

Supplementary Information

Participant-Independent Lower-Limb sEMG and Knee-Goniometry Profiles Across
Movement Tasks in a Public Knee-Abnormality Cohort

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Supplementary technical annex

1 Recording-level out-of-fold predictions

Table 1 lists every recording-level prediction from the combined model. The participant code is a repository-derived analysis key; all three rows with one code were predicted by a model fitted without any record from that participant. The probability column refers to membership in the repository abnormality group and is not a probability of a named diagnosis.

Table 1: Participant-held-out recording predictions.

Participant	Task	Samples	Observed	Predicted	Probability
A01	seated task	16854	1	0	0.181
A01	standing task	11403	1	1	0.538
A01	walking	12973	1	1	0.593
A02	seated task	13677	1	1	0.733
A02	standing task	12834	1	0	0.324
A02	walking	11075	1	1	0.619
A03	seated task	38971	1	1	0.583
A03	standing task	22124	1	1	0.864
A03	walking	43665	1	1	0.720
A04	seated task	30073	1	1	0.827
A04	standing task	33514	1	1	0.837
A04	walking	56544	1	1	0.781
A05	seated task	25258	1	1	0.559
A05	standing task	19669	1	1	0.583
A05	walking	46045	1	1	0.631
A06	seated task	69374	1	1	0.815
A06	standing task	43693	1	1	0.806
A06	walking	51376	1	1	0.946
A07	seated task	14205	1	1	0.846
A07	standing task	15521	1	1	0.830
A07	walking	15725	1	1	0.847
A08	seated task	14912	1	1	0.553
A08	standing task	16572	1	1	0.706
A08	walking	10187	1	0	0.377
A09	seated task	18706	1	0	0.390
A09	standing task	21791	1	0	0.364
A09	walking	32080	1	0	0.390
A10	seated task	19740	1	0	0.455
A10	standing task	16748	1	0	0.311
A10	walking	22896	1	0	0.235
A11	seated task	25302	1	0	0.427
A11	standing task	19425	1	0	0.196
A11	walking	27583	1	0	0.396
N01	seated task	15300	0	0	0.041
N01	standing task	14520	0	0	0.184
N01	walking	5681	0	0	0.436
N02	seated task	15300	0	0	0.040
N02	standing task	14520	0	0	0.188
N02	walking	7384	0	0	0.369
N03	seated task	16860	0	1	0.721
N03	standing task	9539	0	0	0.495
N03	walking	6922	0	0	0.488
N04	seated task	15600	0	1	0.638
N04	standing task	13820	0	0	0.243
N04	walking	7522	0	0	0.117
N05	seated task	13480	0	0	0.168
N05	standing task	15260	0	0	0.234
N05	walking	6563	0	0	0.182
N06	seated task	20500	0	0	0.073

Participant	Task	Samples	Observed	Predicted	Probability
N06	standing task	15480	0	0	0.400
N06	walking	7300	0	0	0.129
N07	seated task	22460	0	0	0.392
N07	standing task	15940	0	1	0.731
N07	walking	8147	0	1	0.784
N08	seated task	24160	0	0	0.412
N08	standing task	18340	0	1	0.580
N08	walking	9227	0	0	0.459
N09	seated task	21140	0	0	0.305
N09	standing task	22860	0	0	0.410
N09	walking	5343	0	0	0.241
N10	seated task	29220	0	1	0.536
N10	standing task	36900	0	0	0.461
N10	walking	5845	0	0	0.159
N11	seated task	16848	0	1	0.889
N11	standing task	10659	0	1	0.881
N11	walking	5890	0	1	0.964

2 Acquisition-confound audit

Recording duration is an acquisition quantity that can encode task execution, operator instructions, or group-specific protocol handling. In these data it differs substantially between repository groups. Raw detected-peak count is mechanically related to duration and was excluded for the same reason. Peak rate divides the count by record duration and is less directly confounded, although it remains sensitive to the peak detector and task structure.

Excluding obvious shortcuts does not guarantee the absence of confounding. Signal amplitude can still reflect electrode placement, gain, skin impedance, or body composition. Angle range can reflect starting posture or instructions. A prospective design should standardize these quantities or record them so that their influence can be modeled. The current analysis treats them as limitations rather than retroactively assigning a physiological cause.

Table 2: Potential shortcuts and their handling.

Variable or signal	Risk	Handling in the present analysis
Recording duration	Encodes protocol and task completion time	Excluded from all classifiers; reported by group and task
Raw peak count	Scales with record duration	Excluded; duration-normalized peak rate retained
File name	Directly encodes group and task	Used only to construct metadata, never as a predictor
Raw sample count	Equivalent to duration at fixed sampling rate	Excluded from all classifiers
sEMG amplitude	Sensitive to electrode and anatomy	Median-centered; interpreted as acquisition-scale, not normalized activation
Angle offset	Sensitive to goniometer zero	Range, dispersion, and velocity emphasized over absolute mean

3 Feature reproducibility specification

Every feature is computed once per complete record. Median centering is applied independently to each sEMG channel. Frequency features use the periodogram over the full record and therefore describe an average spectrum rather than time-varying fatigue. Zero crossings use a threshold based on one percent of the channel standard deviation to suppress very small sign changes. The Savitzky–Golay smoothing window for angle is bounded by record length and is always odd. These rules are deterministic and require no information from the held-out participant.

The combined configuration contains all eligible sEMG and goniometry features after excluding duration and raw peak count. The sEMG-only and goniometry-only configurations are strict subsets. Standardization is estimated separately inside each training fold. This is essential because whole-cohort standardization would leak held-out participant distribution information even if labels were not used.

4 Clinical-claim boundary matrix

Table 3: Claims supported and not supported by the repository.

Claim type	Status	Reason
Repository-group discrimination	Supported descriptively	Group label and participant-level recordings are available
Task heterogeneity	Supported descriptively	Each participant has three labeled task records
Named-condition diagnosis	Not supported	Diagnosis type, reference standard, severity, and laterality are absent
Treatment response	Not supported	No intervention or longitudinal outcome is present
Causal muscle mechanism	Not supported	Observational group contrast with uncontrolled acquisition factors
Population prevalence	Not supported	Balanced convenience sample and no sampling frame
External deployment	Not supported	One repository, small cohort, no independent device or site

5 Prospective replication protocol

A condition-specific replication should recruit a prespecified clinical group and a comparison group using the same eligibility framework. Reference diagnosis, laterality, symptom severity, age, sex, body size, activity level, and relevant comorbidities should be recorded. Electrode sites should follow anatomical landmarks, skin preparation should be documented, and sEMG should be normalized to a reproducible contraction reference. Goniometer calibration and synchronization should be checked before each session.

Participants should repeat walking, standing, and seated tasks on at least two days with sensor removal and reattachment. Task speed and number of repetitions should either be standardized or treated as measured covariates. Model development should use nested participant-level folds, and one independent cohort should remain untouched for final validation. The final report should include diagnostic-target definitions only if a valid reference standard is collected; otherwise it should retain movement-profile language.

6 Modality contribution and probability interpretation

The combined feature configuration reached balanced accuracy 0.682 and macro-F1 0.681 under participant-level validation. The sEMG-only configuration reached 0.621 and 0.620, while goniometry alone reached 0.561 and 0.556. The combined-minus-sEMG macro-F1 difference was therefore 0.061, and the combined-minus-goniometry difference was 0.126. These contrasts show incremental information under one fixed pipeline; they do not establish causal importance of a modality or statistical superiority in a larger population.

Probability metrics add a different view. sEMG-only ROC AUC was 0.710, slightly above the combined value of 0.697, while its Brier score was 0.221 compared with 0.224 for the combined model. Goniometry-only ROC AUC was 0.627 with Brier score 0.245. Expected calibration error was lowest for goniometry alone (0.026), but a low calibration error can coexist with weak discrimination when probabilities remain close to the base rate. The modality comparison must therefore consider threshold-free ranking, thresholded classification, and probability accuracy together.

The bootstrap interval for combined macro-F1 was wide (0.500–0.818), reflecting only 22 participants. Intervals for sEMG-only (0.442–0.770) and goniometry-only (0.485–0.606) also caution against precise ranking. A larger replication should prespecify a smallest relevant performance difference, use paired participant-level resampling, and retain an external cohort for the final contrast.

7 Task heterogeneity and acquisition confounding

Task-stratified macro-F1 was 0.636 for the seated task, 0.681 for the standing task, and 0.725 for walking. Each stratum contains one record per participant, so these values are descriptive and have limited precision. They nevertheless show that a single pooled score does not characterize every movement context. Task-specific signal amplitude, joint excursion, record duration, and muscle recruitment can alter both separability and model confidence.

Duration is a major confounding concern. Mean walking-record duration was approximately 30.01 s in the knee-abnormality group and 6.89 s in the comparison group, with a standardized difference of 1.91. Duration and raw peak count were excluded from the model, but record length can still affect the stability of RMS, spectral, and range features. Excluding a duration variable does not erase acquisition differences embedded in other summaries. A prospective study should standardize repetition count or analyze equal-duration segments before interpreting group discrimination as biomechanical separation.

Feature effects were task dependent. Vastus medialis RMS showed a standardized difference of 1.65 during standing and 0.55 during walking, but only 0.10 during the seated task. Knee-angle range was higher in the repository abnormality group during the seated task (standardized difference

1.25) but lower during standing and walking. Velocity RMS was lower in the abnormality group during walking (standardized difference -1.02). These patterns justify movement-profile language and argue against collapsing all tasks into one mechanistic claim.

8 Minimum requirements for clinical translation

A clinically interpretable study would need a named target condition, reference-standard diagnosis, severity, laterality, symptoms, treatment status, and eligibility criteria. It would also need sEMG normalization, electrode-placement reliability, joint-angle calibration, and repeated sessions. Performance should be estimated for a prespecified clinical decision, not merely for the balanced repository labels. Decision-curve analysis or clinical utility claims are inappropriate until the consequences of false-positive and false-negative classifications are defined.

External validation must preserve the complete pipeline. Signal filtering, feature extraction, scaling, model parameters, and thresholds should be locked before the external cohort is accessed. Reporting should include participant flow, missing recordings, protocol deviations, classwise errors, calibration, and uncertainty clustered by participant. Until those obligations are met, the present results remain a participant-independent secondary analysis of public movement records rather than a diagnostic model.

9 Feature dictionary

Table 4: Feature definitions and interpretation limits.

Family	Features	Interpretation limit
sEMG amplitude	RMS, mean absolute value	Acquisition-scale amplitude; not normalized force or activation percentage
sEMG waveform	Mean absolute first difference, thresholded zero crossing	Descriptive complexity; affected by noise and filtering
sEMG spectrum	Median frequency, normalized spectral entropy	Whole-record summaries; not localized fatigue trajectories
Cross-muscle	Anterior/posterior RMS ratio, four-muscle coefficient of variation	Descriptive balance; not a validated co-contraction index
Knee angle	Range, standard deviation	Depends on calibration and task execution
Angular velocity	RMS and peak absolute velocity	Derived from smoothed angle and nominal sampling rate
Repetition tempo	Peaks per second	Duration-normalized; peak detector depends on prominence rule
Protocol audit	Duration and raw peak count	Excluded from classifiers because they can encode acquisition design

10 Participant-level validation contract

All three records from a participant remain in one test fold. Standardization parameters are fitted on the 21 training participants and applied to the held-out participant. The logistic model is then fitted without access to held-out labels. This cycle is repeated for all participants, and each record receives exactly one out-of-fold probability. Modality comparisons use the same folds and regularization so that only the feature family changes.

11 Interpretation checklist

1. Do not call the repository group a single diagnosis.
2. Do not use recording duration, file name, or raw sample count as predictors.
3. Keep all tasks from one participant in the same fold.
4. Report modality-only baselines before interpreting a combined model.
5. Stratify by task because effect direction can change across movements.
6. Treat whole-record sEMG amplitude as acquisition-scale unless normalization data are available.
7. Reserve sensitivity, specificity, and clinical utility language for a prospective diagnostic design.
8. Report uncertainty at the participant level, not at the sample level.

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