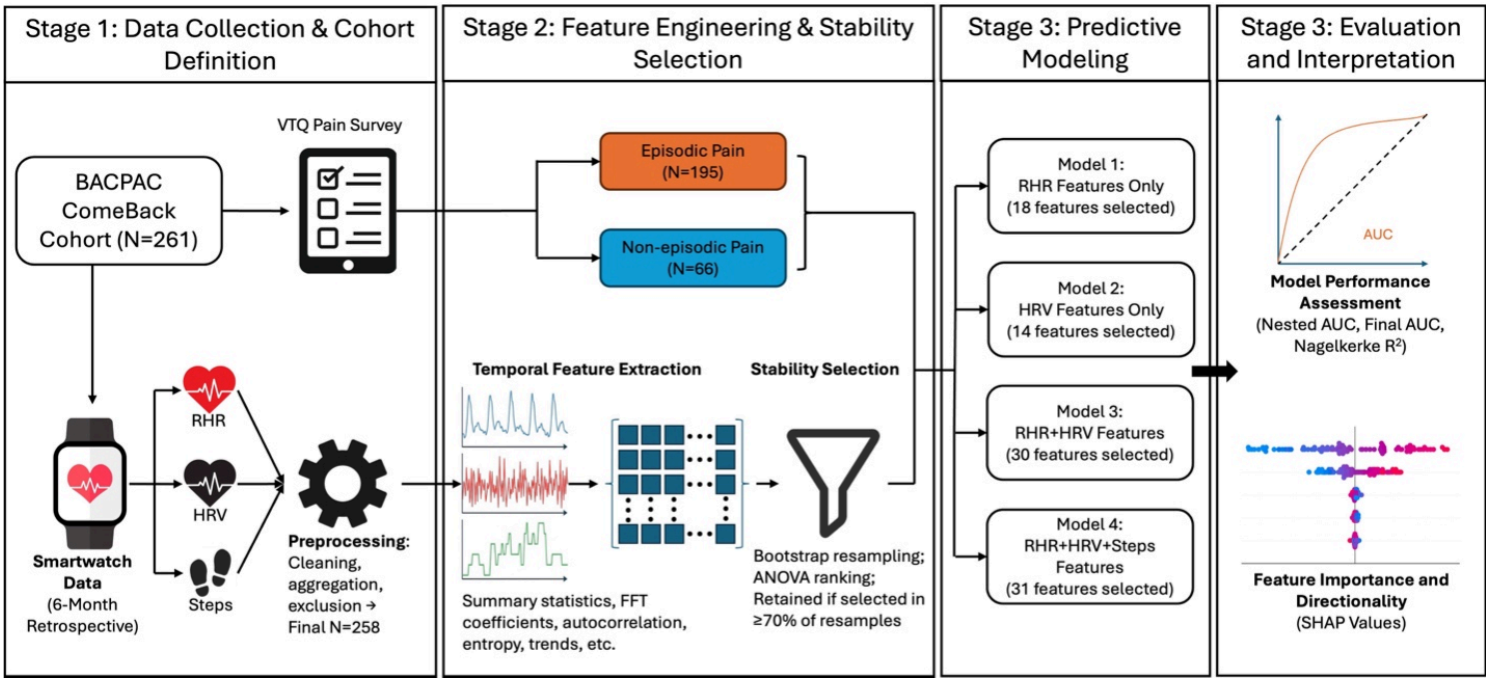


Figure 1

Study design.

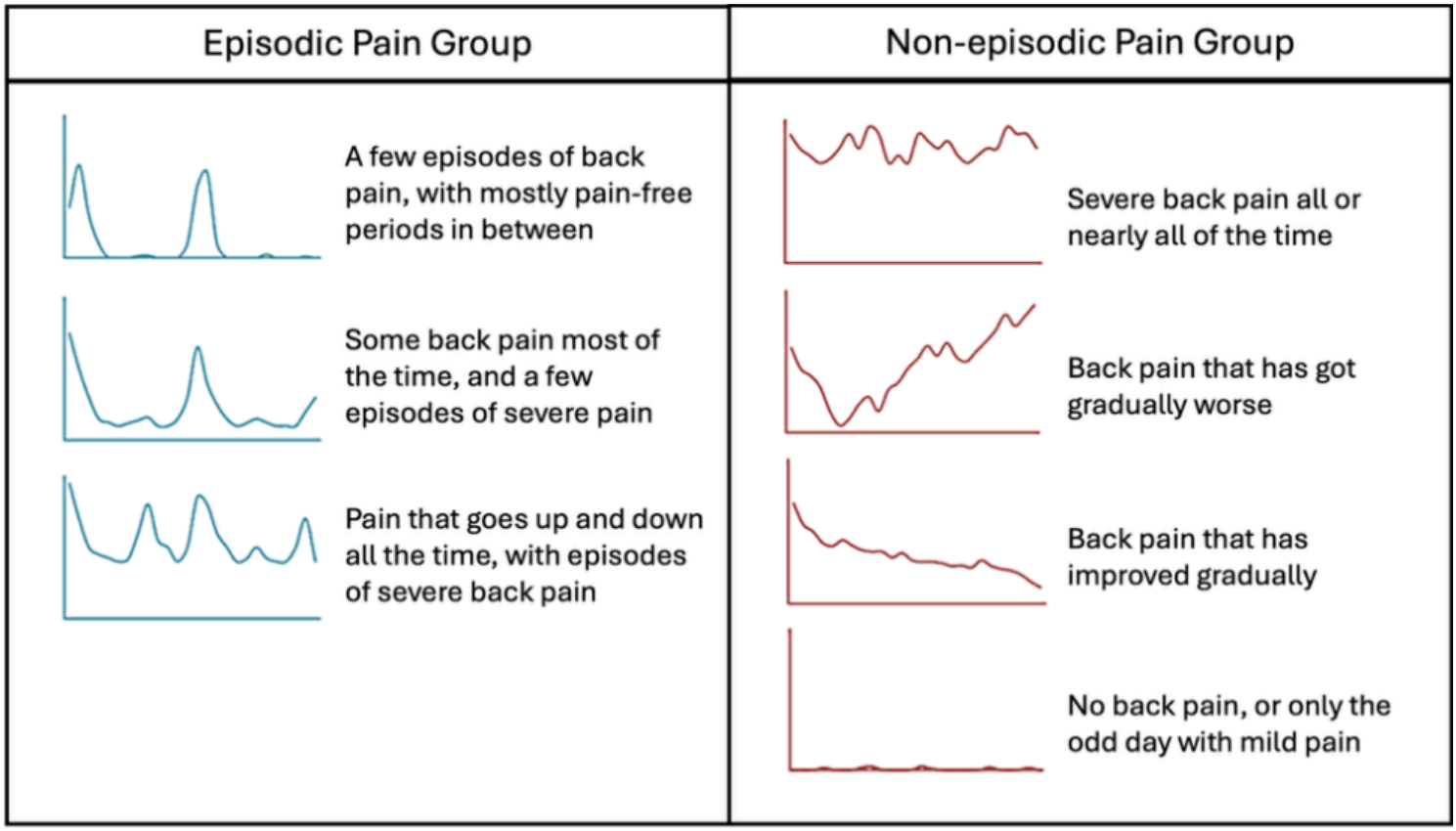


Figure 2

Episodic and non-episodic classification from the Visual Trajectory Questionnaire for Pain.