

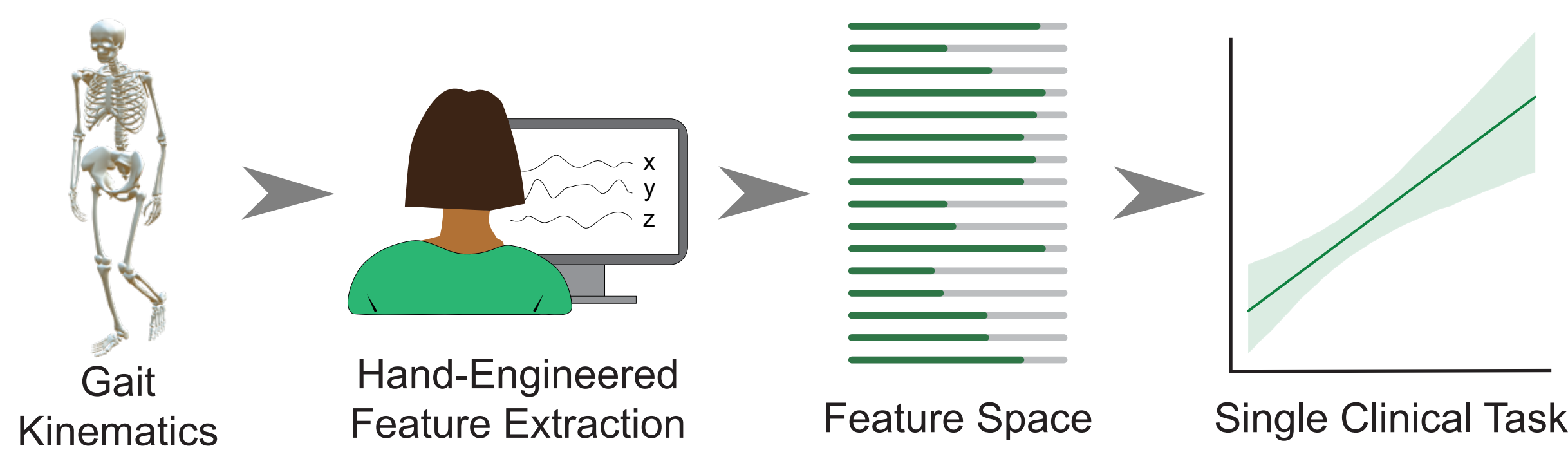


Towards a foundational model of pathological gait kinematics



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Introduction

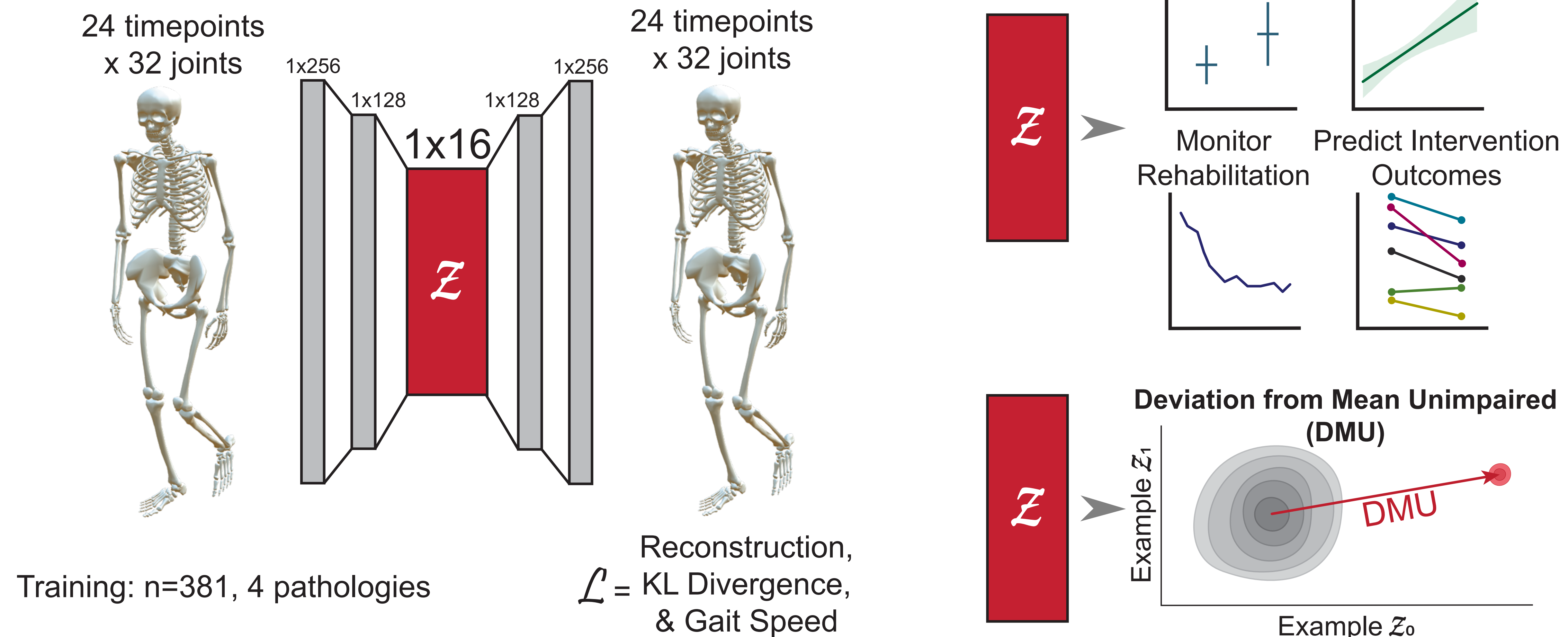


Traditional task-specific modeling

- Recent advancements in markerless motion capture have enabled accurate biomechanics in clinics [1].
- Despite this accessibility, deriving actionable insights from gait data remains a challenge [2].
- Machine learning models show promise, but require large pathology specific datasets [3], which limits generalizability to unseen pathologies.

We aim to enable automated gait analysis that generalizes across diverse pathologies and supports a range of clinically relevant tasks.

Semi-supervised gait kinematics model



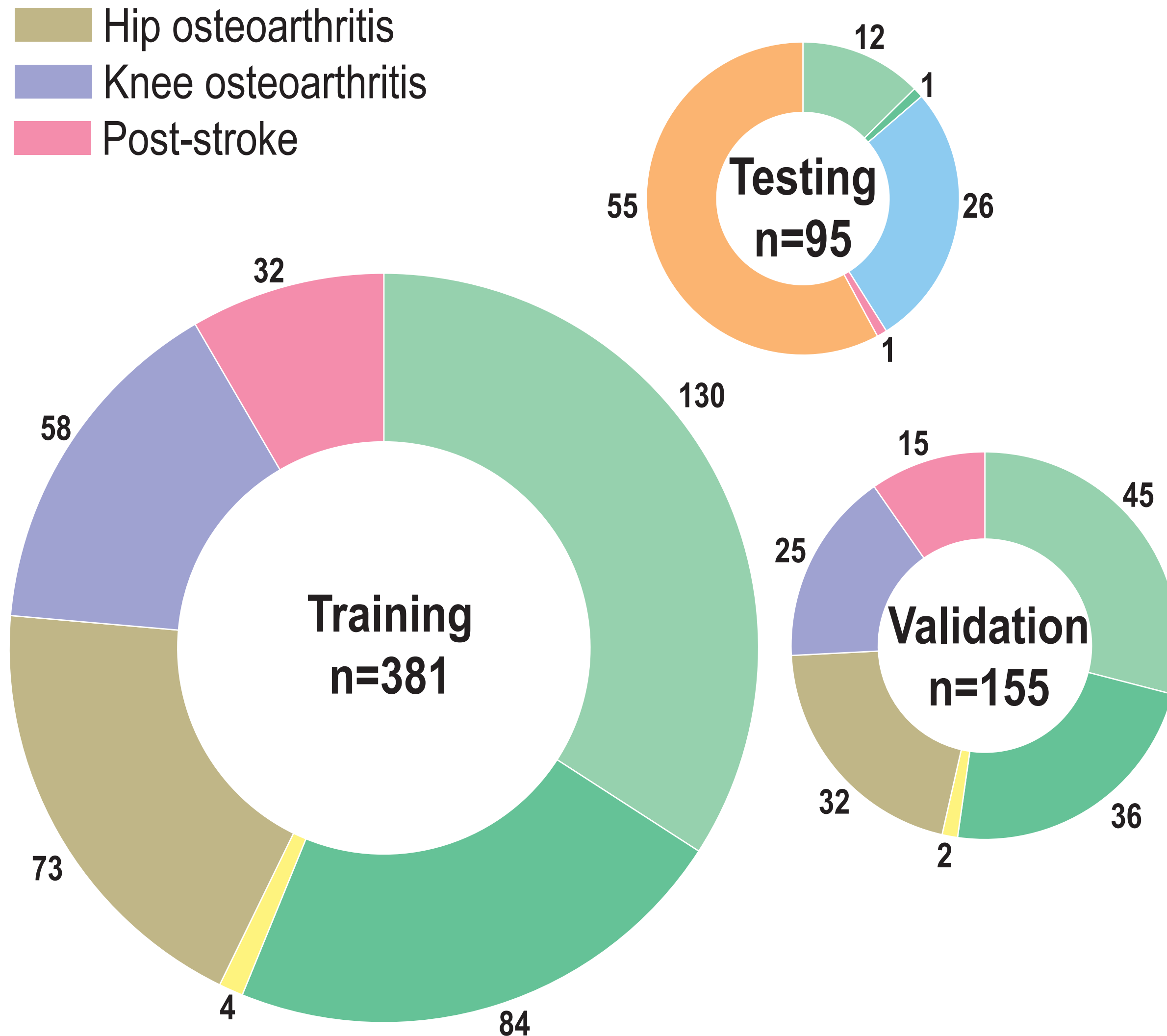
Methods

Training conditions

- Unimpaired (≤ 65)
- Unimpaired (> 65)
- Cerebral Palsy
- Hip osteoarthritis
- Knee osteoarthritis
- Post-stroke

Unseen conditions

- Parkinson's disease
- Myotonic dystrophy



Training the model

- Aggregated a gait kinematics [4, 5] datasets of varied pathologies
- Includes both marked and markerless datasets
- Variational autoencoder (VAE) [6] for semi-supervised learning
- Auxiliary task: predicting gait speed to promote interpretability

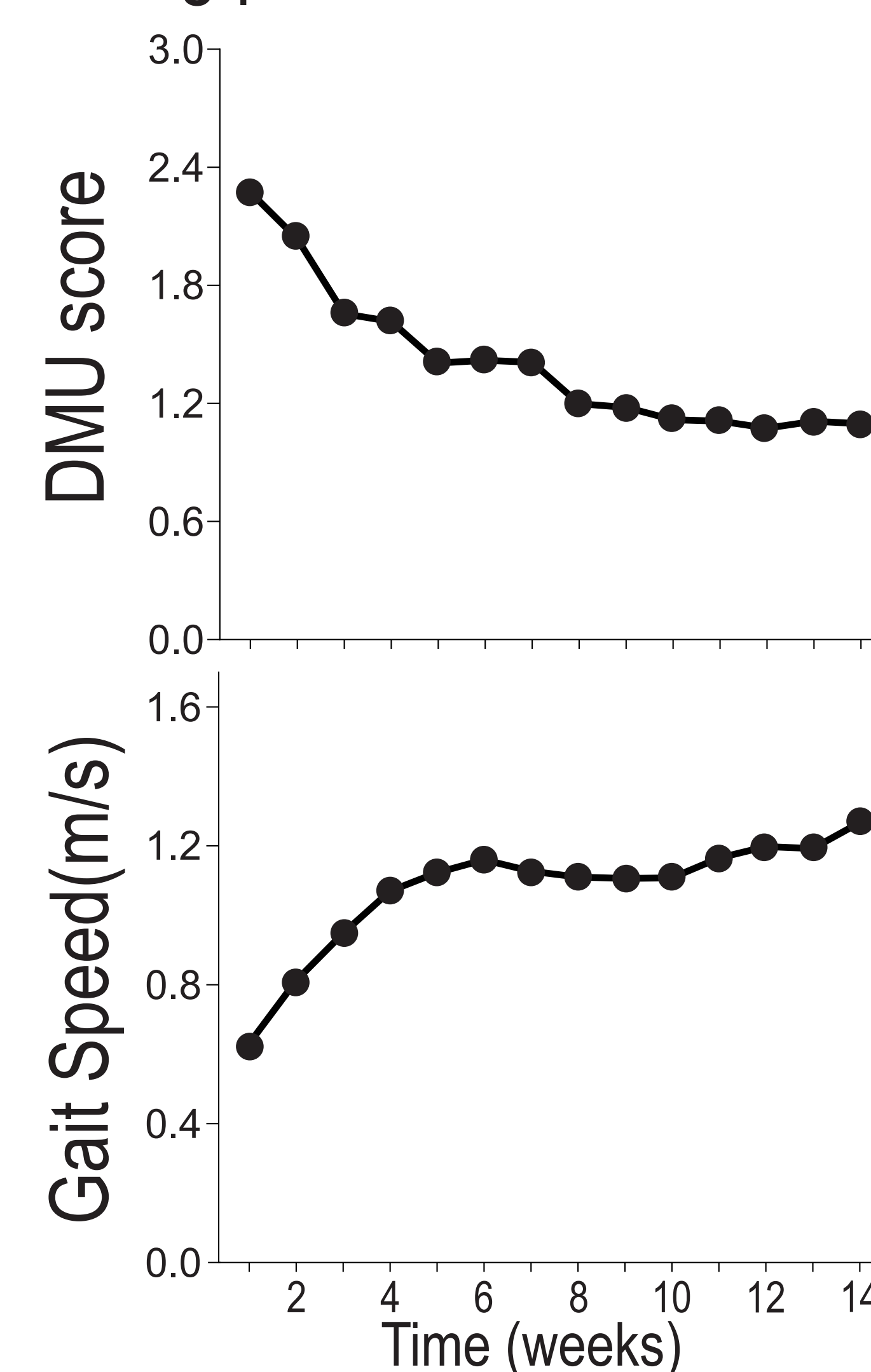
Calculating DMU (Deviation from Mean Unimpaired)

- Distance from the distribution of healthy gait features [7]

Diverse clinical applications and pathologies

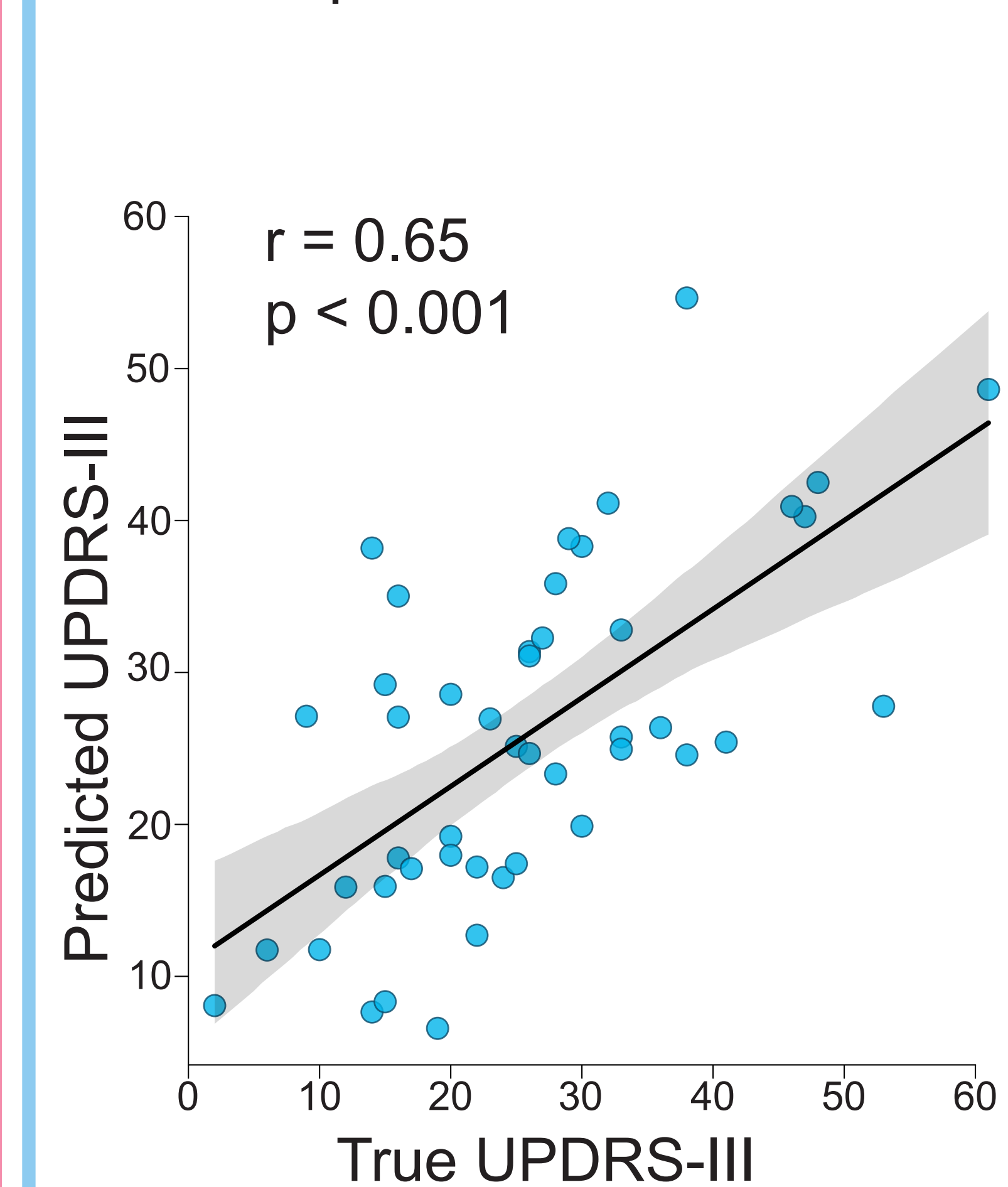
Tracking recovery post-stroke

DMU responds to recovery during post-stroke rehabilitation



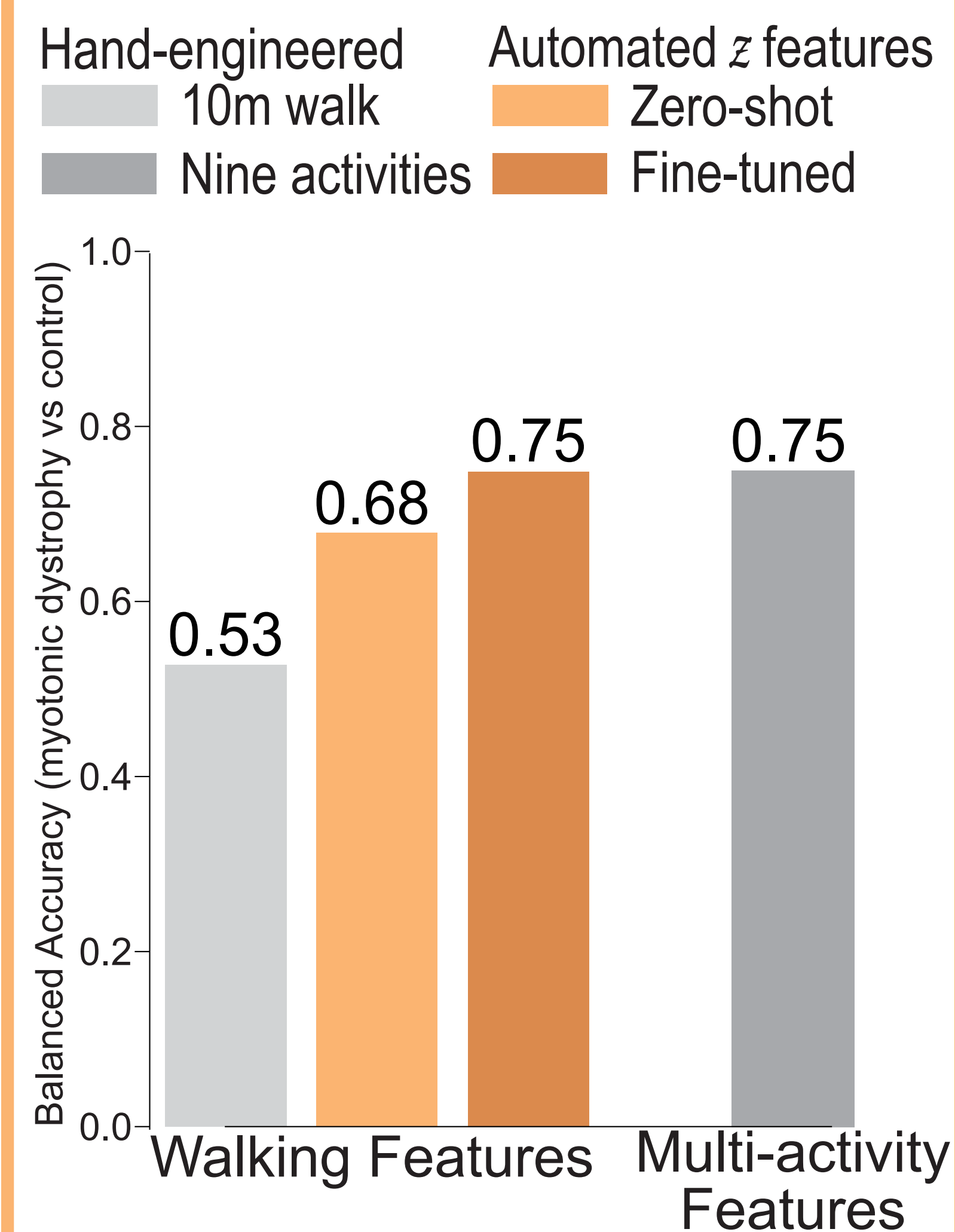
Quantifying severity in Parkinson's disease

z predicts clinician and self-reported scores of PD



Identification of myotonic dystrophy

z outperforms hand-engineered features of walking



Impact

- Estimates impairment, automates feature selection, and can be improved by fine-tuning with small datasets
- Generalizes to unseen pathologies
- Open source and automatically computed during OpenCap gait analysis

References

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