Estimating hand reaction forces from arm segment accelerations during handcycle propulsion using machine learning

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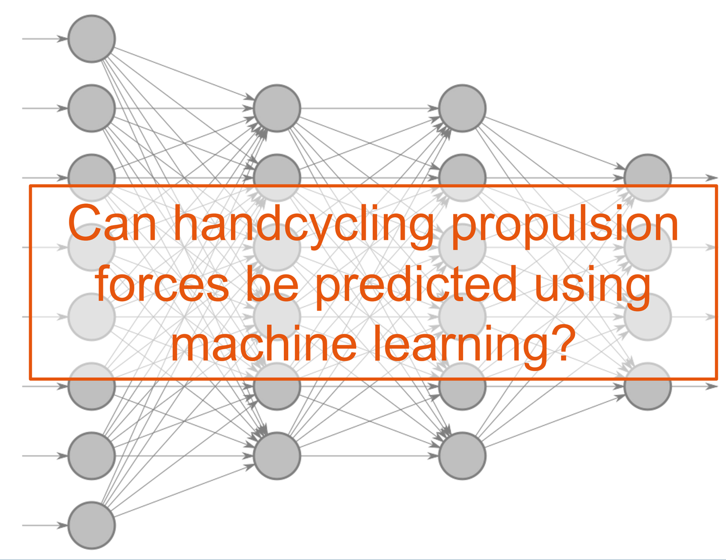
TISSUE BIOMECHANICS LABORATORY

1. Clinical motivation

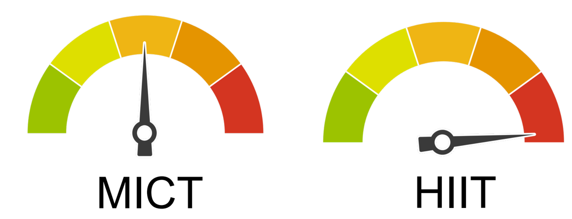
- Persons with spinal cord injuries (PwSCIs) are ~5x more likely to have cardiovascular disease than able-bodied individuals[1] due to low physical activity[2]
- Exercise can help prevent cardiovascular disease but needs to be quantified
- There are no commercially available devices to measure forces during physical activity in PwSCIs
- Accelerations from inertial measurement units (IMUs) can estimate ground reaction forces[3-5] using machine learning



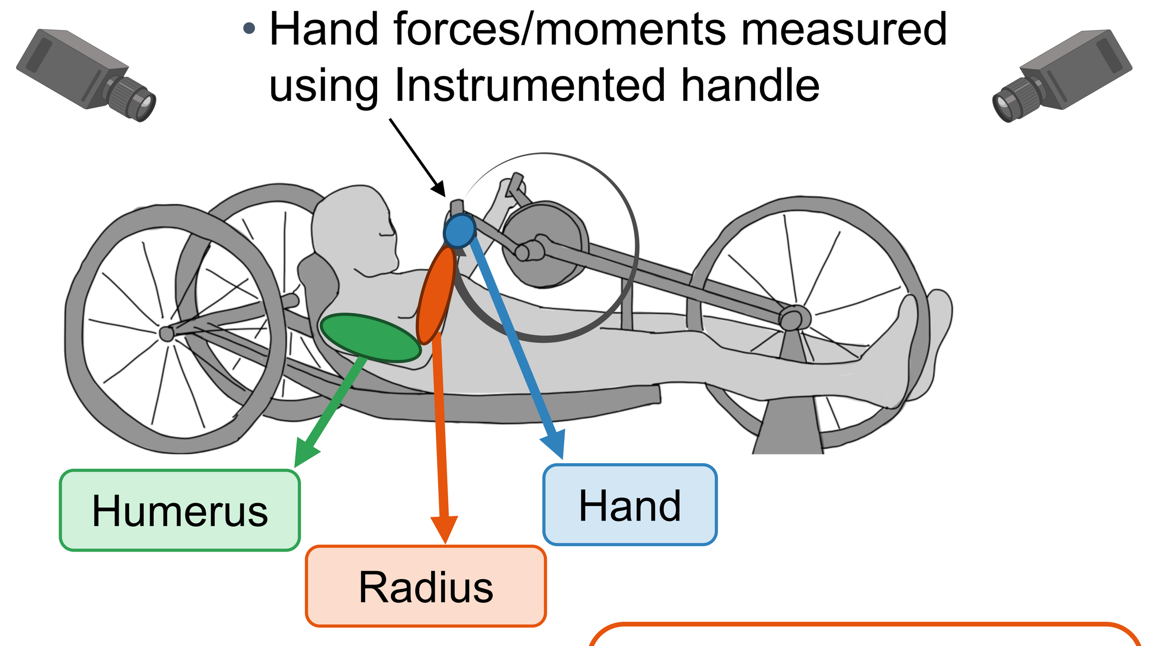
2. Dataset [6]

N = 20 PwSCIs

- 20 min of propulsion in two training modes: moderate (MICT) and high intensity (HIIT)



- Hand forces/moments measured using Instrumented handle

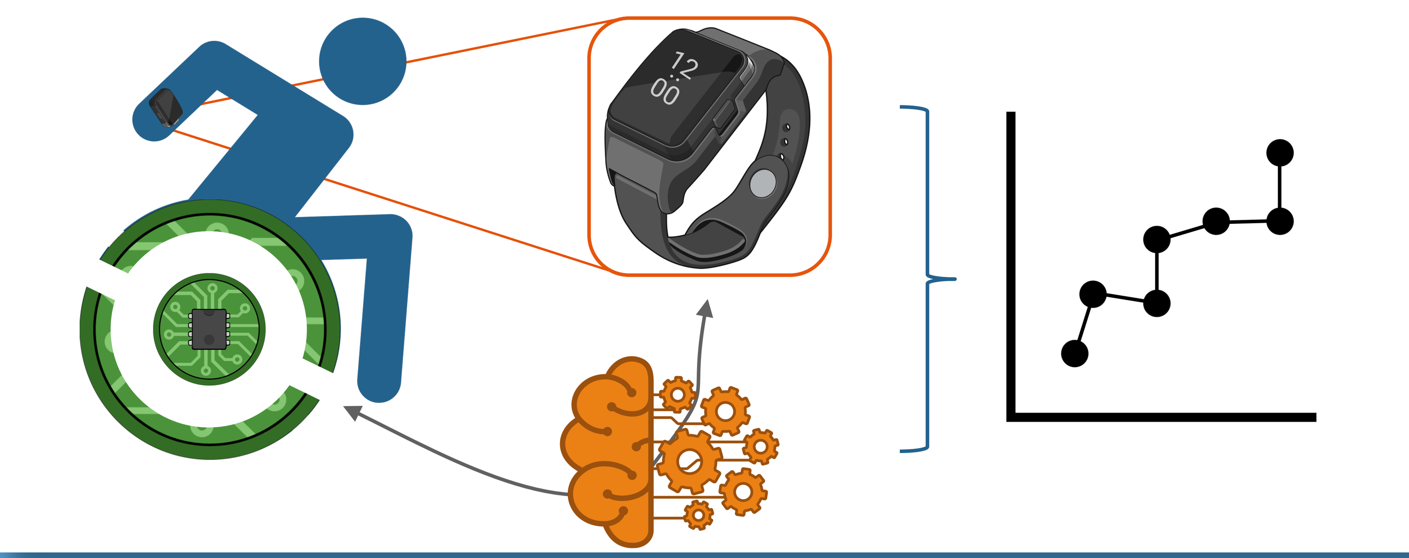


- Segment accelerations and velocities calculated using inverse kinematics

$$a = \begin{pmatrix} a_x \\ a_y \\ a_z \end{pmatrix},\ \omega = \begin{pmatrix} \omega_x \\ \omega_y \\ \omega_z \end{pmatrix}$$

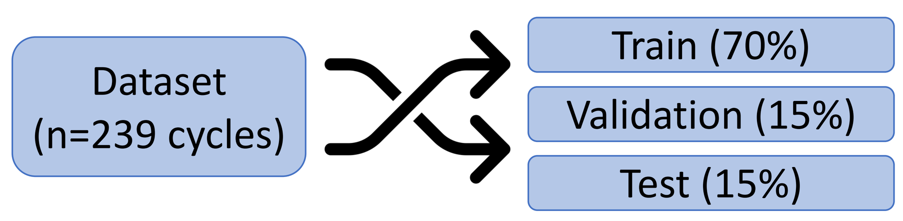
Objective

Determine (1) if data from a given segment best predicts propulsion kinetics and (2) if predictions are sensitive to exercise mode



Exercise videos:

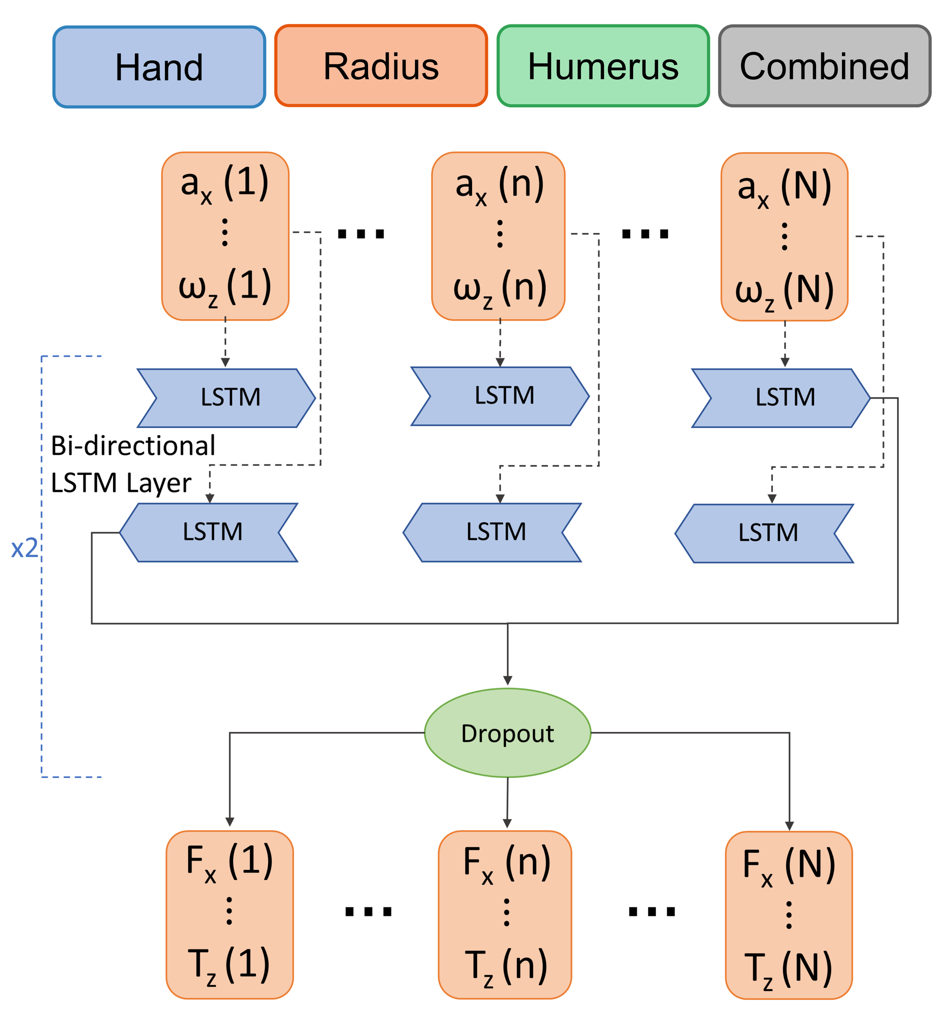
3. Methods



Data Preprocessing:
- Dataset shuffled and split into standardized subsets

$$y_{standardized} = \frac{y_i - mean}{sd}$$

Model Architecture:
- Effect of segment used compared with 4 models
- 2-layer BiLSTM network
- 200 nodes/layer
- 40% dropout after each layer



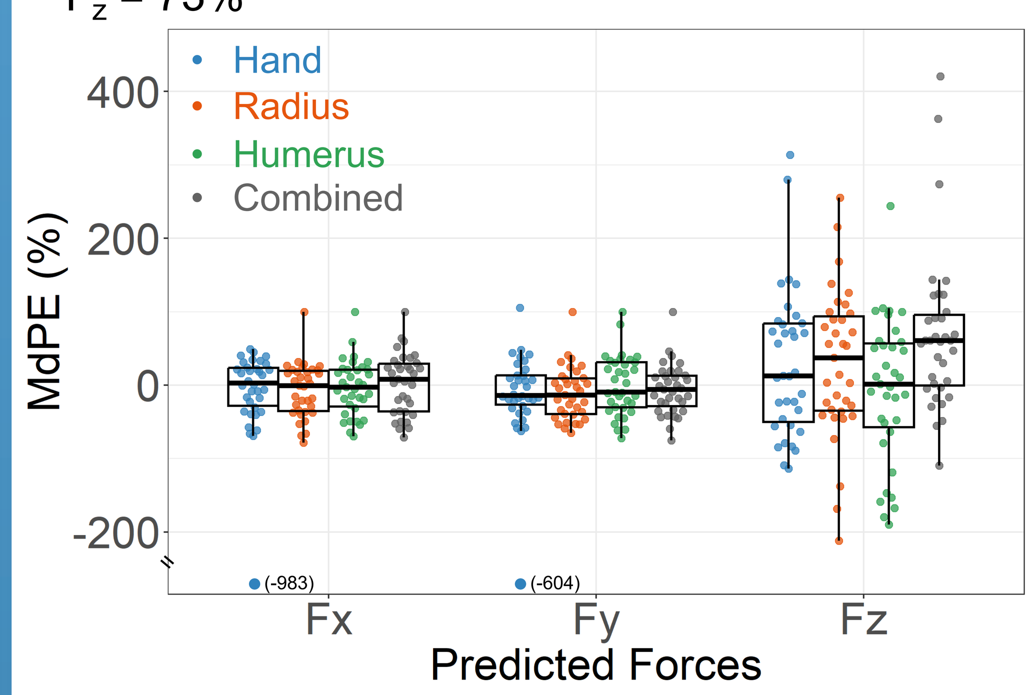
Training Parameters:
- Loss function: MSE
- Optimizer: Adam
- Learning rate: 0.0003

Data Reduction and Analysis:
- Prediction error calculated on test set
- Error compared across model, exercise type, and output variable using Wilcoxon-Signed Rank, Kruskal-Wallace tests

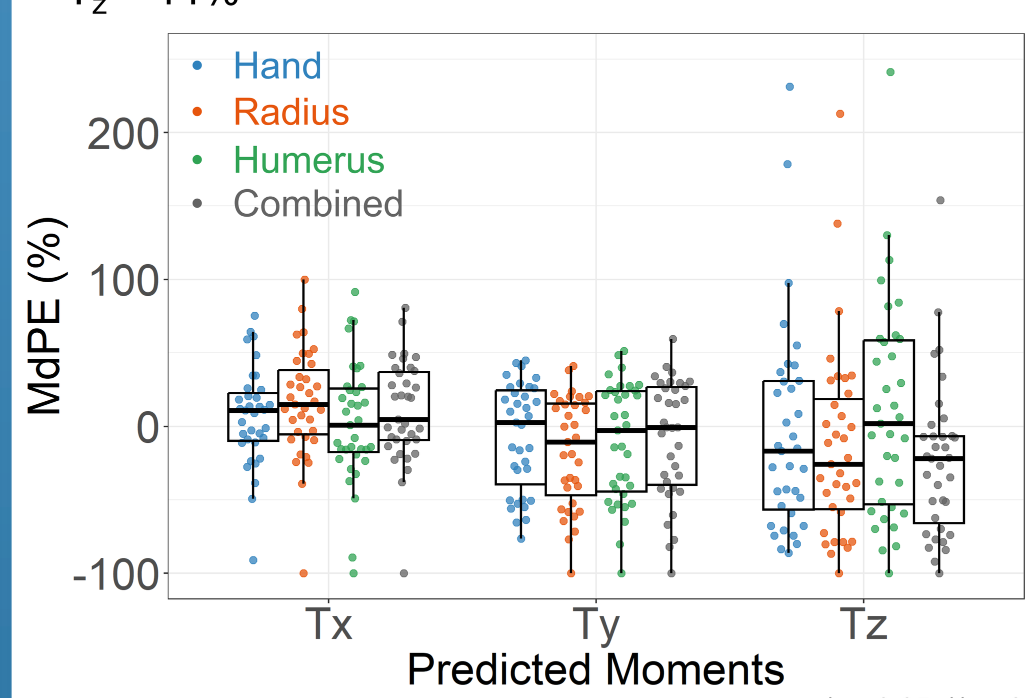
$$MdPE = median\left(\frac{y_{predicted} - y_{actual}}{y_{actual}}\right) * 100$$

4. Key findings

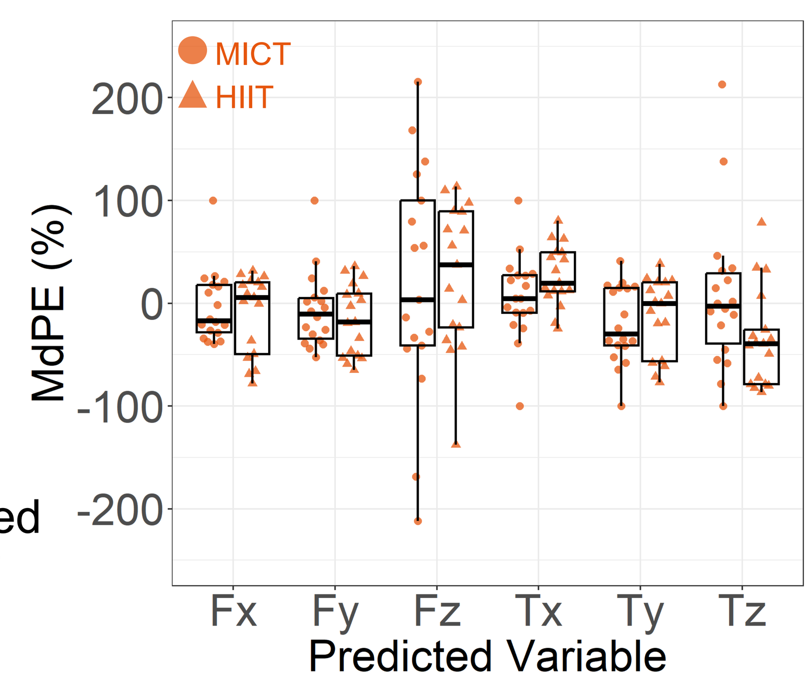
- Individual segment data equally predicts kinetics
- Lowest absolute errors in F_y (21%) and F_x (29%); F_z = 73%

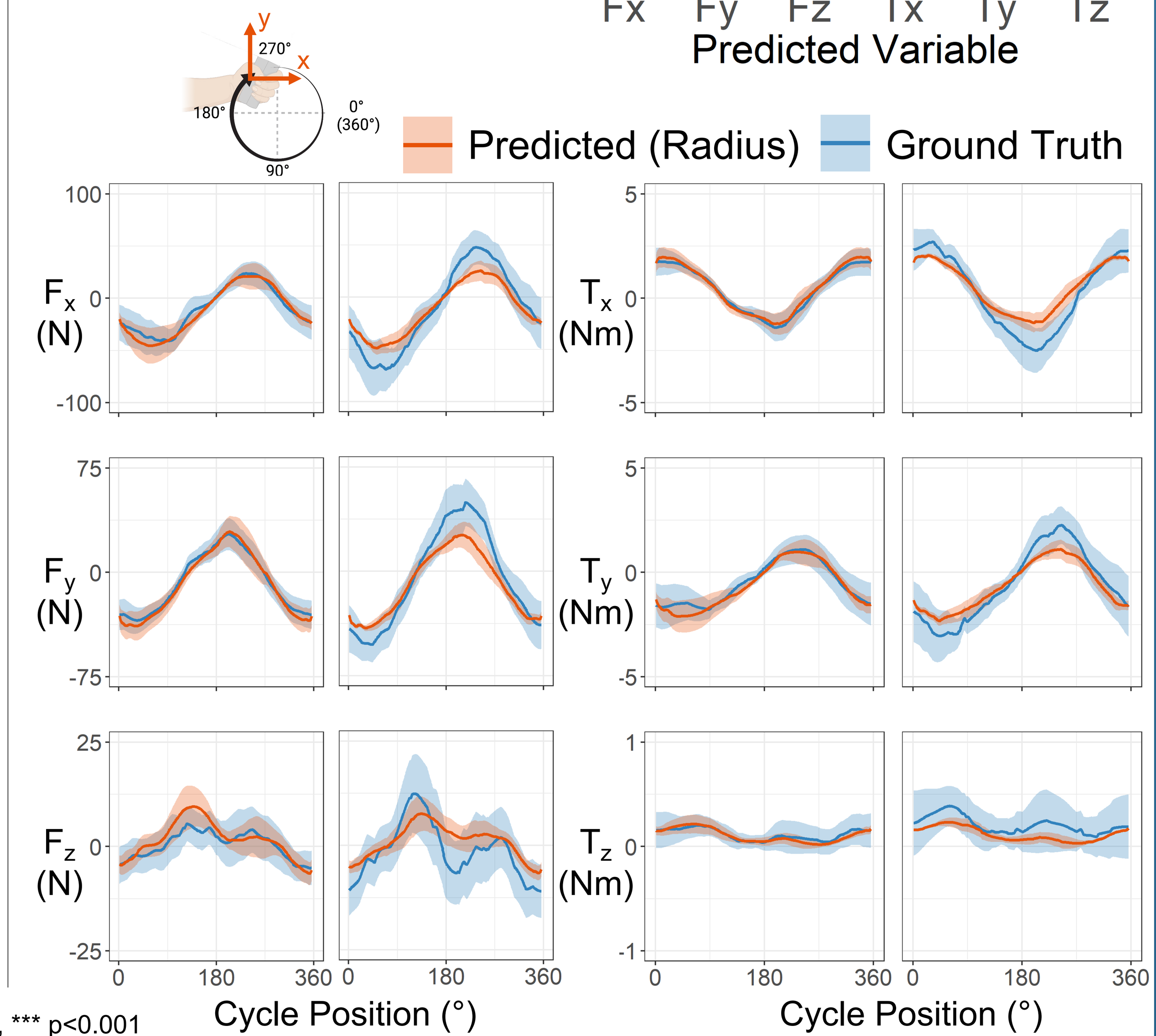


- Lowest absolute errors in T_x (20%) and T_y (27%); T_z = 44%



- Predictions are insensitive to exercise type
- HIIT errors tend to be higher
- HIIT kinetics tend to be underpredicted compared to MICT



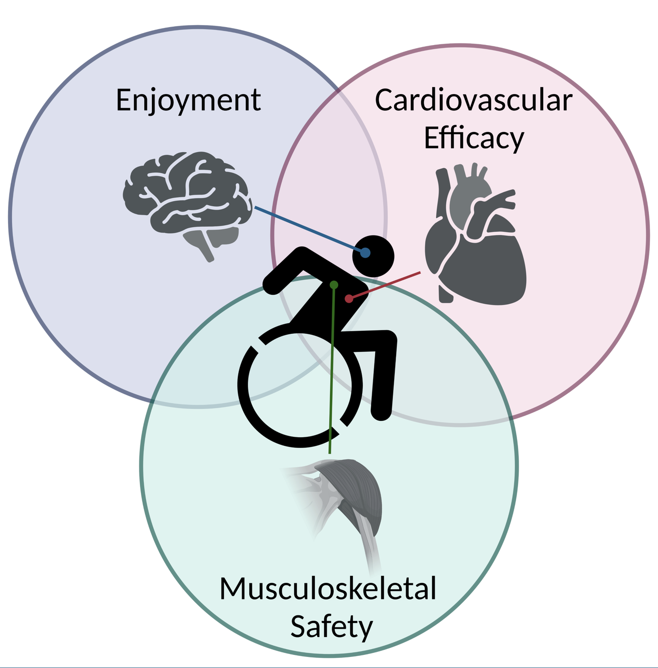


* p<0.05, ** p<0.01, *** p<0.001

6. Conclusions

- Tangential and radial forces (F_x, F_y) are most relevant to propulsion and can be well predicted using machine learning
- Kinetics can be predicted with IMU data from a single segment
- Choice of arm segment does not significantly affect prediction performance
- Exercise type may need to be considered: kinetics during high intensity activities are more challenging to predict

A wrist-mounted IMU may be a viable method to evaluate different exercise intensity aimed to improve cardiovascular health.



Limitations: Inertial data calculated from motion capture
Future study: Will use a wrist IMU to predict hand reaction kinetics during manual wheelchair propulsion

References

[1] Myers+ *Am J Phys Med Rehabil*, 2007, [2] Gorgey+ *World J Orthop*, 2014 , [3] Liu+ *Measurement*, 2022, [4] Alcantara+ *PeerJ*, 2022. [5] Hendry+ *Sensors*, 2020. [6] Halloran+ *J Biomech, 2022.*

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