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Site-specific pain dynamics: associations between accelerometer-measured physical activity patterns and pain in older adults

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Abstract

Background Physical activity (PA) has emerged as a promising non-pharmacological intervention for pain management, the relationship between objectively measured PA patterns and multi-site pain remains poorly understood. This exploratory study investigated associations between accelerometer-derived PA patterns and pain across various anatomical sites in older adults, and evaluated the predictive utility of machine learning model for pain outcomes.

Methods This study utilized data from the National Health and Aging Trends Study in 2021–2022. Wrist-worn accelerometers measured PA, derived total activity, sedentary time, and activity/sedentary fragmentation) and time-frequency domain features. Cross-sectional and longitudinal analyses examined associations between PA patterns and site-specific pain using multivariable logistic regression with false discovery rate correction, while restricted cubic splines explored non-linear dose-response relationships. Random forest models with recursive feature elimination were developed to predict current pain status and pain relief.

Results Cross-sectional analysis indicated that moderate sedentary time was associated with back pain (OR = 2.24, 95%CI: 1.12–4.47) and neck pain (OR = 2.12, 95%CI: 1.07–4.20), while moderate-to-vigorous activity fragmentation was associated with lower leg pain prevalence (OR = 0.34, 95%CI: 0.15–0.78), and moderate sedentary fragmentation with foot pain (OR = 1.89, 95%CI: 1.07–3.33). Longitudinal analysis revealed that moderate-to-vigorous activity fragmentation was associated with pain persistence in head (OR = 0.21, 95%CI: 0.05–0.90), though associations did not survive FDR correction. Machine learning prediction models achieved performance for pain status (AUC: back = 0.56, wrist = 0.54) and pain relief prediction (AUC: wrist = 0.85, back = 0.72).

Conclusion Site-specific tailoring of PA intensity and fragmentation is warranted for effective chronic pain management in older adults based on associations between PA and anatomical pain distribution.

Keywords Accelerometry, Physical activity, Chronic pain, Pain management

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Background

Chronic pain constitutes a significant and pervasive health challenge among the geriatric population. Epidemiological data indicate a pain prevalence ranging from 25% to 50% in individuals aged 65 years and older, with a positive correlation between prevalence and advancing age [1]. The sequelae of pain extend beyond functional impairments and diminished quality of life [2], encompassing robust associations with cognitive deterioration and elevated mortality risk [3, 4]. Moreover, the implications of pain transcend individual health outcomes, imposing a substantial socioeconomic burden. In the United States, pain-related annual healthcare expenditures exceed $600 billion, surpassing the aggregate annual medical costs associated with cardiovascular diseases, neoplasms, and diabetes mellitus combined. This financial burden underscores pain as a critical public health concern with far-reaching economic ramifications [5].

From a physiological standpoint, chronic pain encompasses intricate neurophysiological mechanisms, including sensory system aberrations, metabolic dysregulation, musculoskeletal dysfunction, and neuroendocrine imbalances [6, 7]. These multifaceted alterations not only manifest the impact of pain but may also precipitate a decline in daily physical activity (PA), potentially instigating a pernicious cycle of pain and functional impairment [8]. Among the array of potential intervention strategies, regular PA has emerged as a particularly promising approach for both the prevention and management of chronic pain, owing to its pleiotropic benefits [9, 10]. Judicious implementation of PA regimens may attenuate symptoms through direct modulation of nociceptive pathways and indirect mechanisms, including enhancement of overall physical function, bolstering of psychological resilience, and optimization of physiological homeostasis [11]. Notwithstanding these potential benefits, the accurate quantification and assessment of PA patterns remain a formidable challenge in research paradigms.

The advent of wrist-worn accelerometers has ushered in a new era in objective PA measurement. These devices, leveraging Micro-Electro-Mechanical Systems (MEMS) technology, which integrates miniaturized mechanical and electrical components on a single chip. MEMS-based accelerometers capture kinetic data via triaxial acceleration measurements, offering unprecedented temporal resolution, sensitivity, objectivity, and capacity for longitudinal monitoring [12]. In contrast to traditional self-report methodologies, accelerometers facilitate continuous collection of granular movement data at frequencies ranging from 30 to 100 Hz, enabling accurate recording of even low-intensity activities while mitigating recall bias and subjective assessment errors [13]. This approach permits the capture of more nuanced and diverse activity patterns, encompassing both cumulative metrics and dynamic features of sedentary-active transitions. Despite these advancements, extant research is not without limitations. The preponderance of studies employs cross-sectional designs [14, 15] and focuses on site-specific pain [16, 17], thereby impeding efforts to elucidate the temporal dynamics of activity-pain relationships and the complexity of multi-site pain phenomena.

To address these limitations, our study employs an innovative multi-methodological approach combining traditional statistical analysis with machine learning techniques. Our cross-sectional analysis explores immediate associations between PA patterns and site-specific pain status, while the longitudinal component examines temporal relationships between activity patterns and pain persistence and evolution across body sites. Beyond conventional association analyses, we apply machine learning algorithms to predict pain status and pain relief outcomes, identifying individuals at risk for persistent pain or likely to experience pain improvement. This integrated approach aims to capture dynamic pain features and their interaction with PA over time, while providing actionable insights for personalized pain management strategies.

Methods

Study design and population

This study employs a hybrid design, integrating cross-sectional and longitudinal approaches, utilizing data from the National Health and Aging Trends Study (NHATS). NHATS is a nationally representative longitudinal survey that has, since 2011, annually collected comprehensive health and functional status data from Medicare beneficiaries aged 65 years and older, encompassing community-dwelling individuals, as well as residents of nursing homes and care facilities [18].

Our analysis focuses on the publicly available datasets from Rounds 11 and 12 of NHATS, collected in 2021 and 2022, respectively. Round 11 marked the inaugural implementation of wrist-worn accelerometry for PA measurement, with sampling weights consistent with those of Round 9 to ensure sample representativeness. Of the 872 eligible participants who completed the Round 11 NHATS interview, 747 returned valid accelerometer data. Inclusion criteria for our study comprised: (1) a minimum of three days of valid accelerometer measurements, (2) complete whole-body pain assessment data, and (3) participation in the 2022 (Round 12) follow-up interview. Additionally, we excluded samples with covariate missingness exceeding 20%. After applying these criteria, 546 participants were included in the cross-sectional analysis. The longitudinal analysis further excluded 56 participants who, despite participating in Round 12 interviews, did not provide pain data, resulting in a final

cohort of 490 subjects for longitudinal assessment (Supplementary Fig. 1.a).

Pain assessment

Pain evaluation was conducted using the standardized Sensory Impairment and Symptoms Questionnaire implemented in the NHATS protocol during 2021 (Round 11) and 2022 (Round 12) [19]. This instrument employs a two-stage assessment methodology: Initially, researchers posed the question, "During the past month, have you been bothered by pain?" For respondents affirming pain experience, a subsequent evaluation was performed, assessing pain status across 11 distinct anatomical sites: back, hips, knees, legs, feet, hands, wrists, arms, shoulders, head, and neck (Supplementary Fig. 1.b). In our longitudinal analysis, we focused on the dynamic nature of pain trajectories. For individuals reporting pain in 2021, we employed a binary coding system in the 2022 follow-up assessment (0 = pain persistence, 1 = pain resolution) to quantify longitudinal changes in pain status.

Accelerometer data

PA data were acquired utilizing a research-grade, triaxial, water-resistant accelerometer (ActiGraph CentrePoint Insight Watch, referred to as "Activity Watch"; ActiGraph, Pensacola, FL, USA). The device was affixed to participants' non-dominant wrist during domiciliary interviews, with instructions for continuous wear over a 7-day period, 24 h per diem, permitting removal solely for aquatic activities or prolonged bathing (> 30 min). The accelerometer recorded triaxial motion at a sampling frequency of 64 Hz, with acceleration quantified in gravitational units (g). Raw data underwent preprocessing to generate minute-level summary files for the estimation of active and inactive periods. Non-wear time was operationally defined as continuous periods of 90 min without recorded movement. A valid measurement day was defined as wear time exceeding 1296 min (> 90% daily wear compliance), with data retention restricted to the interval between 05:00 and 23:00 to standardize the analytical time window.

In our analysis of accelerometer data, we utilized the activity state classifications established by the NHATS protocols [20, 21]. According to these protocols, time periods with ≥ 1853 counts per minute are classified as active states, while periods with < 1853 counts per minute are classified as sedentary states. Utilizing this classification, we derived four key activity metrics: (1) Total activity counts: the aggregate of all activity counts across the three axes, normalized by the number of valid days. This metric captures overall physical activity volume, including movements of varying intensities; (2) Sedentary time: the cumulative duration of daily sedentary states, calculated as the average number of minutes per day spent below the threshold of 1853 counts per minute. This includes periods of low movement; (3) Activity fragmentation: calculated as the probability of transitioning from an active state to a sedentary state; (4) Sedentary fragmentation: calculated as the probability of transitioning from a sedentary state to an active state. Activity fragmentation is calculated as the probability of transitioning from an active state to a sedentary state [22, 23]. For example, an activity fragmentation index of 0.25 means that during a typical day, if an individual experiences 20 active periods, approximately 5 of these active bouts are directly followed by transitions to sedentary states. This could represent a pattern where an older adult engages in active periods averaging 15–20 min (e.g., walking, light exercise), followed by longer sedentary intervals. Conversely, a higher fragmentation index of 0.75 would indicate that 15 out of 20 active periods are interrupted by sedentary transitions, suggesting very short active bouts of only 3–5 min interspersed throughout the day with frequent rest breaks.

Active and sedentary times were computed as the mean of 3 days of valid data. To facilitate the detection of both linear and non-linear associations in subsequent regression analyses, all activity metrics were stratified into quartiles, allowing for a more nuanced examination of dose-response relationships. In addition to the four basic PA metrics described above, we extracted comprehensive time-frequency domain features using Time Series Feature extraction based on scalable hypothesis test for machine learning prediction models (tsfresh) [24]. From the raw triaxial accelerometer data, tsfresh automatically calculated 778 features capturing various temporal and spectral characteristics [25], including: (1) Time-domain features: statistical properties (mean, median, variance, skewness, kurtosis), autocorrelation functions, approximate entropy, sample entropy, and longest strike above/below mean; (2) Frequency-domain features: Fast Fourier Transform (FFT) coefficients, spectral energy, spectral centroid, power spectral density, and dominant frequency components; (3) Non-linear features: permutation entropy, multiscale entropy, and detrended fluctuation analysis parameters. These features were computed for each valid day and averaged across all valid days for each participant, providing a rich representation of PA patterns that captures both the intensity and temporal structure of daily movement behaviors.

Covariates

This investigation incorporated an extensive array of covariates, encompassing sociodemographic characteristics, health status indicators, and functional assessments. All covariates were collected at baseline (2021, Round 11 survey). Sociodemographic attributes included age, sex, educational attainment, marital status, income level,

and residential location. Regarding physical health indicators, we calculated Body Mass Index (BMI) based on self-reported height and weight, and evaluated chronic disease burden. The latter was quantified through a cumulative count of self-reported major chronic conditions, comprising eight categories: heart disease, hypertension, arthritis, diabetes mellitus, pulmonary disease, cerebrovascular accident, dementia, and malignancy.

Psychological health status was assessed utilizing the Patient Health Questionnaire-4 (PHQ-4) [26]. The presence of any degree of depressive or anxiety symptoms was operationalized as indicative of mood disturbance. Sleep quality evaluation was predicated on indicators such as difficulty initiating sleep, necessity for pharmacological sleep aids, or early awakening. The presence of any aforementioned condition was classified as sleep disturbance. Physical function was evaluated using the Short Physical Performance Battery (SPPB) [27]. We defined functional impairment as an SPPB total score ≤ 9. Additionally, we collected data on participants' history of falls and hospitalizations (yes/no).

Statistical analyses

This study employed a multi-stage statistical analysis approach to comprehensively investigate the complex relationship between PA patterns and pain distribution. Missing data were addressed using K-Nearest Neighbors (KNN) imputation [28]. We selected KNN because it is computationally efficient, preserves local data structure by imputing based on similar observations (k = 5), does not require distributional assumptions, and naturally captures complex interactions between variables. These properties are particularly suitable for our health and physical activity data, which exhibit clustered patterns and mixed variable types with non-normal distributions. For continuous variables, we applied z-score standardization before KNN imputation and reverse-transformed the imputed values. Categorical variables were rounded to the nearest valid integer category. Among the 747 participants with accelerometer data, the extent of missing data was relatively low across all covariates. The three covariates with the missingness were SPPB score (59 missing, 7.9%), educational attainment (16 missing, 2.14%), and BMI (10 missing, 1.34%), with no variable exceeding 8% missing data. The analytical process comprised the following key steps:

(1) Initial Exploratory Analysis: As an initial exploratory step, we compared PA patterns between participants with limited pain distribution (≤ 1 pain site) versus extensive pain distribution (≥ 2 pain sites). This binary classification was used to provide an overview of PA patterns at baseline. Descriptive statistics were subsequently conducted, reporting 24-hour PA patterns and conducted comparative analyses.

(2) Covariate Selection: To optimize model performance and control for potential confounders, we employed a Random Forest Recursive Feature Elimination (RFE) algorithm, a feature selection method that recursively removes the least important features based on their importance scores. This algorithm was optimized through GridSearchCV, in conjunction with clinical expertise. This process identified 10 key covariates: age, sex, BMI, marital status, educational attainment, psychological health, physical capacity, sleep status, heart disease, and arthritis.

(3) Exploratory analysis: Spearman's rank correlation analysis was conducted to explore associations between PA variables and pain across eligible anatomical sites identified through power analysis. Before conducting regression analyses, we performed statistical power analysis for each pain site using the stats models package in Python. Power calculations were based on observed effect sizes from univariate logistic regression models, with alpha = 0.05. Sites with statistical power < 0.7 were excluded from subsequent multivariable analyses to ensure adequate sensitivity for detecting meaningful associations and reduce Type II error risk. This resulted in 11 sites eligible for cross-sectional analysis and 7 sites for longitudinal analysis (Supplementary Table 3).

(4) Cross-sectional and Longitudinal Analysis: Site-Specific Univariate Screening: For each pain site that passed power analysis ($n = 11$ sites), separate logistic regression models were constructed with pain status (0 = no pain, 1 = pain) as the outcome. Each of the four PA metrics (total activity, sedentary time, activity fragmentation, sedentary fragmentation, and their respective quartiles) was examined in univariate models. Only sites with at least one PA variable showing $p < 0.1$ in univariate analysis were advanced to multivariable modeling. For eligible sites, multivariable logistic regression models were built incorporating PA variables with $p < 0.1$ from univariate analysis, adjusted for the 10 key covariates identified through covariates with $p < 0.1$. To control for false discovery rate across multiple pain sites, we applied the Benjamini-Hochberg FDR correction procedure. For each significant PA variable-pain site combination identified in multivariable models, FDR q-values were calculated treating each site as an independent test. Associations were considered statistically significant at FDR q < 0.05. For participants reporting pain in 2021, we examined pain trajectories at 2022 follow-up (0 = pain persistence, 1 = pain relief). Analysis procedures mirrored the cross-sectional approach, limited to

sites with adequate statistical power ($n = 7$ sites) and sufficient sample sizes for pain state transitions.

(5) Gender-stratified Subgroup Analysis: Twenty-two independent logistic regression models were constructed to investigate gender differences in the impact of PA on pain. For each pain site and gender subgroup, we first conducted univariate analyses. Variables with $P < 0.05$ in the univariate analyses were then included in the multivariate model. This process was repeated independently for each pain site and gender subgroup, resulting in 22 separate logistic regression models (11 pain sites × 2 genders).

(6) Non-linear Relationship Exploration: For PA pattern variables demonstrating power eligible in either cross-sectional or longitudinal multivariable models, we employed Restricted Cubic Spline (RCS) analysis to explore potential non-linear dose-response relationships between PA metrics and pain outcomes. Due to the substantially larger scale of total activity counts compared to other PA metrics, we applied z-score standardization to total activity values before RCS modeling to ensure numerical stability and comparability with other variables. All other PA metrics (sedentary time, activity fragmentation, sedentary fragmentation) were analyzed using their original unstandardized values. The optimal number of knots for each RCS model was determined using the Akaike Information Criterion (AIC), with lower AIC values indicating better model fit while penalizing model complexity. This data-driven approach allows the degree of non-linearity to vary across different PA-pain associations rather than imposing a fixed functional form.

(7) Machine learning Exploration: To evaluate the predictive utility of accelerometer-derived features for pain outcomes, we developed random forest classification models for cross-sectional prediction of current pain status and longitudinal prediction of pain relief among those with baseline pain. We extracted 778 time-frequency domain features from raw triaxial accelerometer data to capture comprehensive temporal and spectral characteristics of PA patterns. To identify the most informative features and reduce dimensionality, we applied Recursive Feature Elimination (RFE) with random forest as the base estimator. For each pain site, RFE was performed five times with different random seeds, and features were ranked by importance with the top 10, 20, and 50 features selected based on average rankings across iterations [29]. For each feature set, random forest classifiers were trained with hyperparameter optimization via GridSearchCV on the training set (80% split). The search space included: n_estimators (50, 100, 200), max_depth (5, 10, 15, None), min_samples_split (2, 5, 10), min_samples_leaf (1, 2, 4), and max_features ('sqrt', 'log2'). Model performance was assessed using area under the receiver operating characteristic curve (AUROC) as the primary metric. Cross-sectional models were evaluated via 5-fold cross-validation on the test set from 2021 data, while longitudinal models were trained on baseline (2021) data and validated on follow-up (2022) outcomes. Separate models were developed for each of the 11 pain sites, providing comprehensive evaluation across anatomical locations and temporal dynamics. All data analyses and visualizations were performed using Python (version 3.10).

Results

Participant characteristics

For the 546 participants included in our cross-sectional analysis, we conducted a comparison with the full sample of 747 participants who provided valid accelerometer data. No significant differences were found in demographic characteristics, health status, or medical history, except for a slightly lower mean SPPB score in the cross-sectional sample (8.3 ± 3.47 vs. 8.83 ± 3.37, $p = 0.005$). This difference, while statistically significant, is small in magnitude and unlikely to substantially impact our main findings. Furthermore, we compared the 490 participants in the longitudinal analysis with the 546 participants in the cross-sectional analysis. No significant differences were observed between these two groups across all examined variables. Detailed comparisons are provided in supplementary Tables 1&2.

The study cohort with a mean age of 77.8 years, predominantly concentrated in the 70–84 year range (81.78%). The cohort was 56.31% female, with 46.25% having sub-high school education and 61.73% living with a partner. Regarding health status, 66.79% reported good mental health while 32.57% experienced depressive or anxiety symptoms. Sleep disturbances were present in 37.49% of participants. Physical function assessment revealed that 52.82% had SPPB scores ≤ 9, indicating functional limitation. Mean BMI was 28.58 ± 5.95 kg/m^2 (Table 1).

Prevalence and conversion rates of pain

Pain prevalence varied across anatomical sites and changed over time. Back pain was most common, increasing from 52.7% in 2021 to 60.4% in 2022. Knee pain also rose from 34.7% to 43.5%. Neck, knee, and shoulder pain showed the largest relative increases at 66.65%, 25.31%, and 30.47%, respectively. Back pain had the highest persistence rate (87.21%), while head and arm pain had the lowest (42.5% and 41.3%). Interestingly, despite having the highest remission rates, head and arm

Table 1 Demographic characteristics

Characteristics	Distribution
Age	70–74: 141 (25.69%)
	75–79: 188 (34.24%)
	80–84: 120 (21.85%)
	85–89: 65 (11.84%)
	≥ 90: 32 (5.83%)
Gender	Male: 237 (43.17%)
	Female: 309 (56.31%)
BMI	Mean ± SD: 28.58 ± 5.95
Total activity	Mean ± SD: 1553346.13 ± 62
Activity minutes	Mean ± SD: 318.57 ± 121.64
Sedentary minutes	Mean ± SD: 761.43 ± 121.64
Activity fragmentation	Mean ± SD: 0.29 ± 0.10
Sedentary fragmentation	Mean ± SD: 0.12 ± 0.04
Highest degree	Below High Education: 254 (46.25%)
	Above High Education: 292 (53.20%)
Marital	Living with partner: 339 (61.73%)
	Living separated: 207 (37.68%)
Mental health	Mental healthy: 367 (66.79%)
	With impairment: 179 (32.57%)
Physical function	SPPB > 9: 256 (46.62%)
	SPPB ≤ 9: 290 (52.82%)
Sleep disturbance	Sleep healthy: 340 (61.86%)
	Sleep disturbance: 206 (37.49%)

pain prevalence remained relatively stable. For head pain, the high remission rate (57.50%) was offset by new onset cases (9.5% of previously pain-free individuals), resulting in a slight decrease in prevalence (-1.4% points). Similarly, for arm pain, the high remission rate (58.6%) was balanced by new onset cases (9.8% of previously pain-free individuals), leading to a stable prevalence (Table 2).

PA patterns

Figure 1a illustrates the differential PA patterns between participants with limited (≤ 1 pain site, $N = 221$) versus extensive (≥ 2 pain sites, $N = 325$) pain distribution across 24-hour periods. Both groups exhibited similar circadian rhythms, with PA intensity rising sharply from early morning (05:00–06:00), peaking during mid-morning to early afternoon (09:00–13:00 h), and gradually declining through the evening. However, participants with extensive pain consistently showed lower mean activity intensity throughout the day, with the most pronounced differences during peak activity hours (9 AM to 4 PM).

The heatmap visualization (Fig. 1b) shows that the limited pain group maintained higher activity intensity levels throughout daytime hours compared to the extensive pain group, particularly during the 08:00–18:00 window. Both groups showed minimal activity during nighttime hours. The differential heatmap (Fig. 1c) reveals a consistent pattern of lower activity in the extensive pain group concentrated during waking hours. The most substantial reductions occurred between 09:00–16:00 h, with some unexpected elevations during early morning (06:00–08:00) and late evening (20:00–22:00) hours, reflecting altered rest-activity patterns in individuals with multisite pain.

Site-specific density plot analyses (Supplementary Fig. 2) revealed that among individual pain sites, only back pain showed statistically significant differences in PA distributions: participants with back pain had lower total activity (1,484,151 ± 573,468 vs. 1,632,395 ± 664,366 counts/day, $p = 0.005$) and longer sedentary time (775.4 ± 119.4 vs. 747.0 ± 131.9 min/day, $p = 0.009$).

Cross-sectional associations between physical activity and pain

Substantial inter-individual heterogeneity and distribution gradients in PA patterns were elucidated within the cohort. Quartile distributions of activity indicators were quantified as follows: total activity (1.13 × 10^6, 1.53 × 10^6, 1.92 × 10^6, 4.48 × 10^6), active time (233, 319, 398, 770 min), sedentary time (682, 761, 847, 1074 min), activity fragmentation index (0.221, 0.267, 0.338, 0.905), and sedentary fragmentation index (0.086, 0.116, 0.144, 0.273). These quartiles were subsequently categorized as light, moderate, moderate-to-vigorous, and vigorous PA levels, respectively, for analytical purposes.

Cross-sectional analyses revealed significant associations between specific PA patterns and pain in four anatomical sites (back, feet, legs, and neck) (Supplementary Tables 4–14). Moderate sedentary time was associated with current back pain (multivariate analysis: OR = 2.24, 95%CI: 1.12–4.47, $p = 0.022$) and neck pain (multivariate

Table 2 Prevalence, sample sizes, and conversion rates of pain

Body part *n*(%)	Back	Hip	knee	Foot	Hand	Wrist	Shoulder	Head	Neck	Arm	Leg
Prevalence in 2021	258 (52.7%)	115 (23.5%)	170 (34.7%)	122 (24.9%)	118 (24.1%)	47 (9.6%)	133 (27.1%)	80 (16.3%)	78 (15.9%)	70 (14.3%)	122 (24.9%)
Prevalence in 2022	296 (60.4%)	151 (30.8%)	213 (43.5%)	150 (30.6%)	136 (27.8%)	79 (16.1%)	173 (35.3%)	73 (14.9%)	130 (26.5%)	70 (14.3%)	162 (33.1%)
Pain-no pain	33 (12.8%)	48 (41.7%)	40 (23.5%)	37 (30.3%)	48 (40.7%)	22 (46.8%)	44 (33.1%)	46 (57.5%)	29 (37.2%)	41 (58.6%)	49 (40.2%)
Ongoing pain	225 (87.2%)	67 (58.3%)	130 (76.5%)	85 (69.7%)	70 (59.3%)	25 (53.2%)	89 (66.9%)	34 (42.5%)	49 (62.8%)	29 (41.3%)	73 (59.8%)

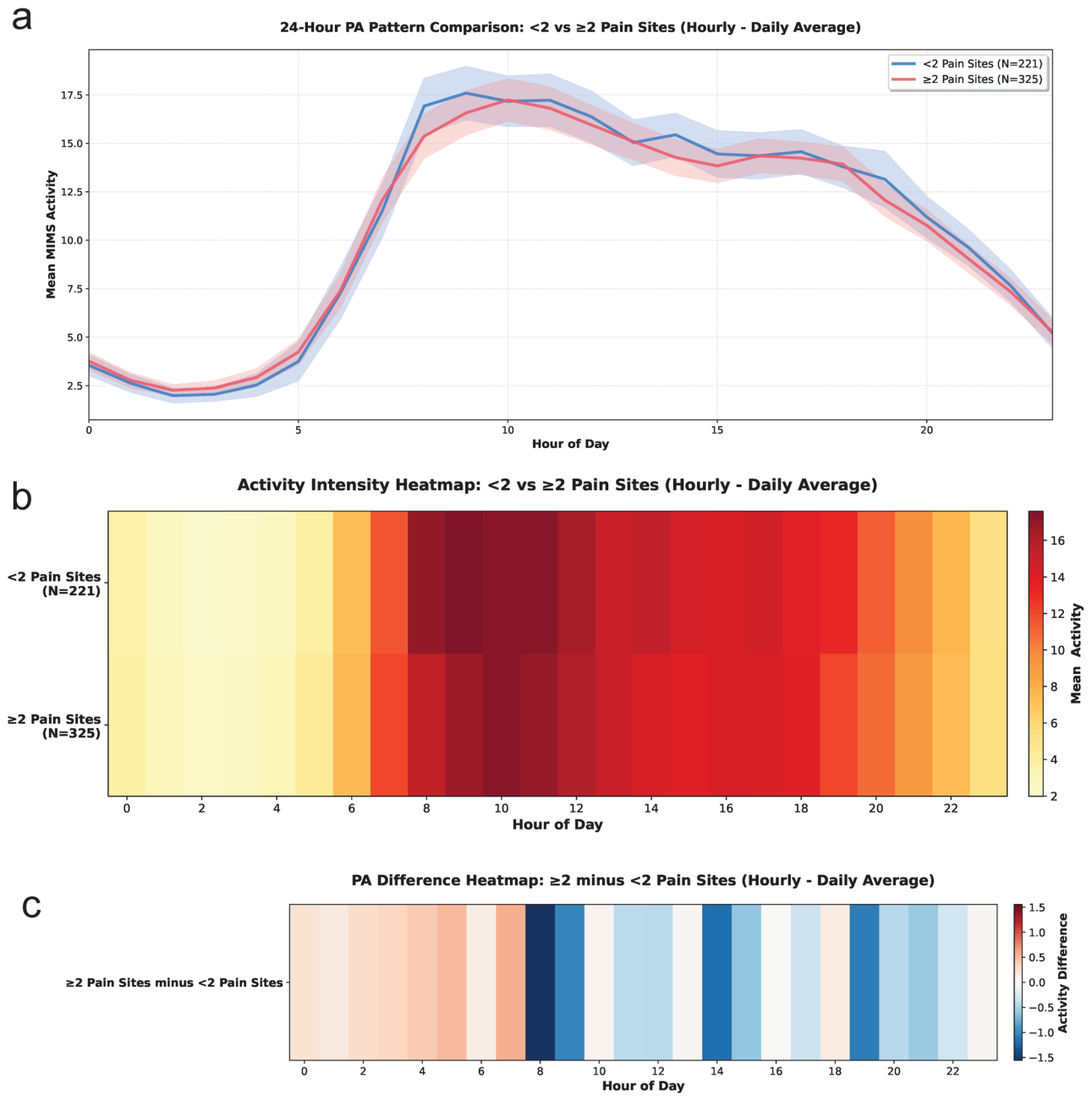


Fig. 1 24-hour Physical Activity Patterns by Pain Site Count. This figure compares the 24-hour physical activity (PA) patterns between individuals with fewer than 2 pain sites ($N = 221$) and those with 2 or more pain sites ($N = 325$), based on hourly daily averages. (**a**) Line plot showing the mean hourly physical activity across the day for both groups. The blue line represents individuals with < 2 pain sites, and the red line represents individuals with ≥ 2 pain sites. Shaded regions indicate standard errors. Both groups show similar diurnal activity patterns, peaking between 9 AM and 1 PM, but the ≥ 2 pain sites group consistently shows slightly lower activity levels throughout the day; (**b**) Heatmap depicting hourly mean activity levels for each group. Darker colors indicate higher activity levels. Individuals with fewer pain sites show higher activity intensity, particularly during morning and early afternoon hours; (**c**) Difference heatmap illustrating the hourly mean activity difference between groups (≥ 2 pain sites minus < 2 pain sites). Negative values (blue shades) indicate lower activity levels in the ≥ 2 pain sites group, most noticeably between 9 AM and 4 PM

analysis: OR = 2.12, 95%CI: 1.07–4.20, $p = 0.031$). Moderate sedentary fragmentation was associated with current foot pain (multivariate analysis: OR = 1.89, 95%CI: 1.07–3.33, $p = 0.028$). Moderate-to-vigorous activity fragmentation was associated with current leg pain (multivariate analysis: OR = 0.34, 95%CI: 0.15–0.78, $p = 0.010$). (Fig. 2a, b, c, d). To account for multiple testing across pain sites, we applied Benjamini-Hochberg FDR correction. Four associations survived FDR correction at $q < 0.05$ (all $q = 0.031$) (Supplementary Table 15).

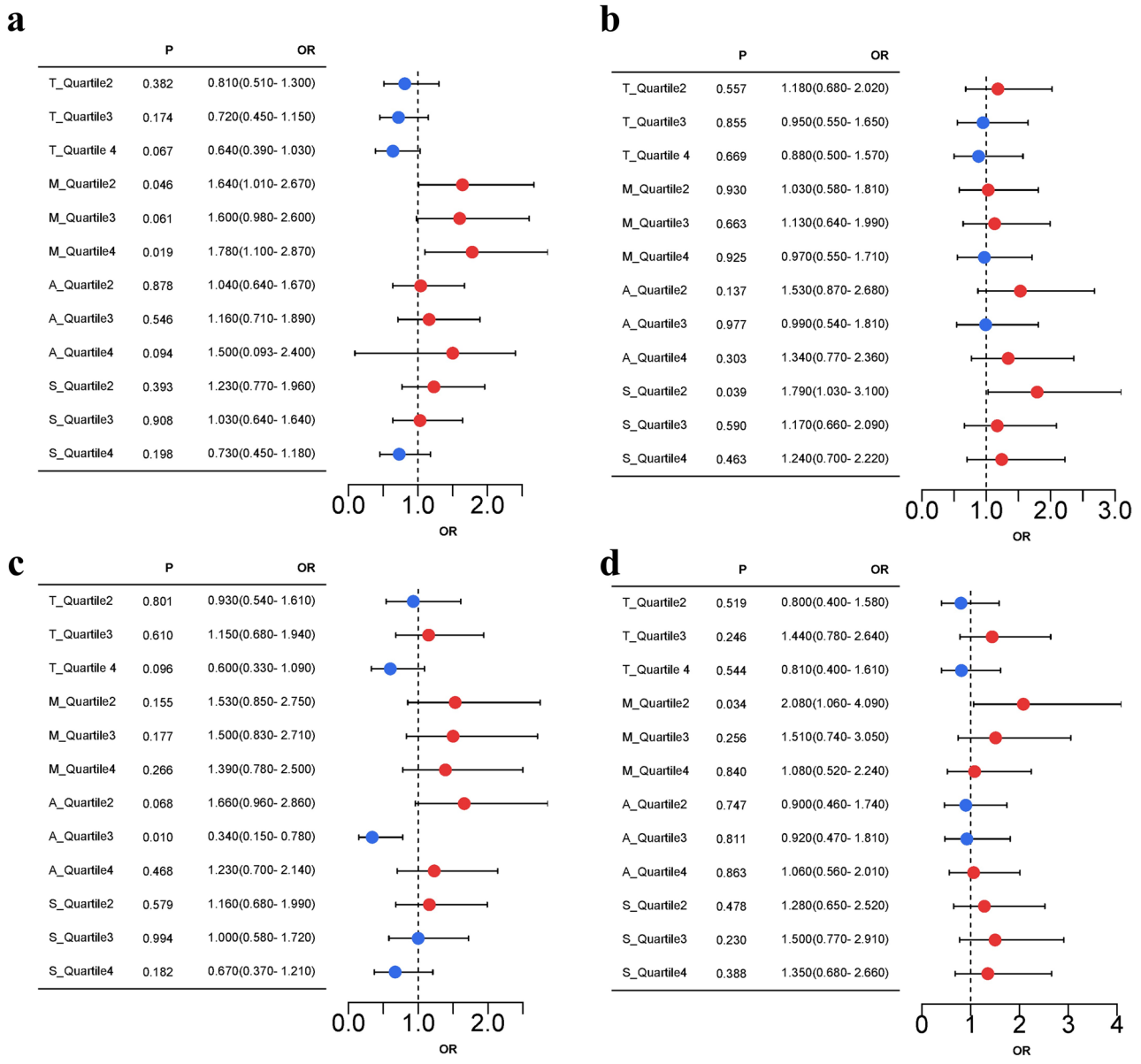


Fig. 2 Logistic regression results analysis of statistically significant physical activity pattern variables in cross-sectional analysis. (**a**) back; (**b**) foot; (**c**) Leg; (**d**) neck

Subgroup analysis

Gender-specific analyses revealed differential associations between PA patterns and current pain status. In the male subgroup, multivariate logistic regression models suggested that moderate and moderate-to-vigorous sedentary fragmentation shows associations with back pain (OR = 2.51, 95%CI: 1.20–5.26, $p = 0.02$; OR = 2.32, 95%CI: 1.11–4.86, $p = 0.03$, respectively). For knee pain, any degree of elevation in activity fragmentation is associated with knee pain (moderate: OR = 3.87, 95%CI: 1.12–13.34, $p = 0.03$; moderate-to-vigorous: OR = 5.71, 95%CI: 1.27–25.76, $p = 0.02$; vigorous: OR = 8.46, 95%CI: 1.59–44.95, $p = 0.01$). Moderate activity fragmentation demonstrated the association with shoulder pain (OR = 2.79, 95%CI: 1.09–7.14, $p = 0.03$).

In the female subgroup, Univariate logistic regression suggested that total activity counts exhibited a pattern of negative associations with back pain, with moderate-to-vigorous and vigorous total activity counts showing negative associations (OR = 0.35, 95%CI: 0.18–0.69, $p < 0.01$; OR = 0.29, 95%CI: 0.14–0.58, $p < 0.01$, respectively). Moderate sedentary time was associated with hand pain (OR = 2.11, 95%CI: 1.07–4.18, $p = 0.03$), whereas moderate-to-vigorous activity fragmentation showed a negative association with leg pain (OR = 0.38, 95%CI: 0.15–0.96, $p = 0.04$). Multivariate logistic regression models for

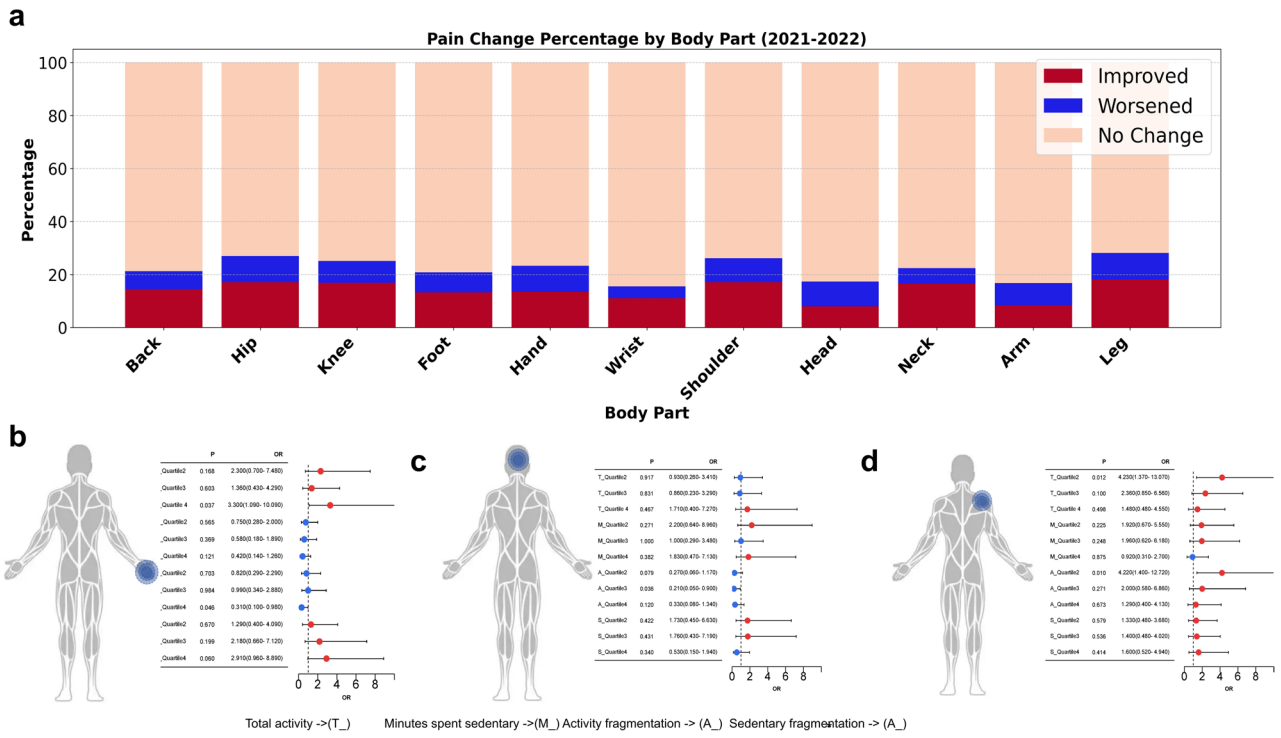


Fig. 3 Logistic regression results of statistically significant physical activity pattern variables in longitudinal analysis. (**a**) pain change from 2021 to 2022; (**b**) hand; (**c**) head; (**d**) shoulder

11 body parts adjusted for variables suggested that only moderate-to-vigorous activity fragmentation was associated with leg pain (OR = 0.24, 95%CI: 0.09–0.64, $p = 0.005$) (Supplementary Table 16).

Longitudinal findings

Longitudinal analyses examined PA predictors of pain persistence versus relief among participants reporting pain at baseline across seven anatomical sites with adequate statistical power. Figure 3a displays pain transition patterns from 2021 to 2022, showing heterogeneous trajectories across body regions. Three sites (hand, head, shoulder) showed nominally significant associations ($p < 0.05$) between baseline PA patterns and subsequent pain outcomes (Supplementary Tables 17–23).

Hand pain analyses suggested that vigorous total activity was associated with pain relief (OR = 3.30, 95%CI: 1.08–10.09, $p = 0.037$), whereas vigorous activity fragmentation was associated with pain persistence (OR = 0.31, 95%CI: 0.10–0.98, $p = 0.046$). For shoulder pain, univariate analysis indicated associations between moderate total activity and pain relief (OR = 4.23, 95%CI: 1.37–13.07, $p = 0.012$) and between activity fragmentation and pain relief (OR = 4.22, 95%CI: 1.40-12.72, $p = 0.010$). Multivariate analysis further confirmed the association between activity fragmentation and pain relief (OR = 4.46, 95%CI: 1.21–16.43, $p = 0.025$). Head pain analysis revealed that moderate-to-vigorous activity fragmentation was associated with pain relief in both univariate and multivariate analyses (OR = 0.21, 95%CI: 0.05–0.90, $p = 0.036$) (Fig. 3b, c, d). However, when applying Benjamini-Hochberg FDR correction across the pain sites, none of these associations achieved the $q < 0.05$ threshold (Supplementary Table 24). The promising associations were for shoulder (FDR q = 0.100), head (FDR q = 0.086), and hand (FDR q = 0.086) activity fragmentation. While not meeting strict statistical significance after multiple testing correction, these findings provide preliminary evidence suggesting site-specific longitudinal relationships that warrant confirmation in larger samples.

Dose-response association between PA patterns and pain

Among anatomical sites with significant associations, physical activity patterns demonstrated distinct dose-response relationships with back, foot, leg, and shoulder pain in cross-sectional study (Supplementary Figs. 3–6). Higher total activity count linearly associated with lower back pain prevalence ($p = 0.016$, p-nonlinear = 0.297), while foot and leg pain exhibited threshold effects, improving only when total activity count exceeded 1.2 and 1.0 standard deviations respectively. Activity fragmentation revealed optimal ranges for pain reduction: leg pain was lowest within 0.27–0.32 ($p = 0.019$, p-nonlinear = 0.009) and shoulder pain within 0.25–0.35 ($p = 0.023$, p-nonlinear = 0.024), with elevated prevalence at extremes. Sedentary fragmentation produced

straightforward benefits for back pain ($p = 0.033$, p-nonlinear = 0.139) and showed an inverted U-shaped relationship with leg pain ($p = 0.047$, p-nonlinear = 0.019). Sedentary time below 630 min associated with lower leg pain prevalence ($p = 0.098$, p-nonlinear = 0.040).

In the longitudinal analysis, PA patterns demonstrated limited but meaningful associations with pain trajectories (Supplementary Figs. 7–10). Total activity count showed a marginally significant relationship with hand pain ($p = 0.08$, p-nonlinear = 0.35), with higher activity count associated with greater hand pain relief over time. Sedentary time revealed no significant longitudinal associations with pain outcomes. Activity fragmentation exhibited a significant non-linear relationship with shoulder pain improvement ($p = 0.055$, p-nonlinear = 0.043), following an inverted U-shaped pattern where an activity fragmentation value of 0.25 corresponded with the greatest shoulder pain relief.

Machine learning prediction of pain outcomes

Random forest models were developed to predict current pain status using 778 time-frequency domain features, with recursive feature elimination identifying optimal feature sets of 10, 20, and 50 features (Supplementary Table 25, Supplementary Figs. 11–13). Cross-sectional model performance varied substantially across anatomical sites and feature set sizes. Back pain showed improvement with increased features (AUROC: 0.484 with 10 features to 0.563 with 50 features). Hand pain achieved the highest cross-sectional performance (AUROC = 0.588 with 50 features). Wrist pain demonstrated stable performance across feature sets (AUROC = 0.540–0.542). Head pain and arm pain showed moderate performance (AUROC = 0.517–0.568 and AUROC = 0.459–0.566, respectively). Foot and knee pain showed variable performance (AUROC = 0.426–0.528 and AUROC = 0.498–0.577, respectively). Several sites demonstrated poor discrimination, including hip (AUROC = 0.381–0.441), neck (AUROC = 0.288–0.431), shoulder (AUROC = 0.422–0.462), and leg (AUROC = 0.446–0.568). Overall, cross-sectional prediction achieved at best moderate discrimination for pain status, with only hand pain exceeding AUROC of 0.58.

Longitudinal prediction of pain relief among individuals with baseline pain showed more promising performance compared to cross-sectional prediction. Wrist pain relief achieved excellent discrimination (AUROC = 0.850 with 10 features), representing the strongest predictive performance across all anatomical sites. Back pain relief showed progressive improvement with feature complexity (AUROC: 0.655 with 10 features to 0.717 with 50 features). Head pain, arm pain, and foot pain demonstrated good to moderate performance (AUROC = 0.519–0.667, AUROC = 0.667 across all feature sets, and AUROC = 0.562–0.679, respectively). Shoulder and neck pain showed moderate performance (AUROC = 0.529–0.562 and AUROC = 0.407–0.537, respectively). Knee pain improved with more features (AUROC = 0.635 with 50 features). Hand pain declined with increased features (AUROC: 0.540 with 10 features to 0.31 with 50 features). Hip and leg pain demonstrated poor predictive performance (AUROC = 0.333–0.37 and AUROC = 0.306–0.413, respectively). Five anatomical sites (wrist, back, foot, arm, head) achieved AUROC ≥ 0.65 in longitudinal prediction. Ranking of feature importance for all predicted sites is in Supplementary file 1.

Discussion

This study provides a systematic examination of the complex relationships between accelerometer-derived physical activity patterns and multi-site pain in older adults through an integrated approach combining cross-sectional and longitudinal observational analyses with machine learning prediction models. Our research explores both cumulative patterns (total activity, sedentary time) and dynamic patterns (activity and sedentary fragmentation), revealing their differential associations across various anatomical sites. The application of machine learning approaches further demonstrates the potential utility of accelerometer-derived features in predicting pain status and pain relief, with performance varying substantially across anatomical locations.

Our cross-sectional analysis revealed site-specific associations between PA patterns and pain prevalence in four anatomical regions after controlling for multiple testing through FDR correction. Moderate sedentary time showed positive associations with both back and neck pain, suggesting that individuals spending moderate amounts of daily time in sedentary states may have higher odds of experiencing trunk pain. For lower limb pain, moderate sedentary fragmentation was associated with foot pain, while moderate-to-vigorous activity fragmentation showed an inverse association with leg pain. These patterns indicate that the temporal structure of PA may be as relevant as total activity volume in understanding pain prevalence in older adults.

Longitudinal analyses examining PA predictors of pain trajectories revealed nominally significant associations for hand, head, and shoulder pain. However, these associations did not survive FDR correction, indicating that they should be interpreted cautiously as exploratory findings rather than definitive conclusions. This highlights a key challenge in longitudinal pain research: the heterogeneity of pain trajectories and limited sample sizes for specific transition states may reduce statistical power for detecting true associations. Future studies with larger cohorts and extended follow-up periods are warranted to

confirm these preliminary longitudinal relationships and establish whether baseline PA patterns can prospectively predict pain course in older adults.

Dose-response analyses revealed complex non-linear relationships between PA patterns and pain outcomes. Total activity count demonstrated a linear inverse association with back pain prevalence, whereas foot and leg pain exhibited threshold effects showing associations only when total activity exceeded specific levels. Activity fragmentation revealed optimal ranges for several pain sites, with leg and shoulder pain prevalence lowest within specific fragmentation ranges and higher prevalence observed at both extremes.

Research on the relationship between PA and pain has evolved significantly over recent decades. Early studies using self-reported PA data identified associations between regular PA and lower prevalence of lower limb and back pain [30–32], despite limitations such as recall and social desirability biases [33, 34]. The introduction of wrist-worn accelerometers has enabled more objective PA measurement. While some studies reported that higher moderate-to-vigorous physical activity correlated with lower pain intensity and interference [35, 36], other investigations found no significant associations [37]. Our study addresses these contradictions by comprehensively analyzing both cumulative PA patterns and dynamic patterns. By introducing fragmentation indices for both activity and sedentary behavior, we extend the understanding of PA as a multidimensional construct [38–40], supporting the perspective that PA patterns may independently associate with health outcomes beyond total activity volume.

The application of machine learning methods offered distinct advantages over traditional regression approaches, particularly in handling the large number of accelerometer-derived features [41]. Our feature engineering process generated 778 features from raw accelerometry data, encompassing temporal, spectral, and statistical characteristics of movement patterns. Traditional statistical methods would face substantial challenges in this high-dimensional setting, including multiple testing burden, multicollinearity among correlated features, and limited power for detecting complex interactions. Machine learning algorithms inherently perform feature selection and can capture non-linear relationships and complex interactions without requiring pre-specification [42]. Furthermore, cross-validation procedures provide robust estimates of predictive performance that generalize beyond the training data. These capabilities enabled us to identify predictive patterns that might be obscured in conventional regression frameworks constrained by dimensionality considerations. Notably, feature importance rankings across all predicted sites consistently showed Fast Fourier Transform coefficients among the highest-ranked features. FFT features capture the spectral characteristics and periodicities of movement patterns, representing the variability and rhythmic structure of daily activities [24, 28]. The prominence of these frequency-domain features suggests that temporal variability in PA rather than simply activity volume may be a core predictive factor for pain outcomes. This finding aligns with our dose-response analyses showing optimal fragmentation ranges and supports the hypothesis that regular variation in movement patterns may be more relevant to pain than sustained activity at constant intensity levels.

This study has several notable strengths including the integration of cross-sectional and longitudinal designs with machine learning approaches, use of objective accelerometer measurements, comprehensive assessment of 11 anatomical pain sites, and application of rigorous statistical methods including power analysis and FDR correction. However, several limitations warrant consideration. The reliance on self-reported pain assessments introduces potential subjective bias. The broad binary classification of pain status does not capture pain severity, frequency, or interference with daily activities. The lack of information regarding pain duration limits our ability to differentiate between acute and chronic pain types. Sample size limitations in the longitudinal analysis reduced statistical power and likely contributed to the failure of longitudinal findings to survive FDR correction. The observational design precludes causal inference as observed associations may reflect reverse causation, confounding, or bidirectional relationships. Future studies should address these limitations through multi-modal pain assessment, integration of accelerometer data with clinical and psychosocial variables, longer follow-up periods, and larger more diverse samples.

Despite these limitations, our findings have several implications for pain management in older adults. The site-specific associations between PA patterns and pain suggest that tailored approaches considering pain location may be more effective than generic activity recommendations. The dose-response relationships identifying optimal PA ranges could inform the development of personalized activity guidelines. The differential performance of machine learning models suggests that accelerometer-based monitoring may have immediate clinical utility for certain pain types while requiring integration with other data sources for others. The prominence of frequency-domain features in predictive models suggests that interventions promoting movement variability may warrant investigation.

In conclusion, this exploratory study demonstrates complex, site-specific associations between objectively measured PA patterns and pain in older adults, with both the amount and temporal structure of activity showing

relevance. While longitudinal associations require confirmation in larger samples, the integration of traditional statistical approaches with machine learning techniques provides a comprehensive framework for understanding PA-pain relationships and highlights the potential for accelerometer-based monitoring to inform personalized pain management strategies.

Abbreviations

PA	Physical activity
MVPA	Moderate-vigorous physical activity
RCS	Restricted cubic splines
RFE	Recursive Features Elimination
KNN	K-Nearest Neighbour

Supplementary Information

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Supplementary Material 1: Supplementary figures and tables

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Author contributions
Fan L, Zhao J and Wang X contributed to the study conceptualization and drafted the initial manuscript. Luo Y, Li F and Li C verified the underlying data and statistical analyses. Liu S and Yang Y provided support on the statistical methods. Wang F and Lin T are the corresponding authors, have full access to all the data and has final responsibility for the decision to submit for publication.

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Data availability
The original data for the study are available on the NHATS website: https://www.nhats.org/researcher/nhats.

Declarations

Ethics approval and consent to participate
The study protocol for the NHATS was approved by the Johns Hopkins Bloomberg School of Public Health Institutional Review Board (JHM IRB), under study protocol # IRB00077995. All participants provided written informed consent. Institutional review board approval was exempted for this study because of the publicly available and deidentified data.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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