Predicting Frailty Using Motor and Heart Rate Interconnection: Application of Convergent Cross Mapping to Identify Autonomic Dysfunction

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Abstract

Frailty is a common syndrome in older adults, marked by low physiological reserve, which can lead to an increased vulnerability to stressors. We utilized a validated upper-extremity function (UEF) test that involves 20-second rapid arm flexion to assess motor and cardiac performance. One hundred and seventy two older adults (≥65 years) were recruited and classified as non-frail, pre-frail, and frail using the Fried phenotype. For UEF, wearable motion sensors captured elbow angular velocity, and heart rate (HR) was continuously recorded using an ECG wearable recording system. The dynamic interconnection between angular displacement and HR was assessed using convergent cross-mapping (CCM). ANCOVA (adjusted for age, sex, and BMI) tested differences between the three frailty groups; effect sizes were reported. Across groups, HR increase differed significantly with smaller changes with frailty ($p < 0.01$; effect size = 0.15), HR recovery showed a trend toward group differences with smaller recoveries for frail individuals ($p = 0.06$; effect size = 0.19), and the HR–motor correlation decreased with frailty ($p < 0.01$; effect size = 0.33). This approach captures both cardiac and motor function within less than two minutes of a physical task while seated, to provide a unique tool for quick and objective assessment of frailty in a clinical setting.

1. Introduction

Frailty reflects diminished reserve across systems and includes autonomic dysregulation, seen as reduced heart rate variability (HRV) and complexity and blunted cardiac response to stressors [1]. Therefore, not only resting heart rate (HR) measures but also HR dynamics during and after physical activity may serve as potential markers of autonomic–cardiac resilience and frailty.

Conventional frailty tools, such as the Fried's phenotype and the Rockwood Frailty Index are useful but labor-intensive, partly subjective, and often impractical for patients with mobility limitations when gait testing is required [2]. A further gap is that existing tools rarely target cardiac function as a biomarker of frailty. To address these gaps and capture both motor and cardiac aspects, we use a previously validated 20-s seated upper-extremity function (UEF) test while recording motion and HR signals [3].

Frailty likely arises from dysregulation between systems rather than within a single system [2]. Building on the UEF platform, we assess motor–cardiac dynamic interaction using the convergent cross-mapping (CCM) approach; prior pilot data showed weaker interaction in pre-frail/frail adults compared to non-frails and suggested that CCM features improve discrimination beyond HR dynamics and motor metrics [2].

Within a larger sample incorporating distinct pre-frail (intermediate stage of frailty) and frail older adults, in the current work, we evaluated four metrics, HR increase during UEF, HR decrease during recovery, CCM correlation, and MSE (the mean-squared prediction error from CCM), to determine their association with frailty stages. We hypothesized a graded pattern across non-frail, pre-frail, and frail, with particular focus on distinguishing pre-frail from frail and pre-frail from non-frail older adults.

2. Materials and Methods

2.1. Participants

We enrolled community-dwelling and clinic-referred adults ≥65 years, with or without advanced heart disease, from primary/community sources and from cardiac surgery clinics at Robert Wood Johnson (NJ) and Banner (AZ). Inclusion criteria were the ability to walk 15 ft for frailty assessment and the capacity to understand and sign informed consent. Exclusions were major motor/neurological disorders (e.g., Parkinson's disease, multiple sclerosis, and recent stroke); severe upper-extremity conditions precluding the UEF task (e.g., bilateral elbow fractures and rheumatoid arthritis); severe cognitive impairment; and terminal illness. To avoid biased HR measurements, we also excluded subjects with arrhythmias, implanted pacemakers, and those currently using β-blockers or similar agents [4]. All participants provided written informed consent; the study was approved by Rutgers University and University of Arizona IRBs and conducted in accordance with the Declaration of Helsinki.

2.2. Frailty Assessments and Clinical Measures

Frailty was classified using the five-component Fried phenotype, including: (1) unintentional weight loss ≥4.5 kg in the past year; (2) weak grip strength (sex/BMI-adjusted); (3) slow 15-ft gait speed (height/sex-adjusted); (4) self-reported exhaustion (2-item CES-D); and (5) low physical activity (short Minnesota Leisure-Time Activity Questionnaire) [5]. Participants were labelled non-frail (0 criteria), pre-frail (1–2 criteria), or frail (≥3 criteria). Clinical covariates included cognition (MoCA), comorbidities (Charlson Comorbidity Index), and depressive symptoms (PHQ-9).

2.3. UEF Test and HR Assessment

Participants rested in a seated position for 2 minutes, performed a 20-second right-arm UEF (rapid arm flexion–extension), then rested another 2 minutes. Prior work showed comparable UEF outcomes for the left/right arms. A brief left-arm practice standardized instruction [6]. Upper-limb kinematics were recorded with two triaxial inertial sensors (LEGSys, BioSensics; 100 Hz) on the right forearm and upper arm; angular velocity was high-pass filtered at 2.5 Hz, flexion cycles were detected, and the continuous kinematic series (motor data) was retained for CCM analysis. Cardiac activity was acquired using a wearable ECG (360° eMotion Faros, Mega Electronics; ECG 1000 Hz; accelerometer 100 Hz) with two left-chest electrodes (upper mid-thorax and inferior to the left rib cage) to obtain an ECG signal with synchronized accelerometry for precise identification of task start/stop. R-peaks were detected via a Pan–Tompkins algorithm with visual verification to generate beat-to-beat HR [7]. Primary cardiac outcomes were HR dynamics, including HR increase during UEF and HR decrease during recovery. HR and motor time series were time-aligned, and their interconnection was quantified using CCM.

2.4. CCM Analysis

We quantified directional nonlinear coupling between HR and motor kinematics using CCM, which tests whether past values of one signal can predict the other. Both series were resampled to 10 Hz (0.1-s intervals) via spline interpolation. Each HR data point represents average HR values over 0.1-s, and the corresponding motor samples were the angular displacement over each 0.1-s of UEF, computed by integrating the rectified elbow angular velocity (denoted by M_f, Eq. 1)

$$M_{f_i} = \int_{t_i}^{t_i+0.1} \omega_e dt, \quad (1)$$

Here, ω_e denotes the rectified elbow angular velocity.

By Takens' embedding theorem, the state of a dynamical system can be reconstructed from a single observed series $X(t)$ using delay coordinates [2]. The reconstructed (shadow) manifold, $\boldsymbol{M}_X$, is formed by E-dimensional vectors built from lagged samples spaced by τ, as in Eq. (2):

$$M_X = \langle X(t), X(t-\tau), X(t-2\tau) \dots X(t-(E-1)\tau) \rangle \quad (2)$$

We built E-dimensional delay-embedded manifolds for both series and set $E = 4$ from the false nearest neighbors criterion, with a lag (τ) of 1-s from delayed mutual information. Using a k-nearest neighbors predictor with $k = E + 1$, we performed directional prediction by locating the k nearest points of the source manifold, mapping their time indices to the target series, and forming a distance-weighted average to estimate the target value, as in Eq. (3); motor-to-HR and HR-to-motor were computed.

$$\hat{Y}(t) = \sum_{i=1}^{E+1} \omega_i Y(t_i), \quad (3)$$

Here, $Y(t)$ is the original HR time series, and $\hat{Y}(t)$ is the predicted HR value at time t. The weights ω_i were computed based on the relative Euclidean distances between points in the source manifold and its i^{th} nearest neighbors. CCM strength was summarized by the Pearson correlation coefficient r between the predicted and observed target series, and by the mean squared error (MSE) to capture the magnitude of prediction error.

2.5. Statistics

Normality was assessed with the Shapiro–Wilk W test; variables failing normality were rank- or log-transformed. Group differences in numeric demographics (age, height, weight, and BMI) were examined with univariate ANOVA, and sex distributions with chi-square. For outcomes, ANCOVA tested three-group differences (non-frail/pre-frail/frail) for each dependent variable, adjusting for age, sex, and BMI. Effect sizes for the three-group ANCOVAs were quantified as Cohen's f and computed in G*Power. All analyses were conducted in JMP Pro (version 18; SAS Institute Inc., Cary, NC, USA), with significance set at $p < 0.05$.

3. Results

We enrolled 172 older adults (40 non-frail, 104 pre-frail, and 28 frail as defined by Fried); age and BMI differed across groups (p<0.04), while sex distribution was comparable (χ^2 p=0.11) (Table 1). During the UEF task, HR increased in all groups but less with greater frailty level: the frail group showed a 31.9% smaller increase than non-frail and 15.4% smaller than pre-frail, with a significant three-group effect (p<0.01; effect size=0.15). Post-task recovery showed the same pattern; using the absolute HR percent decrease, the frail group recovered 30.8% less than non-frail and 15.8% less than pre-frail, with a trend for three-group differences (p=0.06; effect size=0.19). Motor–cardiac coupling also weakened with frailty; the HR–angle correlation declined across groups (p<0.01; effect size=0.33), 26% lower in frail vs non-frail and 11.4% lower vs pre-frail, while prediction error (MSE) increased across groups (p<0.01; effect size=0.29), indicating progressively weaker coupling (Figure 1).

Table 1. Participant Demographics by Frailty Status

Demographic Information	Non-frail (n = 40)	Pre-frail (n = 104)	Frail (n = 28)
Age (mean ± SD)	71.2 ± 8.4	77.4 ± 9.1	77.9 ± 8.7
Female, n (%)	23 (58%)	58 (56%)	10 (36%)
BMI (mean ± SD)	25.8 ± 4.8	28.2 ± 5.5	28.9 ± 6.6

4. Discussion

This study demonstrates that both HR dynamics and heart–motor interactions obtained during the UEF test were significantly different across frailty groups. Frail adults showed attenuated HR increase during UEF, slower post-task HR recovery, and weaker heart–motor coupling compared with pre-frail and non-frail peers. Together, these group differences align with autonomic dysregulation in frailty, which is caused by an imbalance between sympathetic and parasympathetic control. This imbalance between sympathetic/parasympathetic control indicates a reduced capacity to mount and recover from stress responses [8].

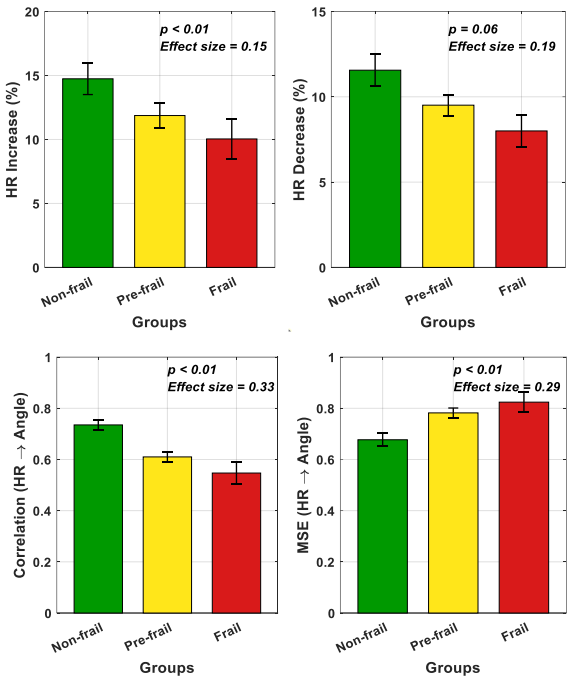

Figure 1. Group differences in HR response and heart-motor coupling across frailty groups

HR dynamics in response to UEF provide a sensitive marker of autonomic dysfunction in frailty. Unlike resting HRV, whose utility is limited by between-subject variability, diurnal fluctuation, and sensitivity to breathing and environmental conditions, HR dynamics capture sympathetic activation during movement and parasympathetic rebound during recovery, yielding a dynamic index of cardiac resilience; the significant group differences we observed support this value [9]. In our cohort, baseline HRV metrics commonly used to index autonomic balance, SDRR (standard deviation of RR intervals), RMSSD (root mean square of successive RR differences), pNN50 (percentage of successive RR intervals differing >50 ms), and non-linear Poincaré indices SD1/SD2, showed no significant three-group differences in ANCOVA (non-frail/pre-frail/frail), adjusting for age, sex, and BMI (all p>0.2), indicating that resting HRV did not discriminate frailty status in this sample. In contrast, task-evoked HR dynamics did [10]. Complementing HR dynamics, CCM quantified HR–motor dynamic interaction and showed weaker coupling in frail participants, indicating reduced cross-system integration.

From a clinical standpoint, these findings are highly relevant for populations with advanced heart disease, where frailty is common and disease-specific tools are limited. The UEF-based approach is brief, requires minimal mobility, and can be performed at the bedside, making it feasible for patients unable to complete walking-

based frailty tests. The clear group differences support integrating task-evoked HR dynamics and heart–motor coupling into a multimodal frailty risk score. Also, we have already validated the feasibility of smartwatch-based frailty assessment using built-in gyroscopes and PPG sensors. The future integration of these measures into wearable platforms could enable practical monitoring in both clinical and home settings [11].

Future studies should recruit larger, balanced samples across frailty groups, include longitudinal follow-up, and test reproducibility in diverse clinical populations.

5. Conclusion

We introduced a brief, seated multimodal assay that combines HR dynamics with motor–cardiac coupling quantified by CCM during a 20s UEF task to index autonomic and motor resilience in older adults. Frailty was associated with a blunted HR increase during the task and an attenuated HR decrease during recovery, whereas resting HRV features were not discriminatory, highlighting the value of dynamic HR responses in frailty assessment. CCM captured the dynamic interaction between physiological systems and differed significantly among the three frailty groups (non-frail, pre-frail, and frail). Using CCM, we could assess coupling deficits between frail and pre-frail (the intermediate stage of frailty), demonstrating clear stage sensitivity. HR dynamics showed the same pattern of groupwise differences and stage sensitivity. Because UEF is short, objective, and feasible even for hospitalized or bed-bound patients, this approach can complement or substitute walking-based assessments when mobility is limited. This work establishes the CCM-based integration of motor and cardiac performance as a candidate frailty marker in cardiac patients, which, to our knowledge, has not been reported. Using the current work as a proof of concept, future work will develop and validate a multimodal frailty score that includes motor performance and cardiac dynamics to improve the generalizability of our frailty assessment scoring system.

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