Detecting Pre-Frailty and Frailty Using Free-Living Activity Monitoring from a Thigh-Worn Sensor

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Objectives

Low-burden frailty screening in senior housing:

- 10-day thigh-worn accelerometry to classify robust vs. pre-frail/frail.
- Compare two definitions: Fried Frailty Phenotype (FFP) vs. CGA-based Frailty Index (CGA-FI).
- Benchmark ridge, lasso, random forest, and neural network on 36 movement features.

Background

- Frailty elevates risk of falls, hospitalization, and mortality; pre-frailty often goes unnoticed.
- Wearable sensing offers scalable screening with less clinical burden.
- Thigh-mounted accelerometers capture gait, posture transitions, and diurnal rhythms with strong validity in older adults.
- Few free-living studies compare frailty definitions; we test 10-day ActivPAL data to classify robust vs. pre-frail/frail under FFP and CGA-FI and identify definition-specific drivers.

Data Collection

- Participants (N=44) were senior-housing residents (age 63–97; 84% women) from five HSL sites.
- ActivPAL devices (20 Hz) were worn continuously for 10 days; valid days required ≥20 h wear.
- PAL Suite GHLA algorithm labeled walking, standing, and sitting/lying; daily means/SDs were averaged across 10 days and paired with intra- and inter-daily stability metrics.
- CGA-FI and FFP were assessed in-person.
- Frailty counts: FFP (8 robust, 26 pre-frail, 10 frail) and CGA-FI (16 robust, 16 pre-frail, 12 frail), binarized as Robust vs. Pre-frail/Frail.

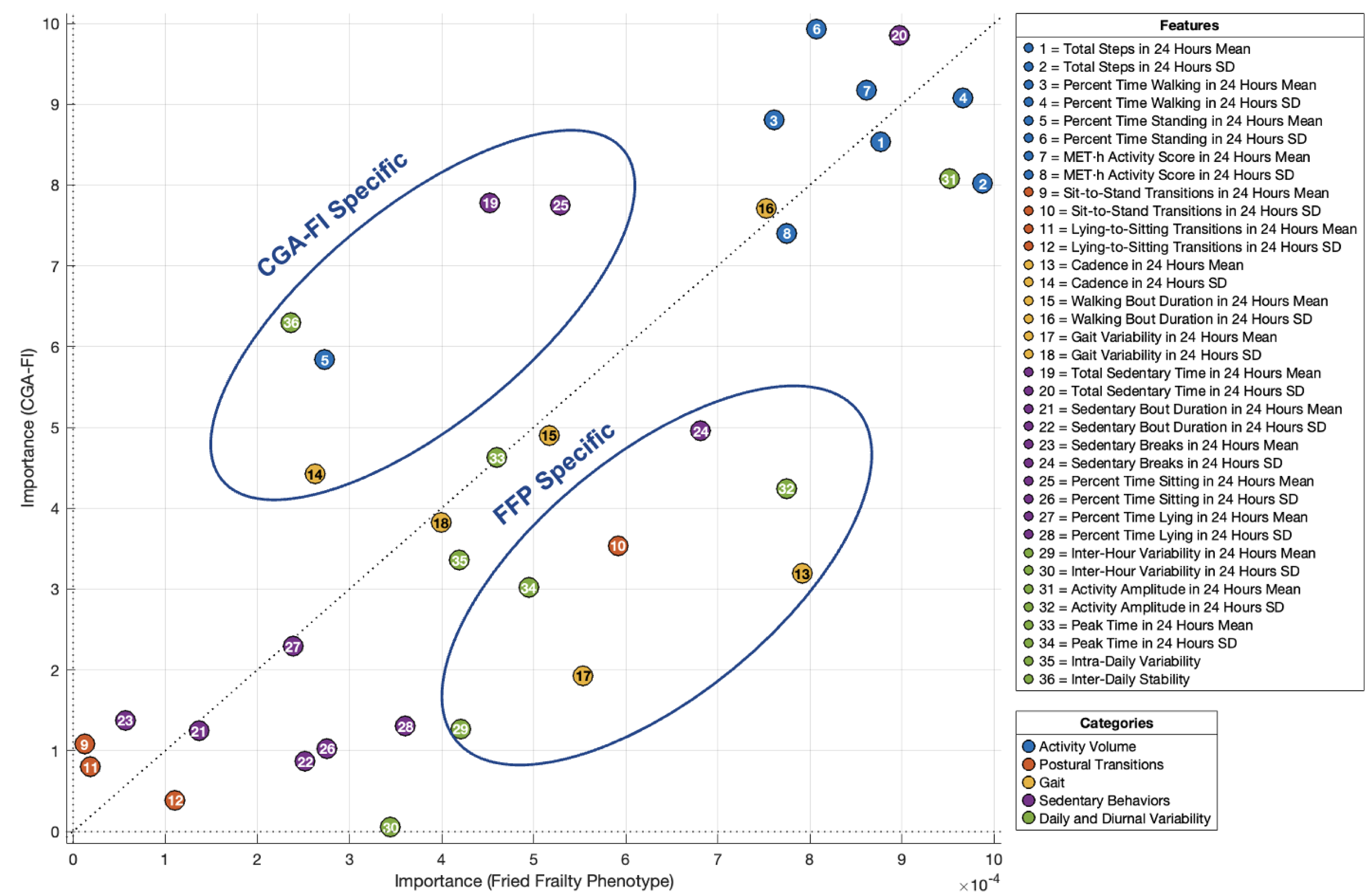

Figure 1. Ridge model feature importance for FFP and CGA-FI classifications.

Sensor-Derived Features

Thirty-six ActivPAL metrics summarized 10 days of wear.

- Activity volume: steps, walking/standing time, MET-h.
- Transitions and gait: cadence, speed, sit-to-stand counts.
- Sedentary accumulation: total time, bouts, breaks, % sitting/lying.
- Diurnal patterns: inter-hour variability, activity amplitude, peak time, intra-/inter-daily stability.

Machine Learning Pipeline

- Models: ridge, lasso, 200-tree random forest, and a 2-layer neural net (8/4 ReLU, softmax).
- Stratified 5-fold CV repeated 20x. Train-fold Z-scoring and balanced class weights.

Results

Model	FFP	CGA-FI
Ridge logistic	0.81	0.78
Random forest	0.74	0.70
Lasso logistic	0.69	0.69
Neural network	0.67	0.69

Table 1:Model performance (AUC) for classifying Robust vs. Pre-Frail/Frail under FFP and CGA-FI definitions.

- Ridge logistic regression performed best (FFP: AUC 0.81, F1 0.77; CGA-FI: AUC 0.78, F1 0.77).
- Shared predictors: lower activity volume, greater total sedentary time, reduced daily activity amplitude.
- FFP leaned more on gait metrics; CGA-FI leaned more on sedentary accumulation and inter-daily rhythm stability.

Conclusion

- Ten days of thigh-worn accelerometry distinguished robust vs. pre-frail/frail for both FFP and CGA-FI.
- Ridge delivered the best performance by AUC, showing lightweight models can handle correlated wearable features.
- Continuous passive monitoring was feasible in senior housing (100% valid wear).
- Daily variation and sedentary accumulation were stronger signals than volume alone.
- Overlapping predictors suggest common physiological underpinnings across definitions.
- Some predictive features diverged by definition. Wearable-based frailty tools should declare the targeted definition and consider generalizability.

Limitations & Next Steps

- Small, demographically narrow sample (N=44; single housing network) limits generalizability.
- Cross-sectional design requires external validation for predictive utility.
- Next: larger and more diverse cohorts, testing consumer wearables, and comparing additional frailty definitions and intrinsic capacity metrics.

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