PulseRide: A Robotic Wheelchair for Personalized Exertion Control with Human-in-the-Loop Reinforcement Learning

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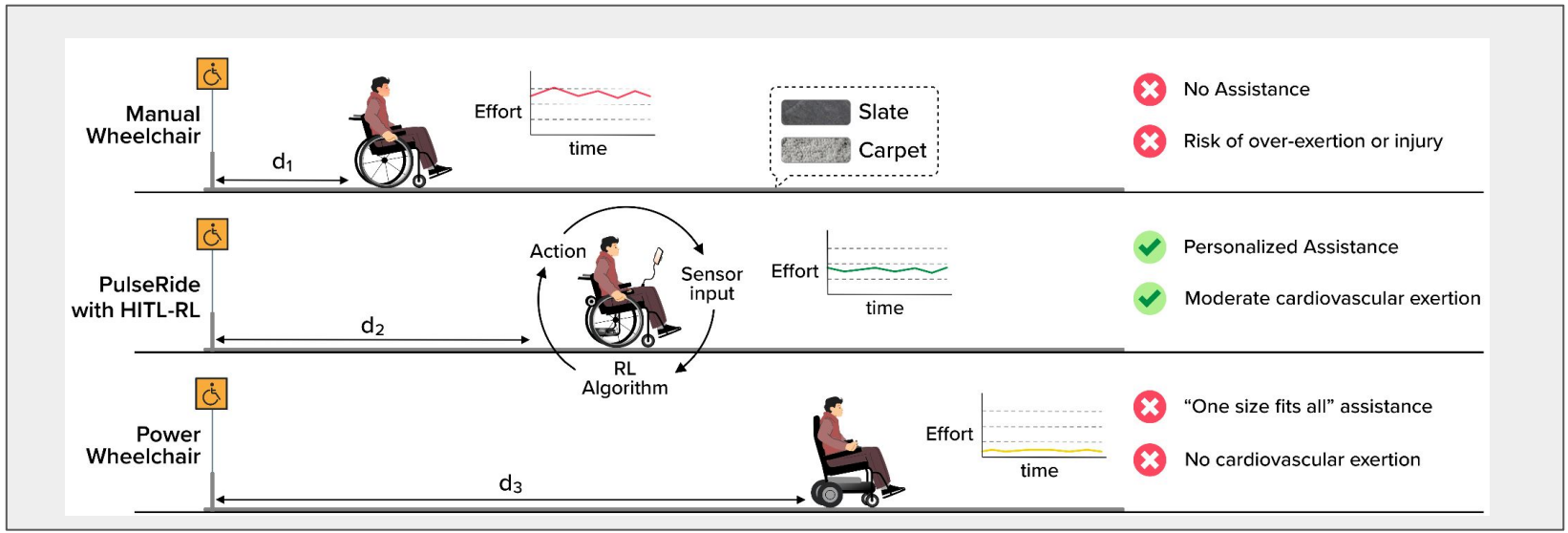
The Challenge of Wheelchair Mobility

- Manual wheelchairs: High physical effort, risk of shoulder injuries (42-66% prevalence).
- Power wheelchairs: Promote inactivity, leading to obesity and deconditioning.
- **Need for a balanced solution that promotes physical activity while minimizing injury risk**.



Our Research Focus

- RQ1: How can we design an autonomous wheelchair system that promotes physical activity while supporting daily mobility?
- RQ2: How can we personalize assistance levels by dynamically adapting to users' physiological states?
- RQ3: How can we ensure adaptive assistance is effective across diverse environments?

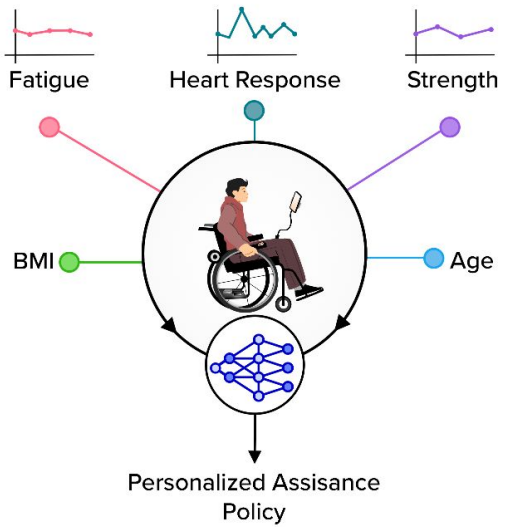
Mobility

Personalization

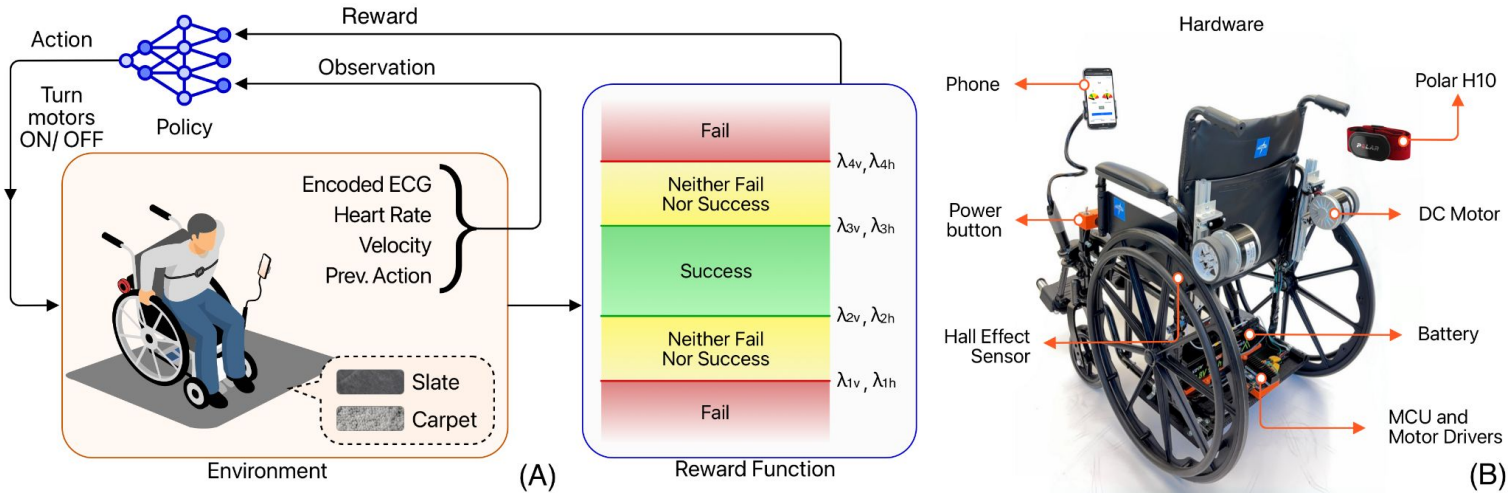
Environmental Adaptability

PulseRide: A New Paradigm

- Adaptive wheelchair system using Human-in-the-Loop Reinforcement Learning (HITL-RL).
- Integrates physiological data (heart rate, ECG) with wheelchair speed for personalized assistance.
- Goal: Maintain moderate exertion levels to promote health without over- or under-exertion.



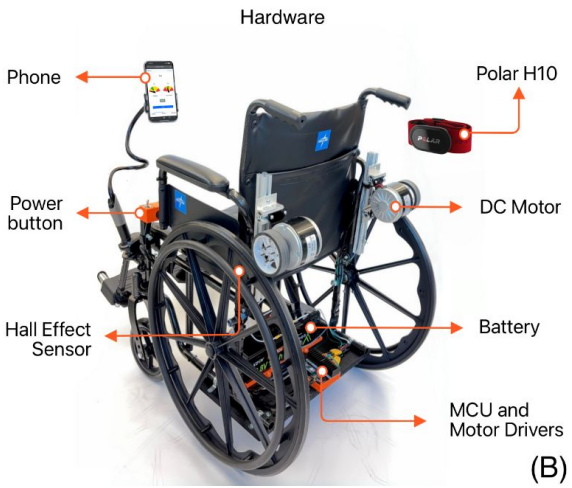
How PulseRide Works



PulseRide system overview

How PulseRide Works

- Power button for safety.
- Hall effect sensor for wheelchair rpm.
- DC motors for assistance.
- Polar H10 for receiving heart rate and ecg data.
- We utilized Arduino uno to control the motors based on the intelligent actions.



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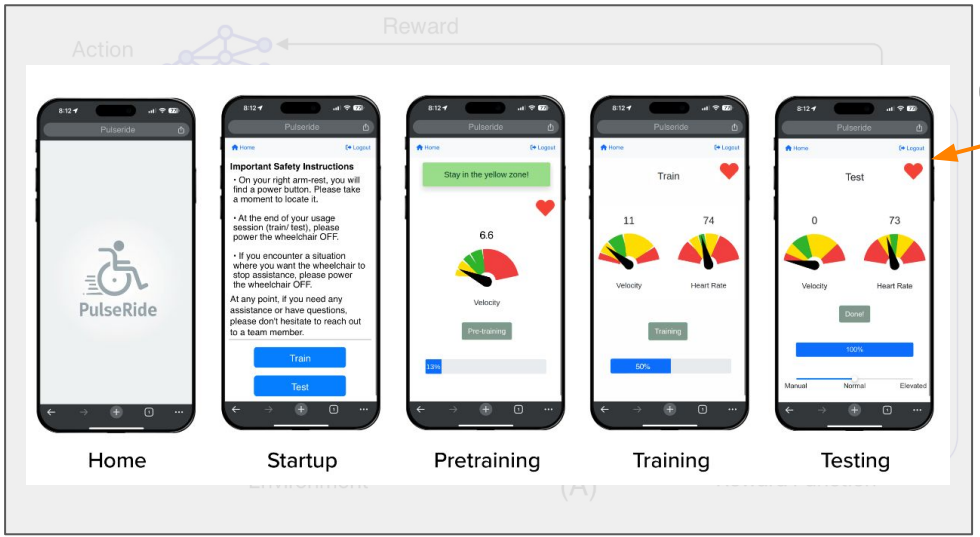

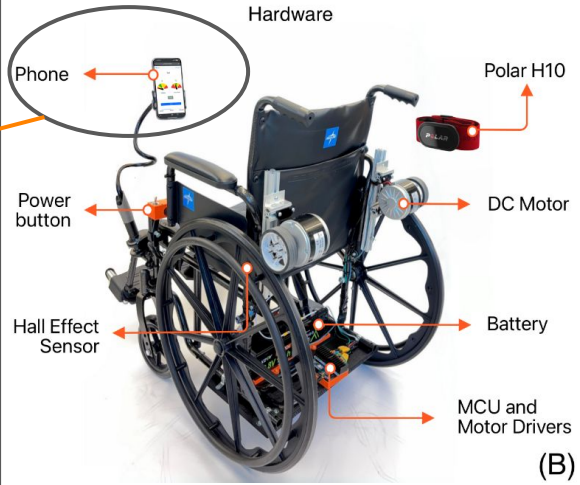

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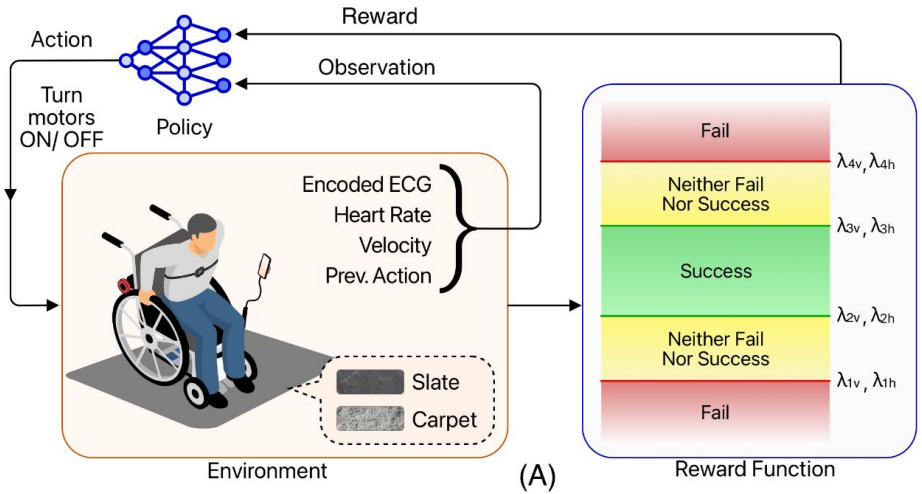

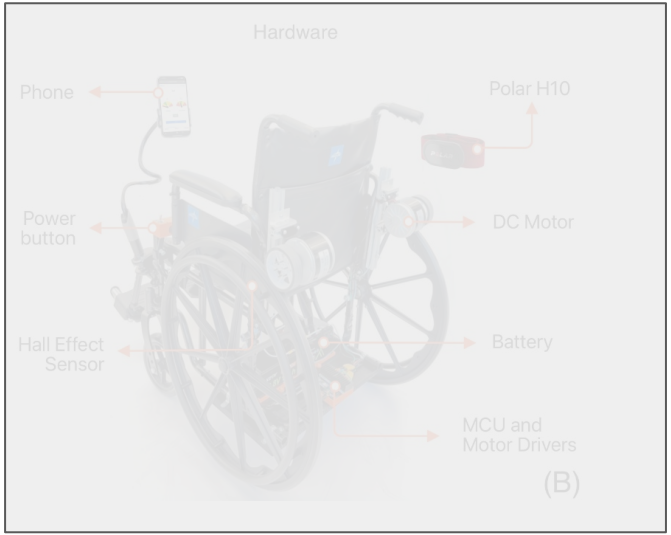

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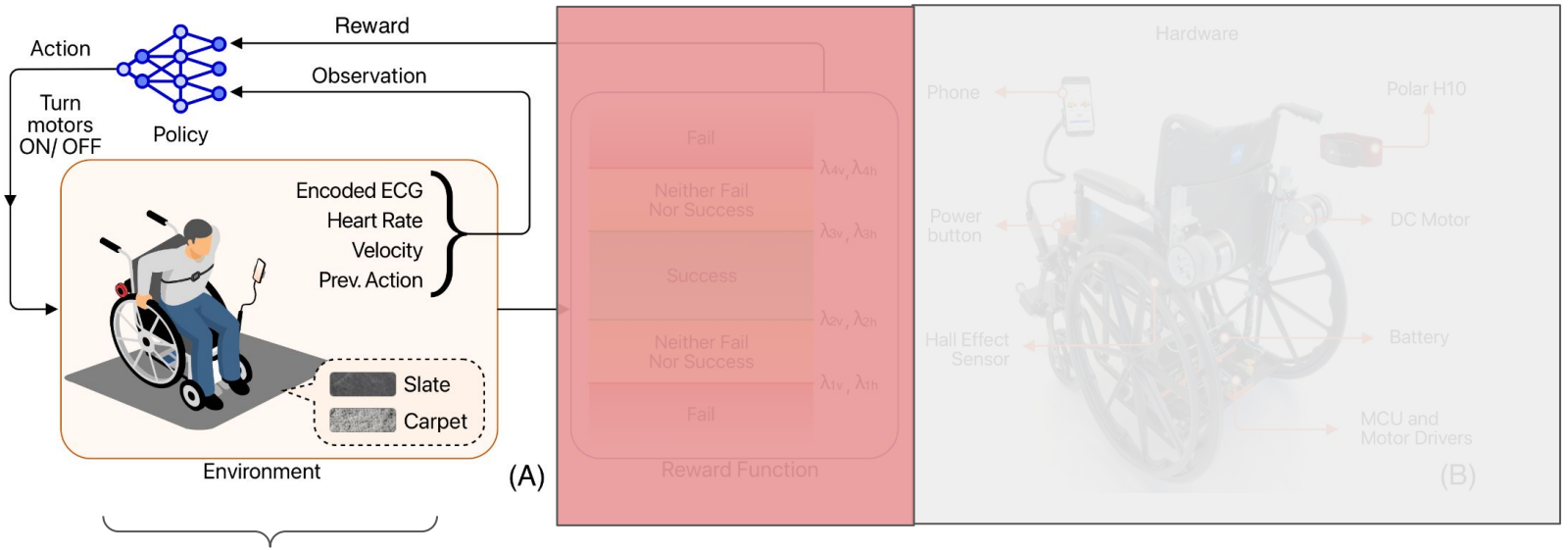
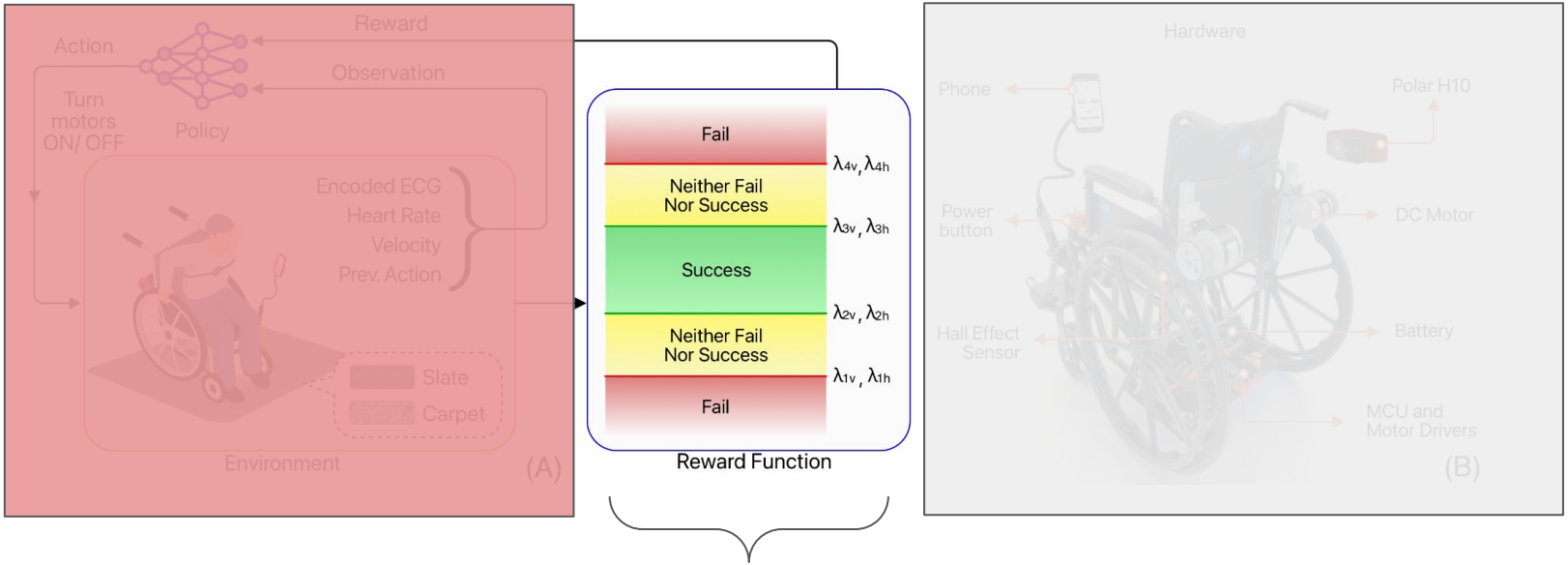


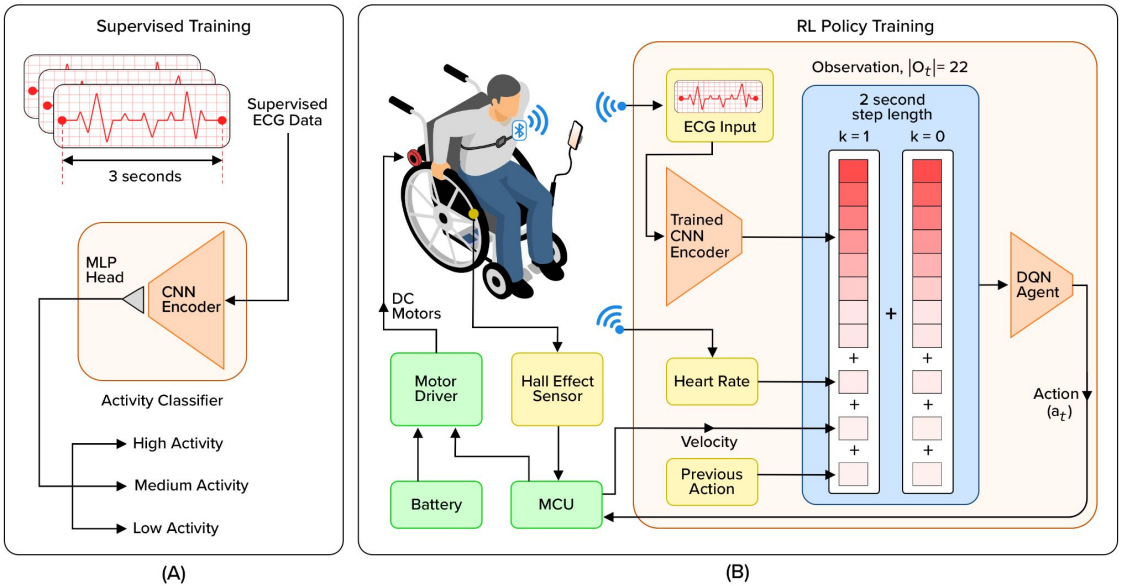
Human in the Loop RL

How PulseRide Works



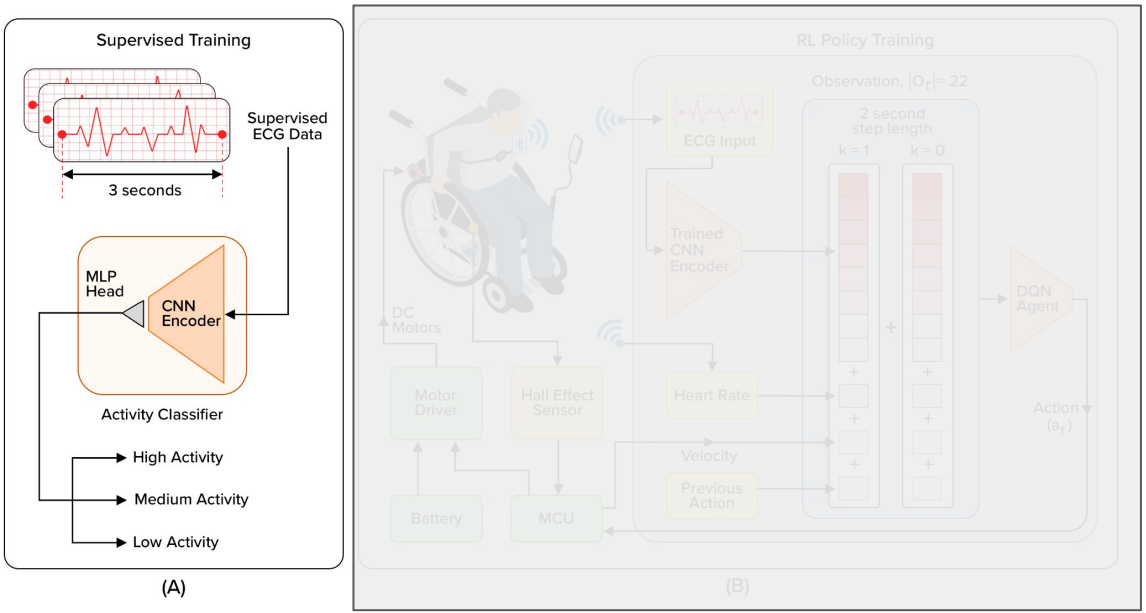
Reward Function

Human-in-the-Loop Reinforcement Learning



- HITL-RL integrates user physiological data (heart rate, ECG) and wheelchair speed.
- Deep Q-Network (DQN) with experience replay and target network for stable learning.

Human-in-the-Loop Reinforcement Learning



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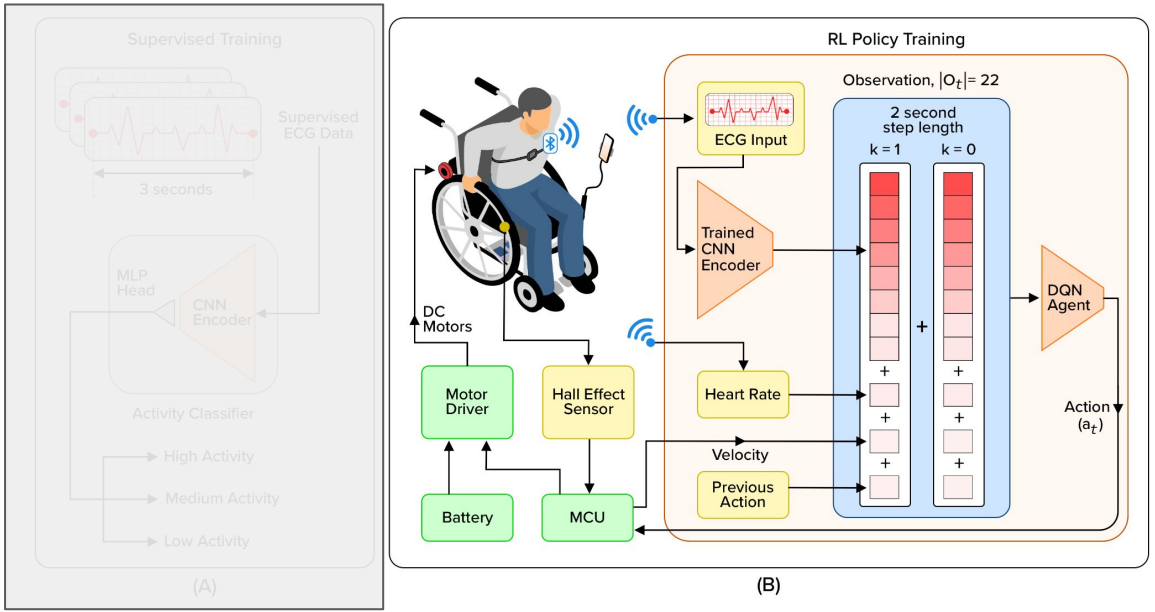
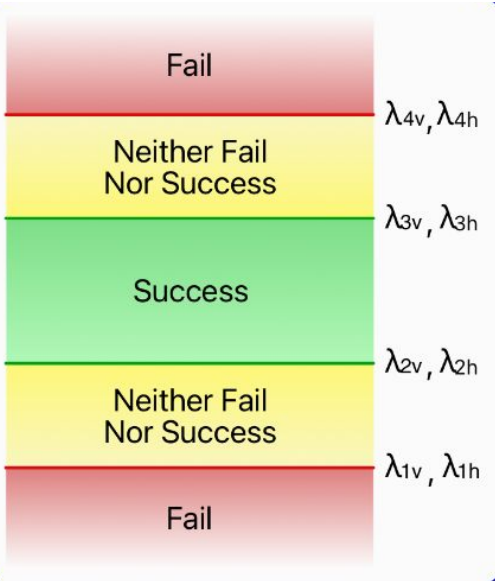


Reward Function

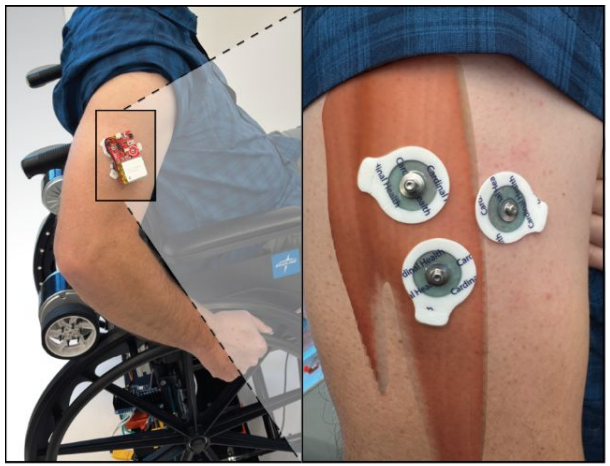


Reward function balances velocity and heart rate to maintain moderate exertion.

- Personalized green, yellow and red regions.
- Green (Success) → personalized moderate activity zone.
- Yellow (Neither fail nor success) → low activity (lower), intense activity (higher)
- Red (Fail) → No activity (lower), extreme activity (higher)

Experimental Setup

- Participants: 10 individuals without disabilities (for safety and baseline consistency).
- Measures: **Muscle contractions**, heart rate zones, environmental adaptability, fatigue reduction.



Myoware 2.0 EMG sensors on both arms biceps.

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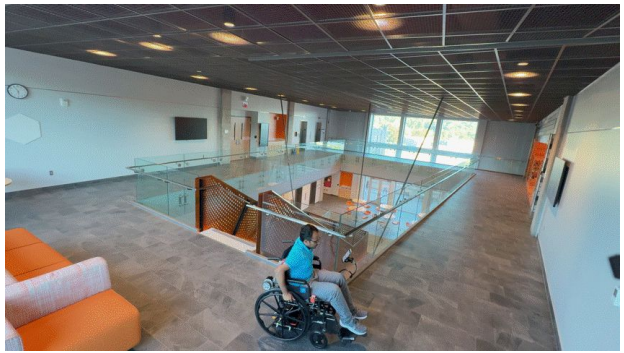

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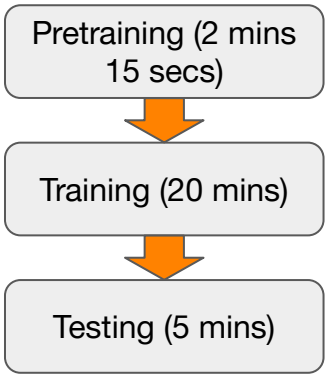

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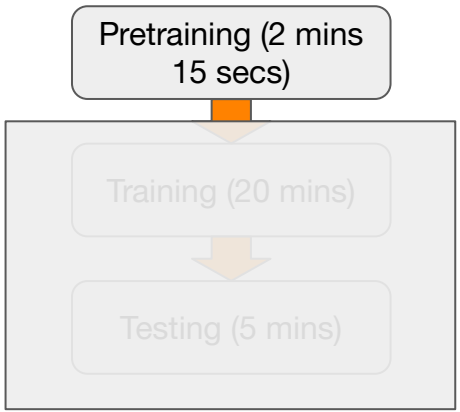

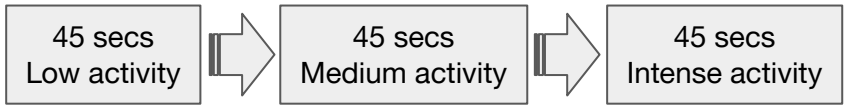

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Special instruction to slow down at around 12 mins for additional 2 mins, and then push intense at around 16 mins for additional 2 mins. Else push to maintain velocity to the green region.

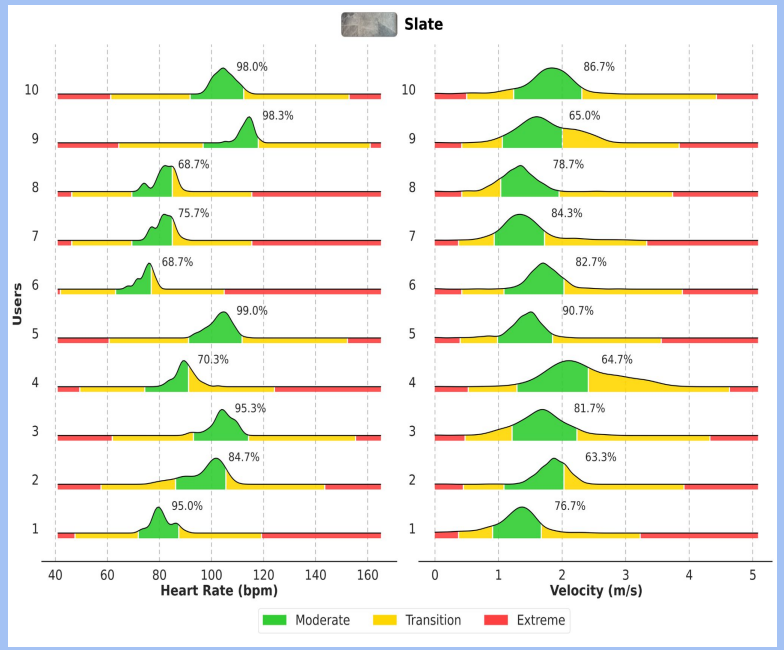
Experimental Setup

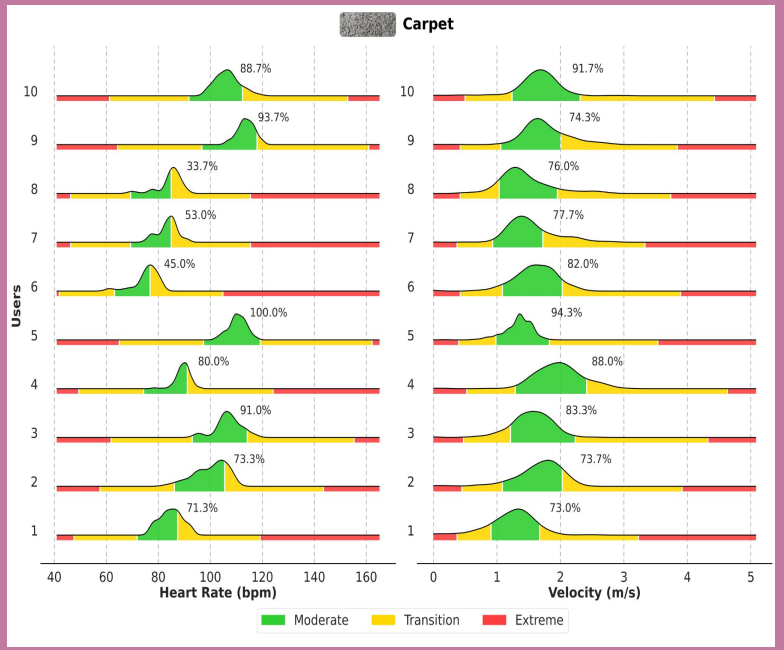
- Participants: 10 individuals without disabilities (for safety and baseline consistency).
- Measures: Muscle contractions, heart rate zones, environmental adaptability, fatigue reduction.
- Procedure: **Pre-training (2.25 min), training (20 min), testing (5 min on slate and carpet).**

Test instruction was to maintain velocity on the green region

Personalized Assistance

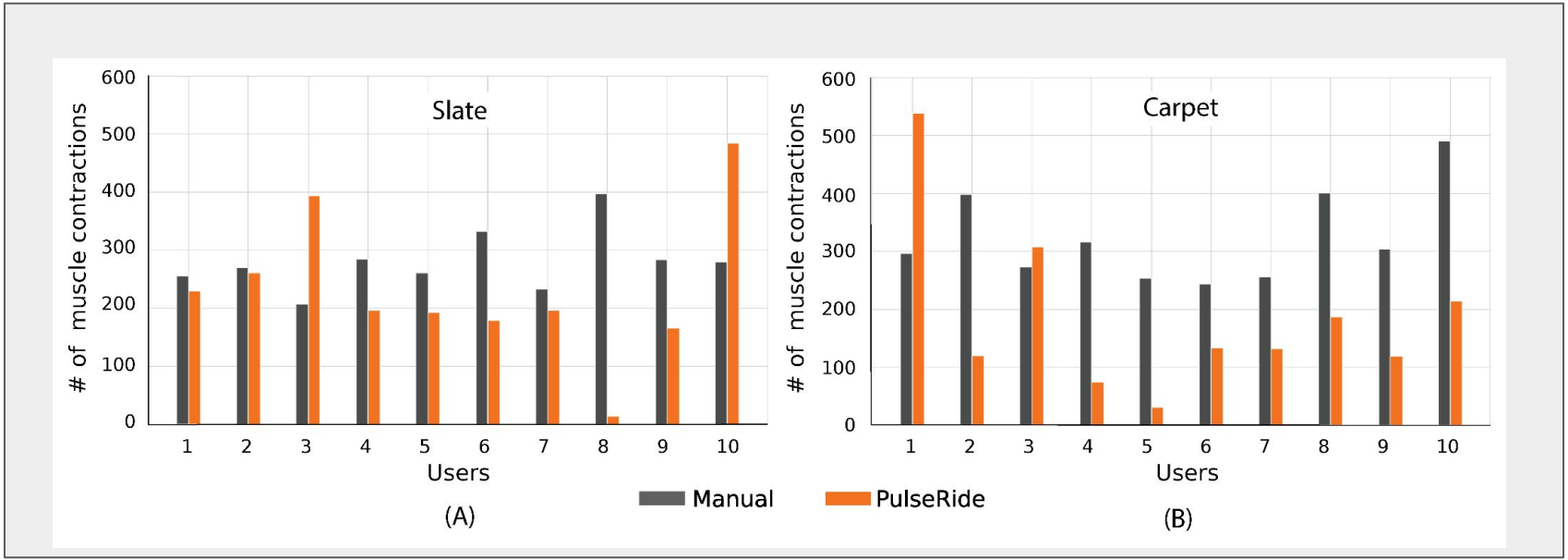
- PulseRide maintained heart rates in moderate zones up to 71.7% longer than manual wheelchairs.
- Heart rate and velocity distributions show effective personalization.
- Outliers (e.g., Users 6, 7, 8) spent more time in transition zones due to higher velocities.





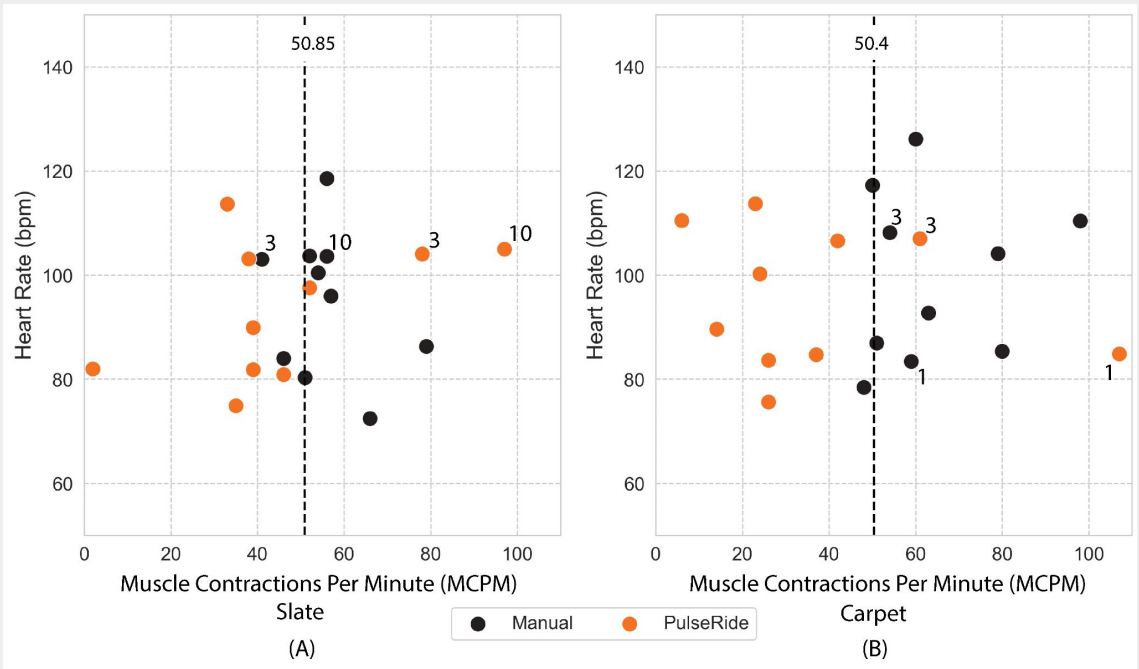
Results - Muscle Contraction Reduction

- Average reduction in muscle contractions: 41.86% (slate), 24.94% (carpet) vs. manual wheelchairs.
- Outliers (e.g., User 3) showed stable heart rates despite higher contractions.



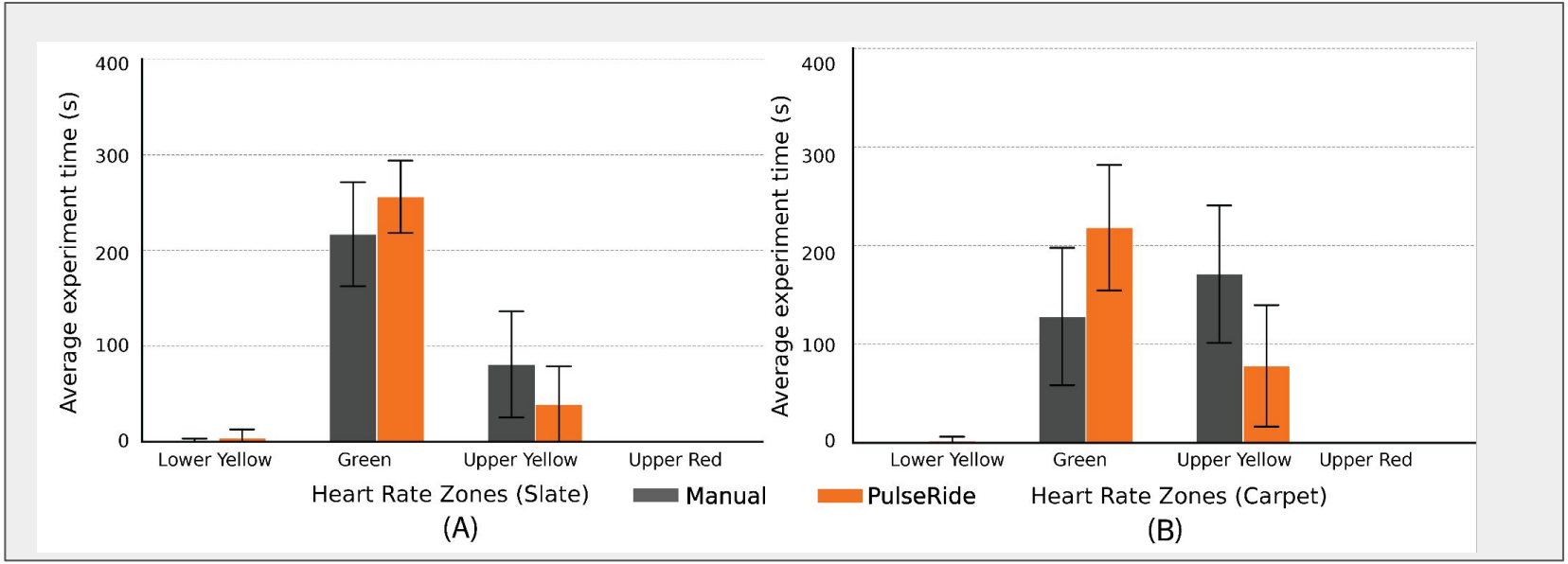
Results - Muscle Contraction Reduction

- Clustering in muscle contractions per minute highlights efficiency (Figure 9).



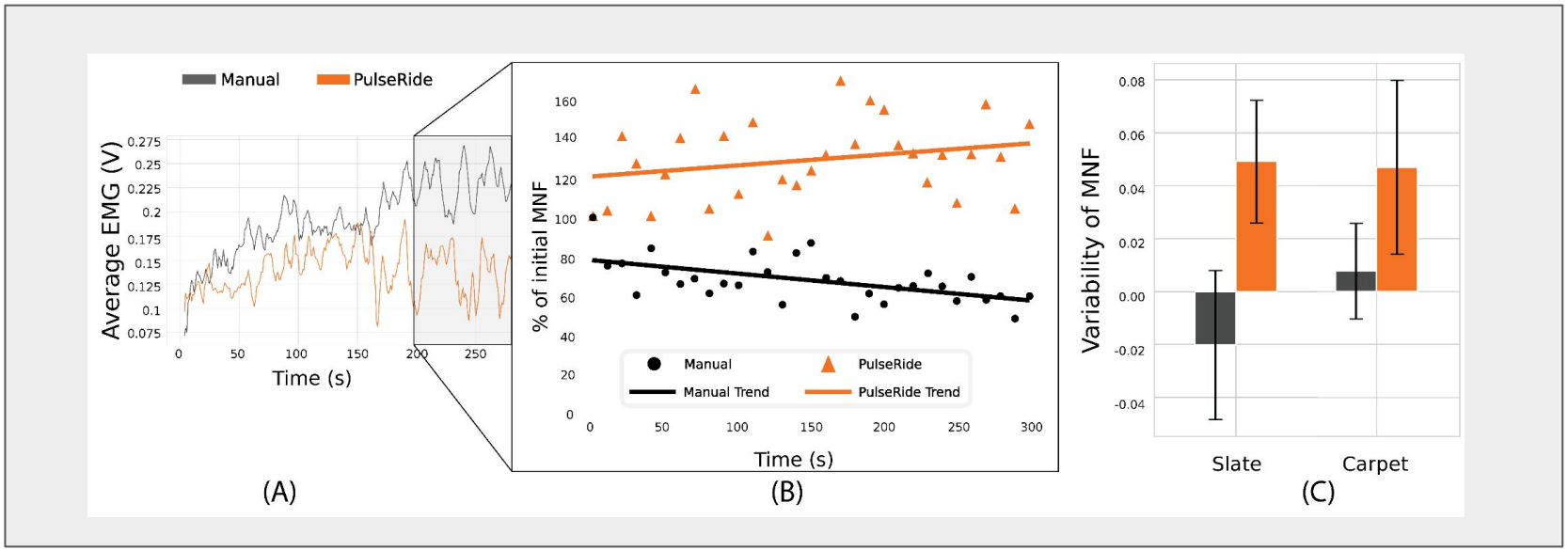
Results - Environmental Adaptability

- Slate: 85.6% in moderate zone, 13.1% in upper yellow zone.
- Carpet: 73.15% in moderate zone, 26.2% in upper yellow zone.
- Manual wheelchairs: Less consistent, with 57.2% in upper yellow zone on carpet.



Results - Fatigue Reduction

- PulseRide shows positive MNF trends, indicating less fatigue (Figure 11B).
- Manual wheelchairs show negative MNF trends, signaling faster fatigue.
- Consistent across all participants in both environments (Figure 11C).



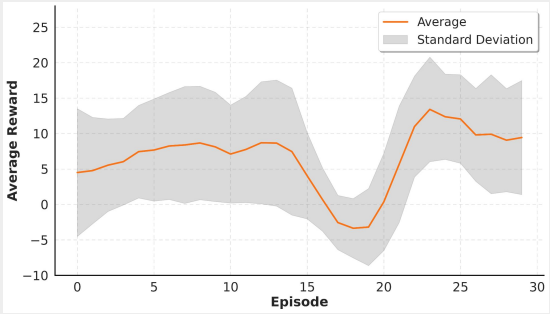
Conclusions

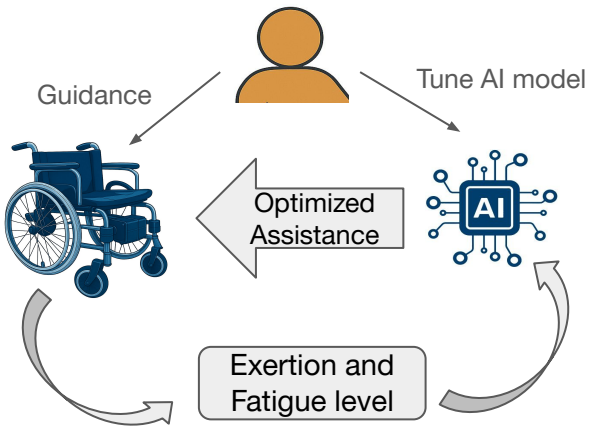
Key Takeaways:

- PulseRide bridges the gap between manual and power wheelchairs.
- Successfully personalized assistance and reduces fatigue.
- Limitations: Tested with non-disabled participants; no braking capability.
- Reward plot shows effective learning despite data scarcity.

Next steps:

- Test with wheelchair users, explore advanced RL algorithms, add continuous motor thrust control.
- Potential for rehabilitation and personalized activity plans.





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