# HUMAN-ROBOT INTERACTION

## DEEP DIVE

Dana Kulić

AuSRoS 2024

# Today's Talk

**INTRO TO HRI**

- What is it?
- Key subfields and concepts
- Approaches and challenges

**LEARNING FOR HRI**

- Overview
- Key objectives and formulations

**EXAMPLE PROJECTS**

- Shared Autonomy Drone Piloting
- Gait guidance for people with Parkinson's Disease


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# WHAT IS HUMAN-ROBOT INTERACTION (HRI)?

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# HUMAN-ROBOT INTERACTION

## DEFINITION

*Human-Robot Interaction (HRI) is a field of study dedicated to understanding, designing, and evaluating robotic systems for use by or with humans.*

Goodrich and Schultz, 2008. Human-robot interaction: a survey

## WHY?

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# HUMAN-ROBOT INTERACTION

## DEFINITION

*Human-Robot Interaction (HRI) is a field of study dedicated to understanding, designing, and evaluating robotic systems for use by or with humans.*

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## WHY?

- Robots that serve people – healthcare, education, entertainment
- Robots that collaborate with people – cobots, search-and-rescue, field robotics
- Robots that work in human environments
- Robots that embody human goals, values and preferences

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# HRI Taxonomies

By agency and proximity

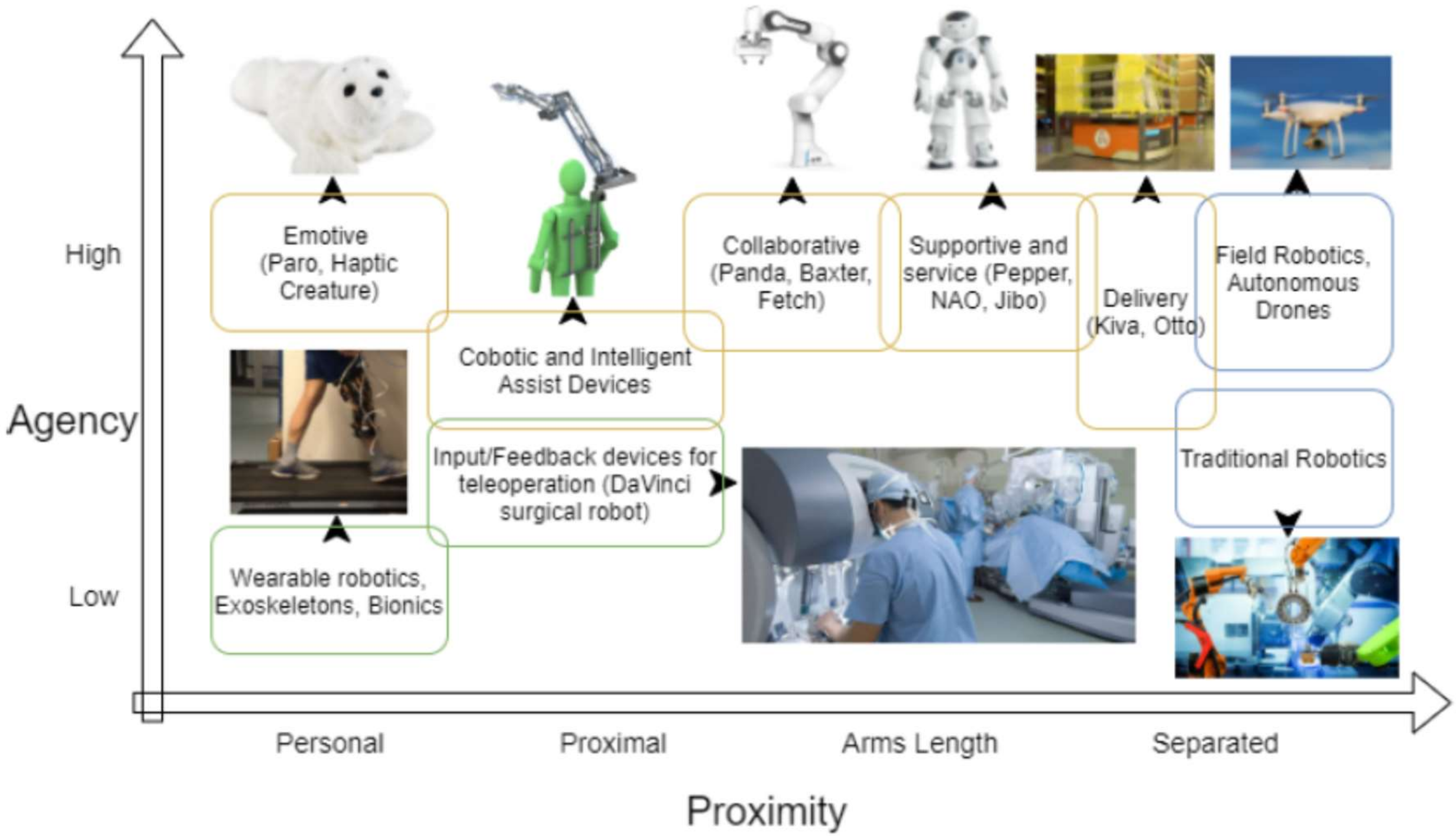


Image courtesy of L. Tian, ECE4078 Lecture Notes

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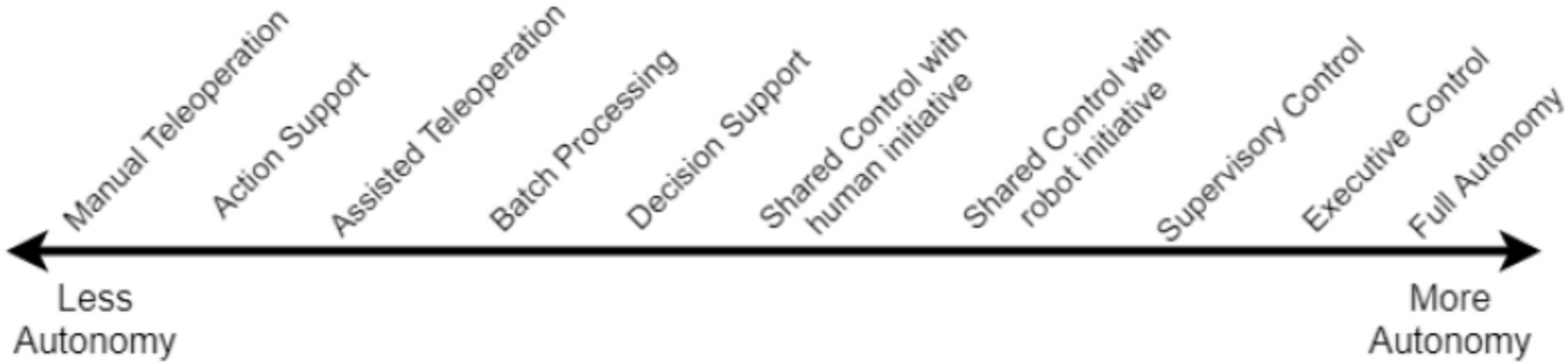
# HRI Taxonomies

By level of autonomy




Beer et al. 2014 Toward a Framework for Levels of Robot Autonomy in Human-Robot Interaction

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# HRI Taxonomies

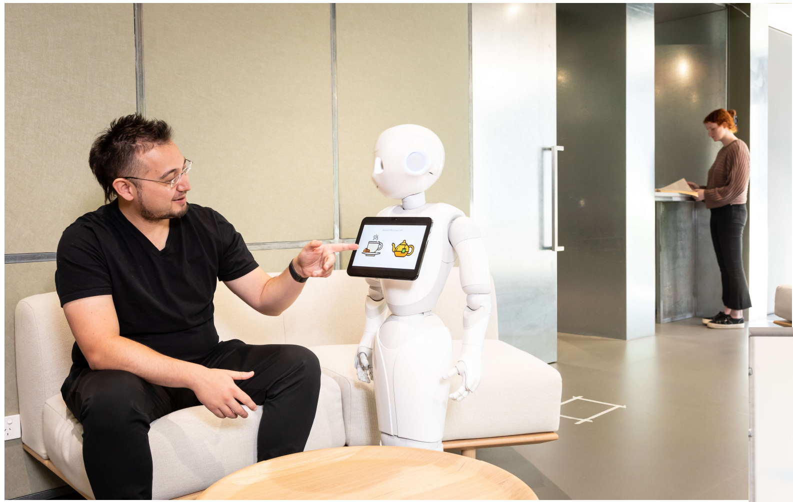
By role

**ROBOT ROLE**

- Teacher
- Learner
- Peer/Collaborator

**HUMAN ROLE**

- Researcher/Designer
- Supervisor/Operator
- Collaborator
- User
- Bystander



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# HRI DESIGN AND RESEARCH

**PHYSICAL DESIGN**

- Robot morphology
- Robot appearance
- Anthropomorphism

**PERCEPTION AND INTERACTION DESIGN**

- Methods
- Modalities

**EVALUATION**

- HRI Experiments
- Evaluation Metrics

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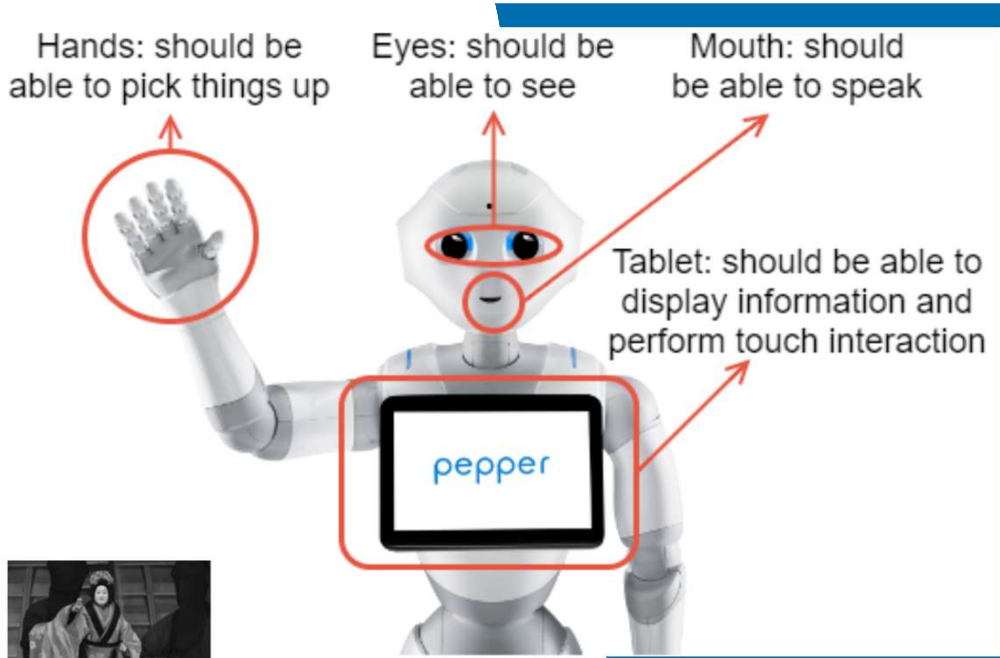
# PHYSICAL DESIGN

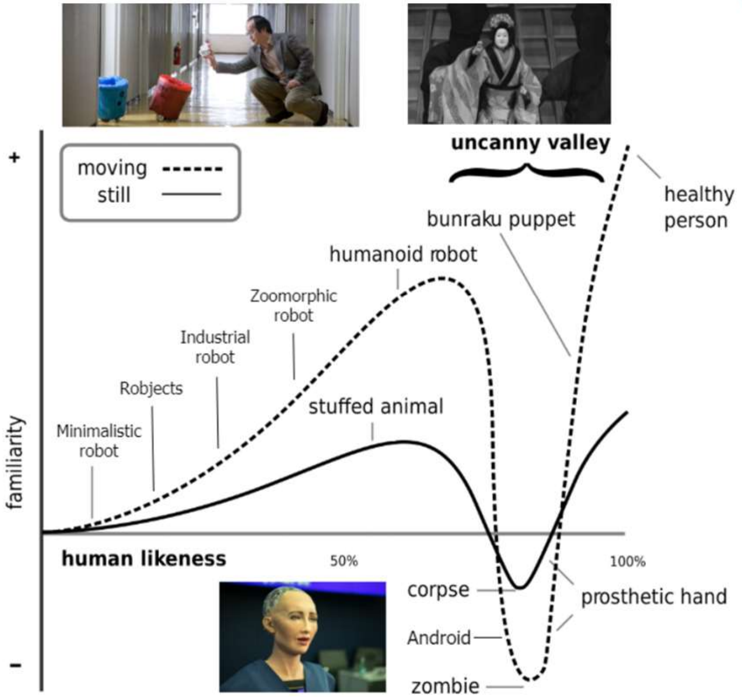



## ROBOT MORPHOLOGY

- Functional form
- Affordances

## ROBOT APPEARANCE

- What does appearance signal?




## ANTHROPOMORPHISM

- Should the robot look human-like?

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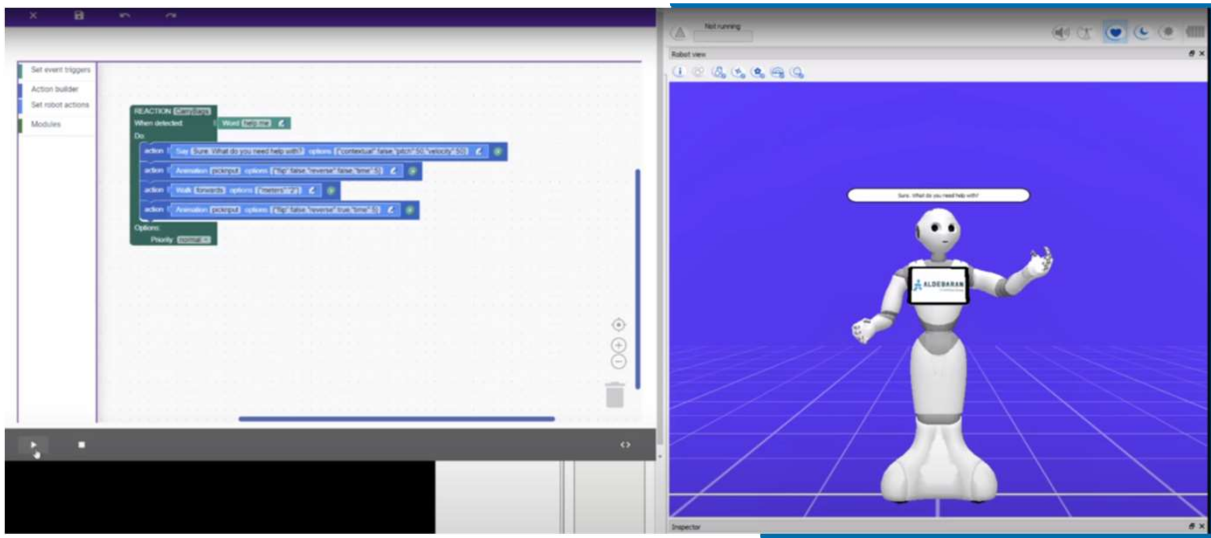
# INTERACTION DESIGN



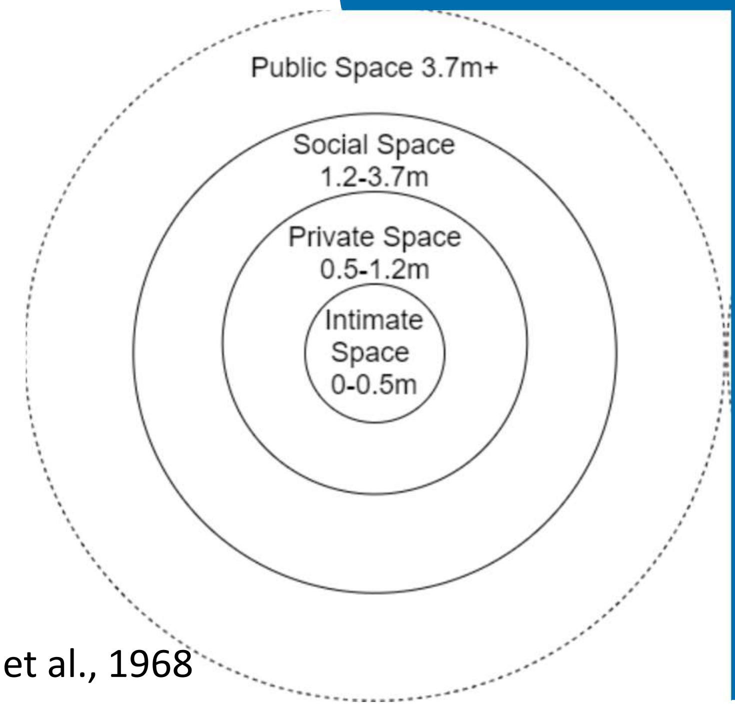
Tian et al. 2020

**METHODS**

- Designer specified
- User-centred design, participatory design
- Data driven/Learning

**MODALITIES**

- Spatial Interaction
- Teleoperation
- Physical interaction
- Verbal Interaction
- Non-verbal interaction – gaze, facial expressions, gestures, etc.




Hall et al., 1968

# HRI EVALUATION

**EXPERIMENTS**

- Simulations
- Video/remote studies
- Partial simulations
- Physical Experiments
    - Lab settings/convenience samples
    - Realistic settings/target population

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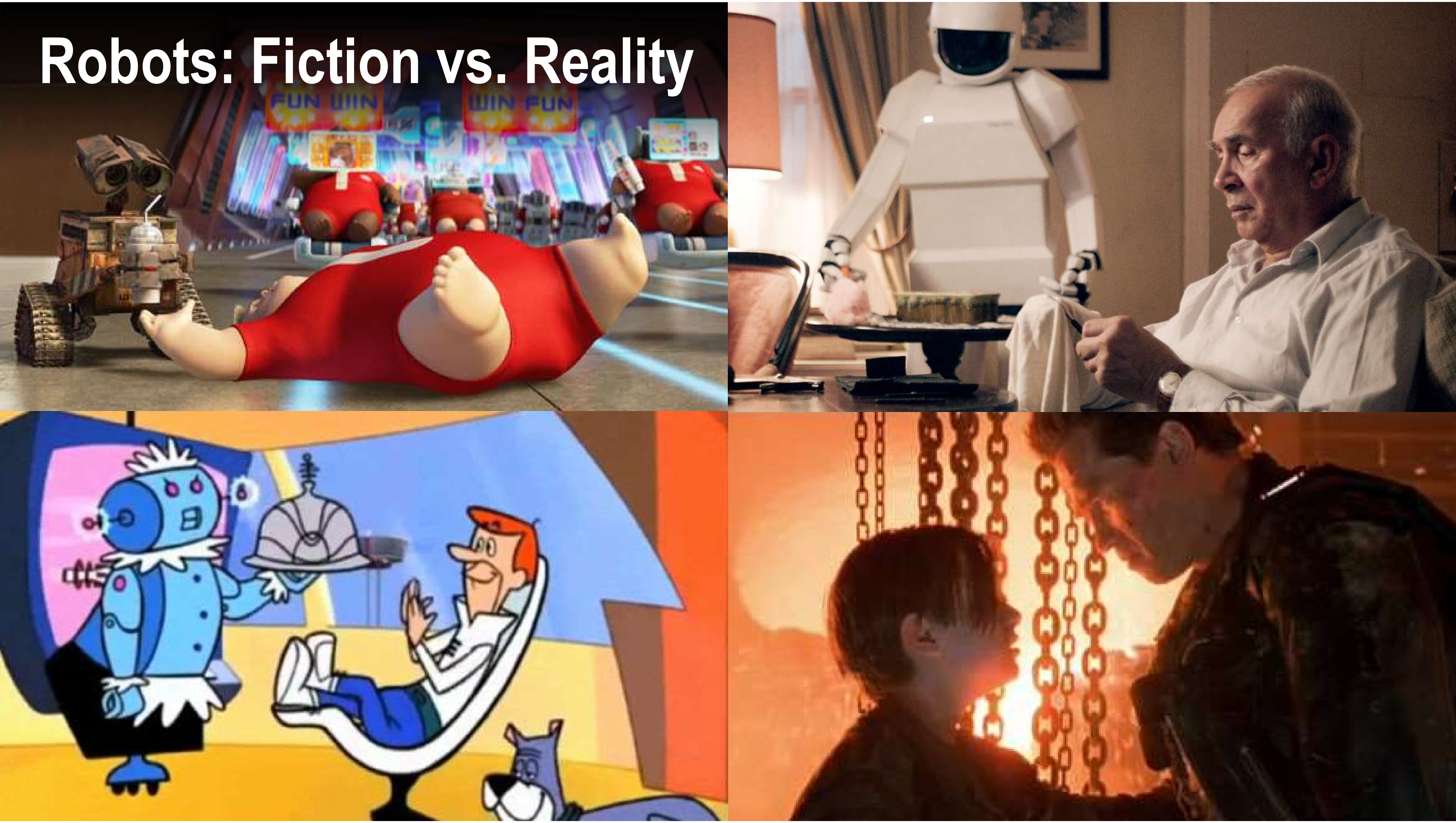
# Robots: Fiction vs. Reality



# HRI EVALUATION

**EXPERIMENTS**

- Simulations
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**EVALUATION METRICS**

- Quantitative Metrics:
  - Measurements
  - Questionnaires
- Qualitative Metrics

# EVALUATION METRICS

| Agent | Construct | Measurement | Example Metrics |
|---|---|---|---|
| Robot | Autonomy | Independent Performance | Neglect Tolerance |
| | Social attributes | Perceived Safety | Godspeed Q |
| | Productivity | Task Performance | Individual Success Rate |
| Human | Situational awareness | Scene Understanding | Freeze Frame Q (e.g. SAGAT) |
| | Social Attribute | Behavioural | Demonstrated Trust |
| | Workload | Physiology | Heart rate |
| Human-Robot Team | Safety/Reliability | Failures | Intervention counts |
| | Fluidity/Efficiency | Task Performance | Performance Time |
| | Effectiveness | Task Performance | Team Success Rate |

# Human-Robot Teams


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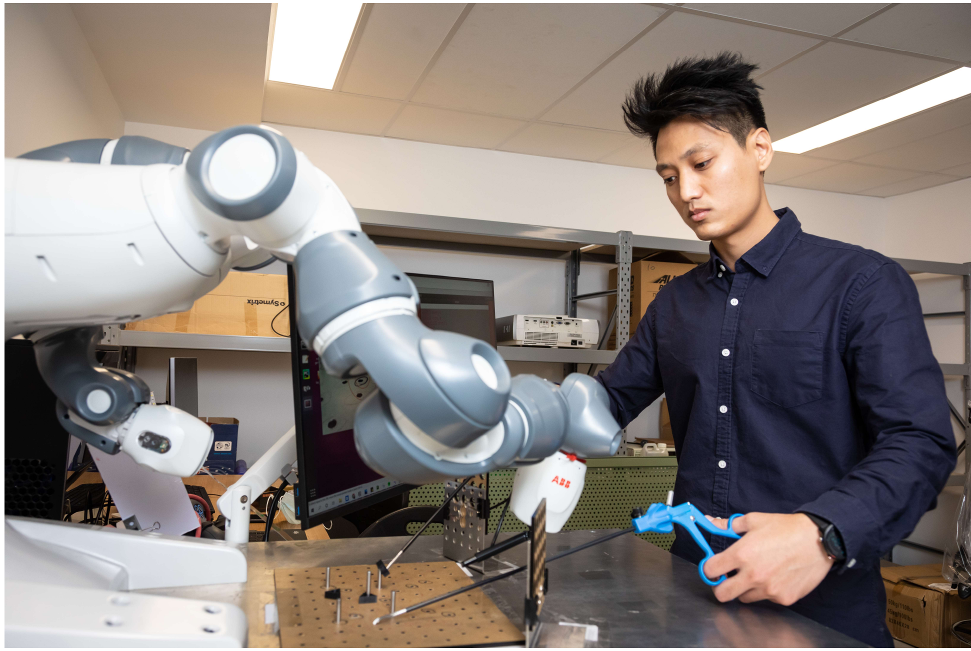
# What makes an effective human-robot team?

**ROBOT CAPABILITY**

- Autonomy
- Learning

**HUMAN CAPABILITY**

- Domain expertise
- High level perception/planning
- Individual objectives/preferences
- Learning/adaptation



**COMMUNICATIONS**

- Establishing shared objectives and shared situational awareness
- Conveying and inferring own and partner current state and capabilities
- Conveying and inferring own and partner future plans
- Error recovery

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# Understanding Human-Robot Teams

Nicole Robinson

N. Robinson, J. Williams, D. Howard, B. Tidd, F. Talbot, B. Wood, A. Pitt, N. Kottege and D. Kulić, Human-Robot Team Performance Compared to Full Robot Autonomy in 16 Real-World Search and Rescue Missions, THRI 2024

# What makes an effective human-robot team?

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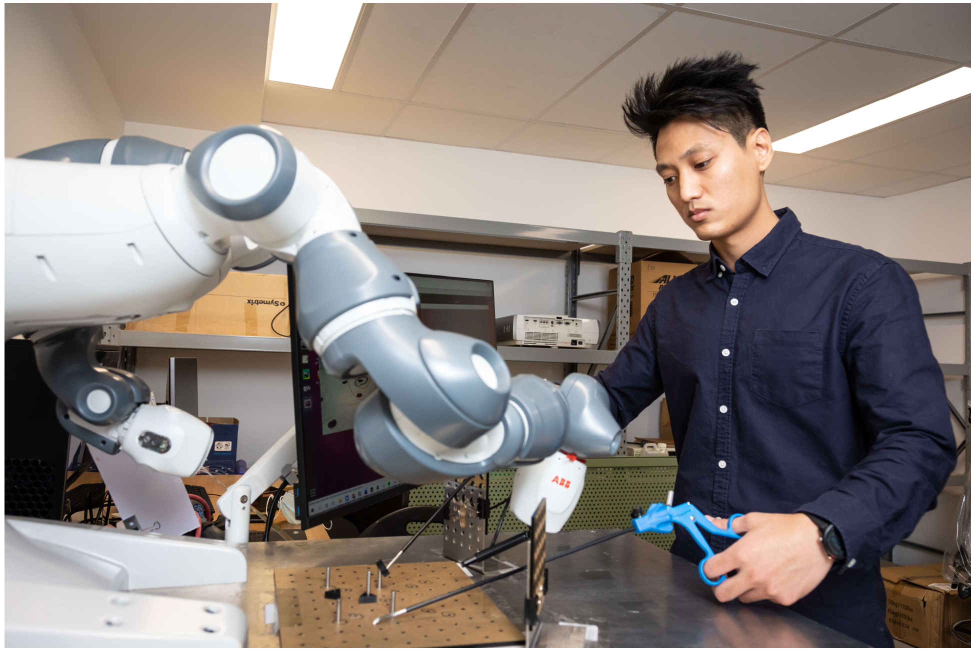

## COMMUNICATIONS

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# Learning for effective HRT

- Learning before acting:
  - From demonstrations (Pamela Carreno, TRO-2022)
  - From human-human interaction (Leimin Tian et al, HRI 2023)
  - In simulation with human models:
    - For human motion analysis and fatigue prediction (Yanran Jiang et al., 2021, 2022)
    - **For drone piloting** (Kal Backman et al., 2021, 2023) (Pamela Carreno et al., CoRL 2022)
    - For navigation in crowds (Nick Ah Sen et al., ICSR 2022)
- Learning during interaction:
  - **Learning the human model (Tina Wu et al., 2021)**
  - Learning the human objectives/constraints (Zhongxiang (Tom) Chen et al., 2021, 2023)
  - Learning the policy (Rachel Love et al., 2022)
  - Learning how to communicate (Liam Roy et al., 2023)

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# Learning from Human Models

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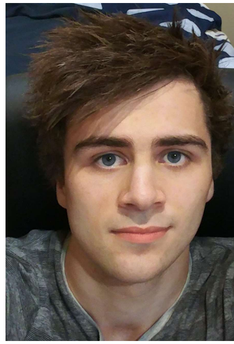
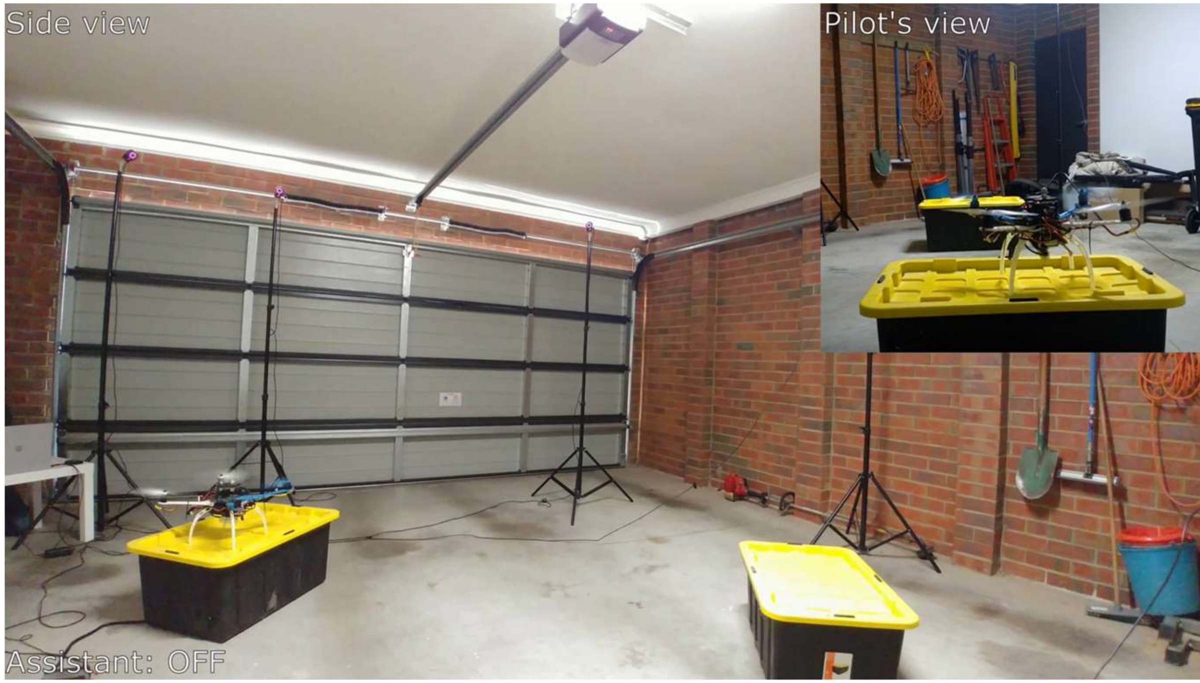
# Learning to assist drone landings



Kal Backman

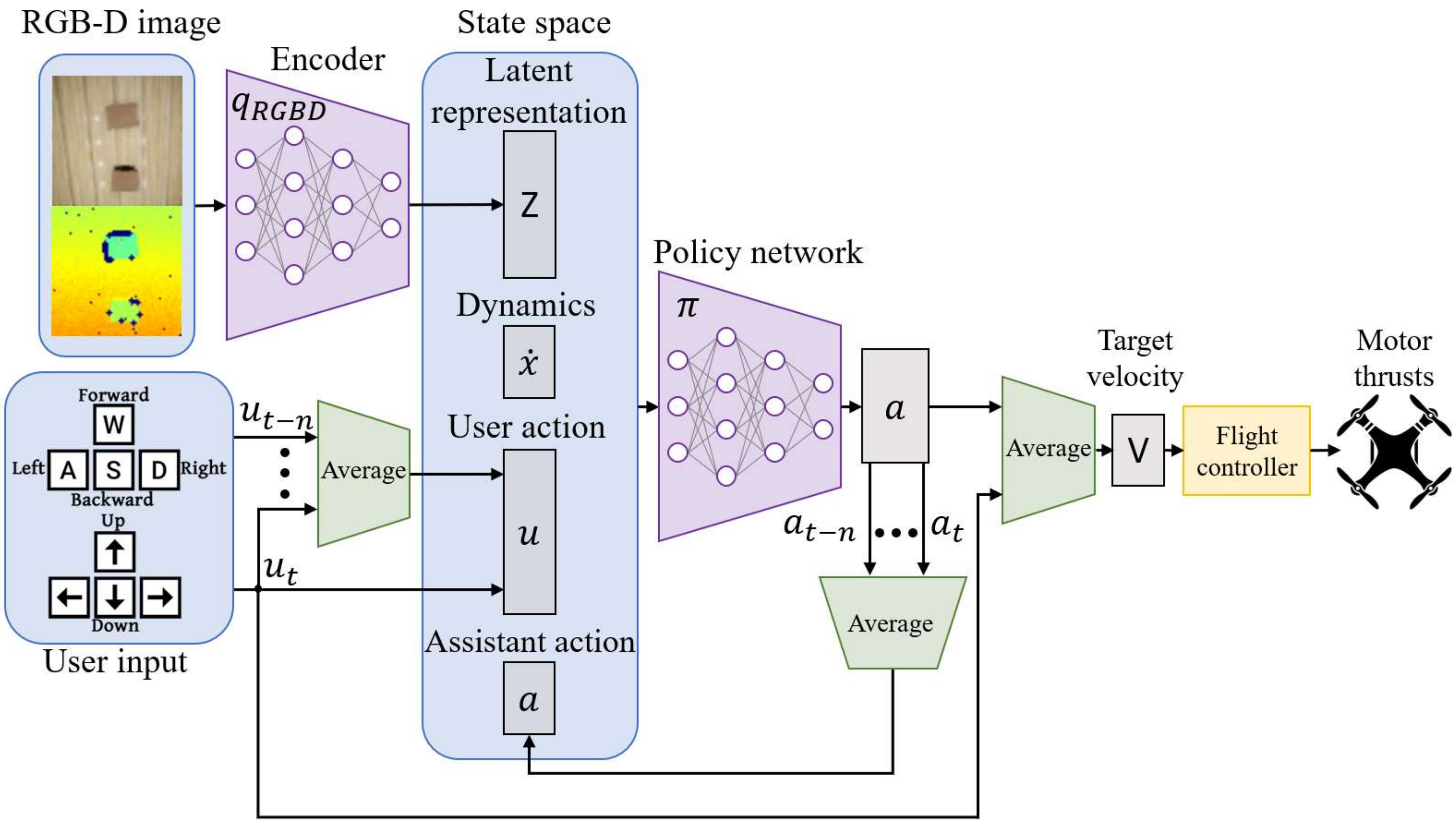
**LEARNING FOR COLLABORATIVE TASK EXECUTION**

- Human and robot team members may have different knowledge and capabilities
- Drone piloting is a very cognitively demanding and difficult skill to learn – involves perception, dynamic model learning and manual dexterity
- A novice human pilot knows where to land, but not how to command the drone to do so
- Develop shared autonomy framework that provides assistance to (novel) pilots during landing




K. Backman, D. Kulić and H. Chung, Learning to Assist Drone Landings, RA-L, 2021.
K. Backman, D. Kulić and H. Chung, Reinforcement Learning for Shared Autonomy Drone Landings, Au-Ro 2023.

# Proposed Approach – Flying in simulation

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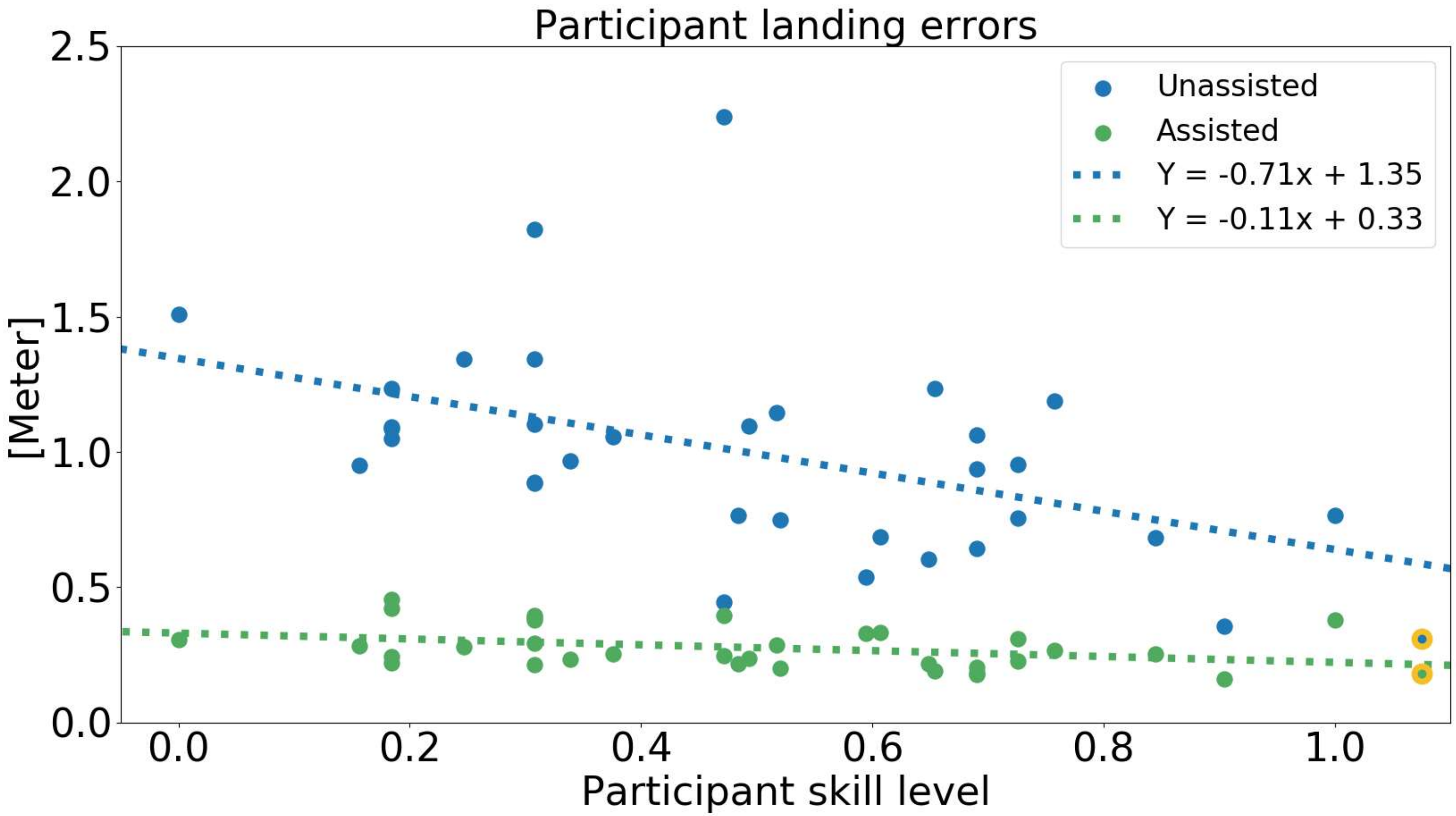
# Experimental Results – Human pilots in simulator

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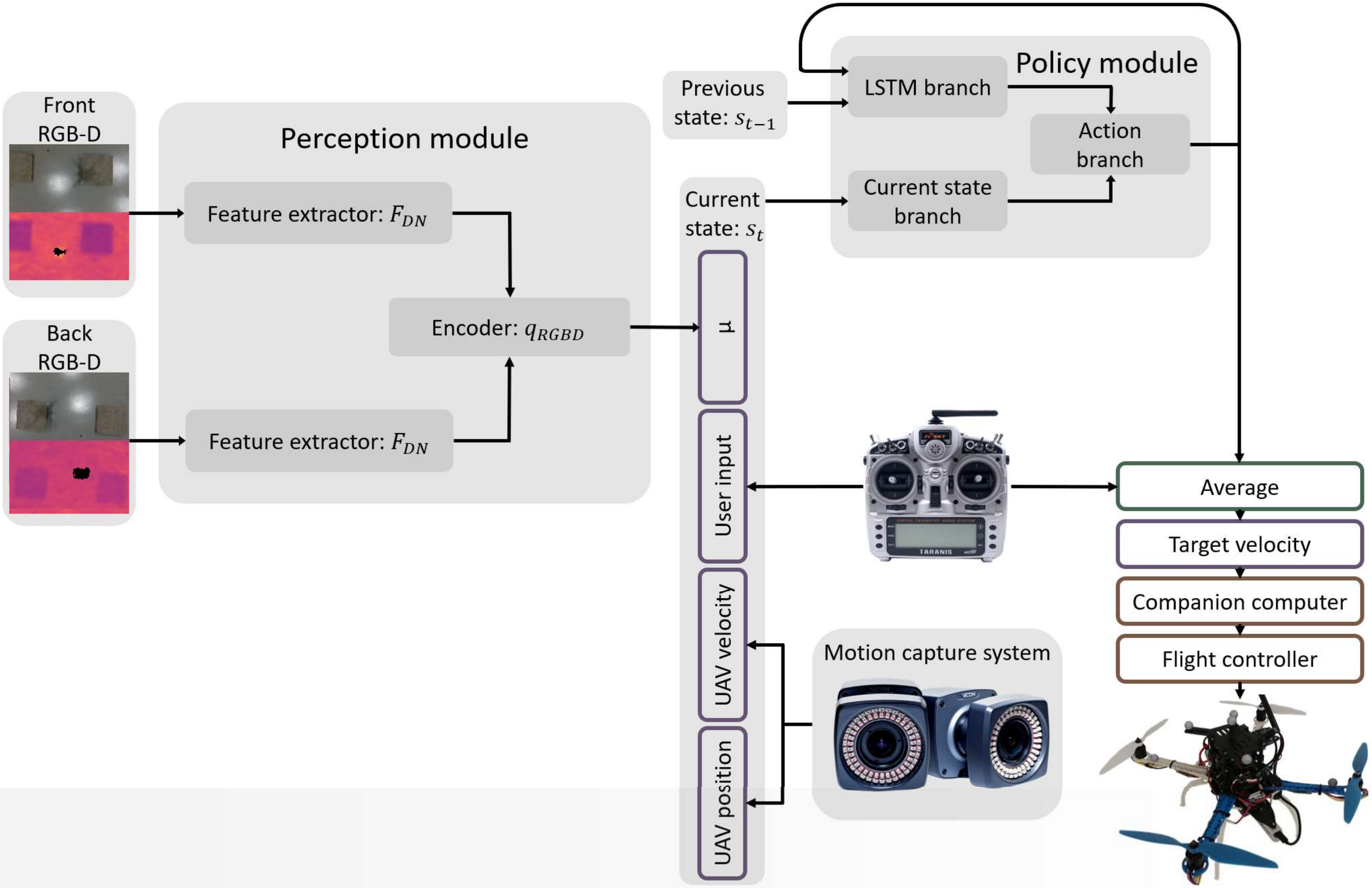
# PHYSICAL IMPLEMENTATION

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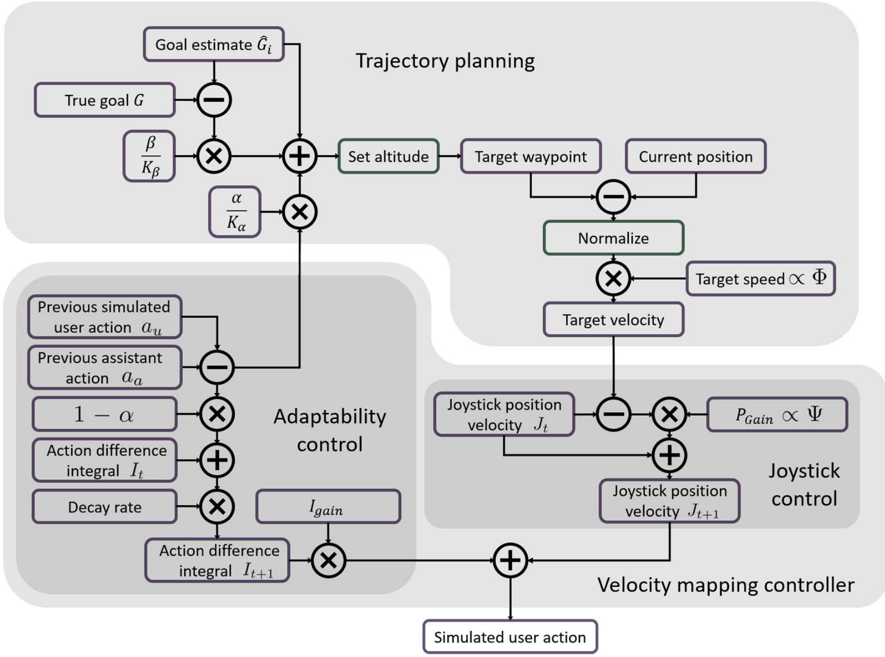
# SIMULATED USER MODEL




## MODEL STRUCTURE

- State machine with 2 states:
    - Approach state:  flying towards the target
    - Descent state: landing
- User has a perceived goal location
- Generate waypoints according to planning strategy
- Generate velocity from current position to next waypoint

## MODEL PARAMETERS

- Perceptual capability β: how similar is the user’s perceived goal location to the actual goal
- Acceptance of assistance α: how much does the user adapt to the actions of the assistant
- User’s preferred speed Φ
- Joystick operating capability Ψ

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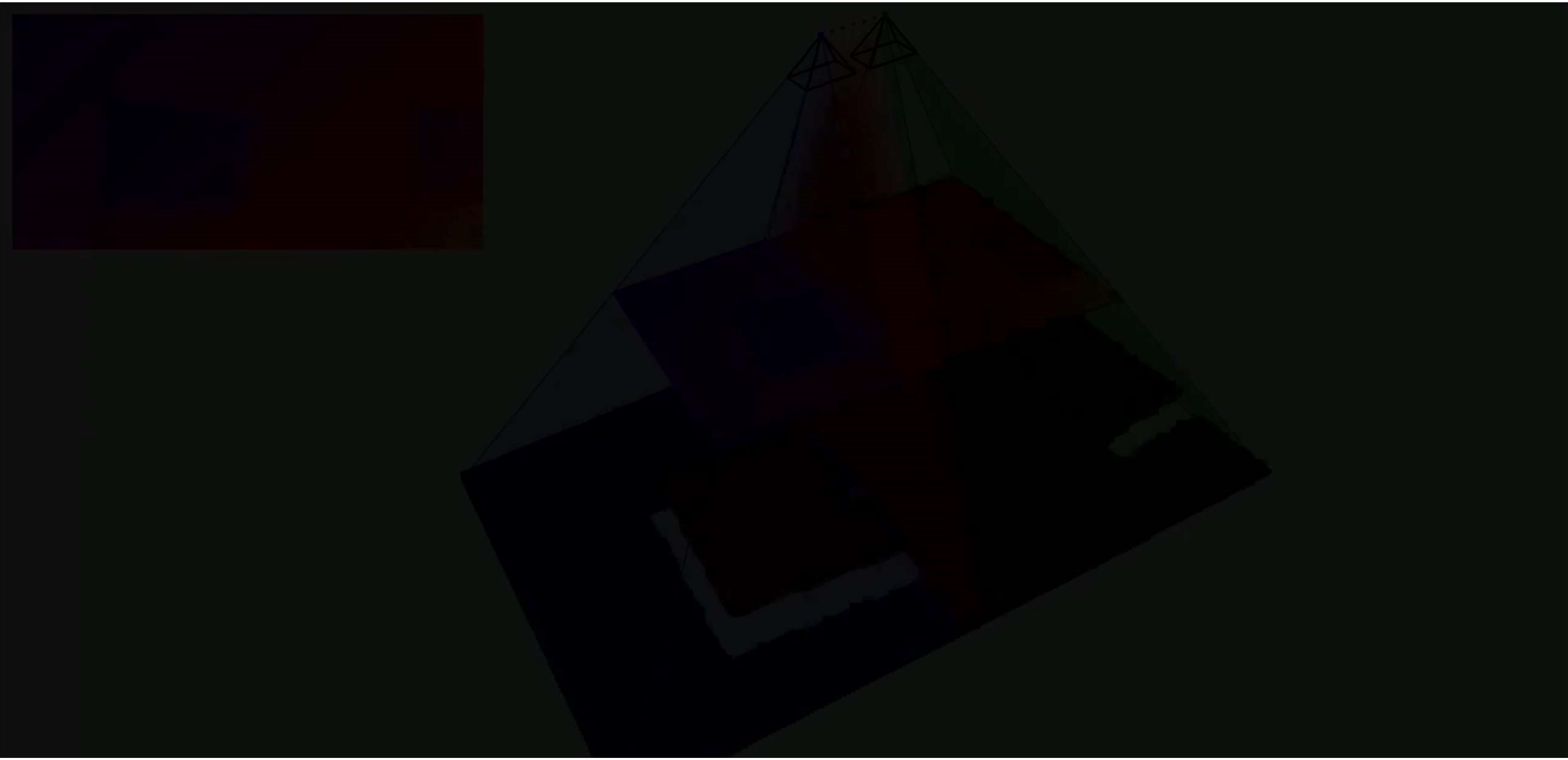
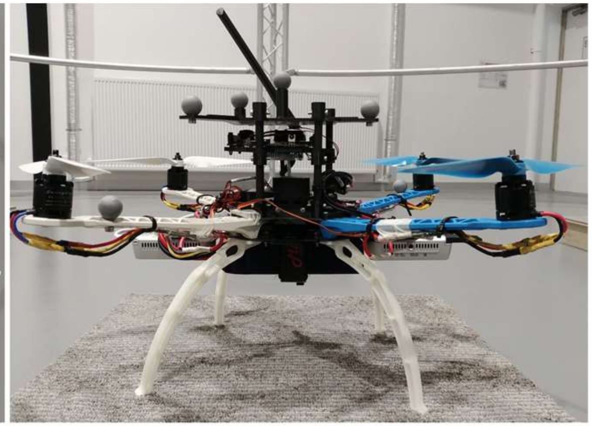
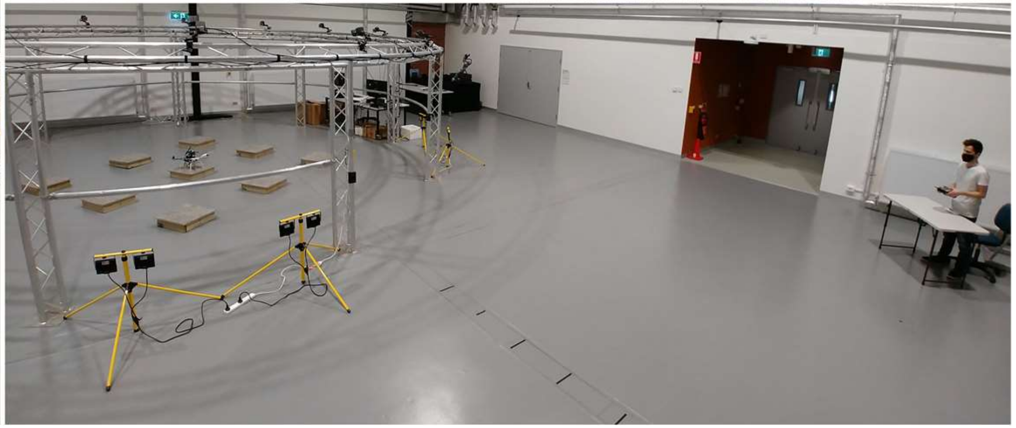
# POLICY TRAINING IN SIMULATION

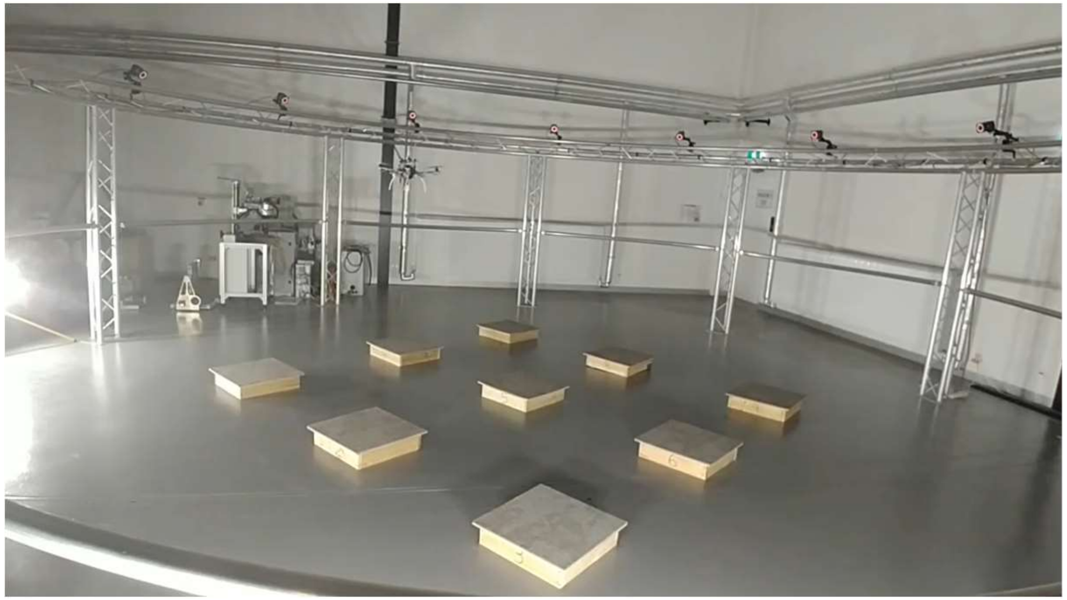


# EXPERIMENTS

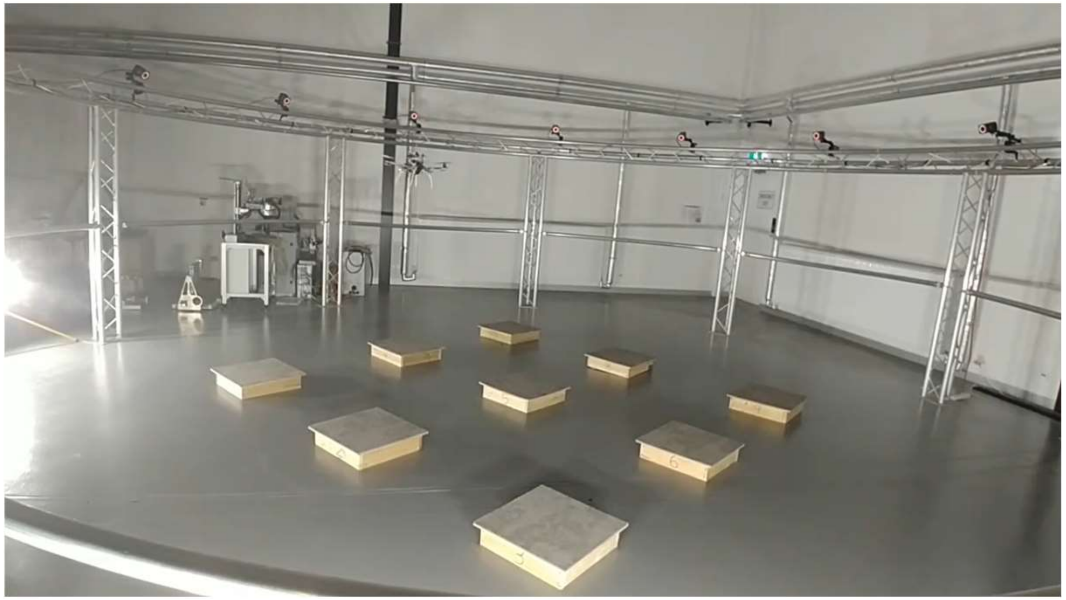




# Novice Pilots



Novice Unassisted



Novice Assisted

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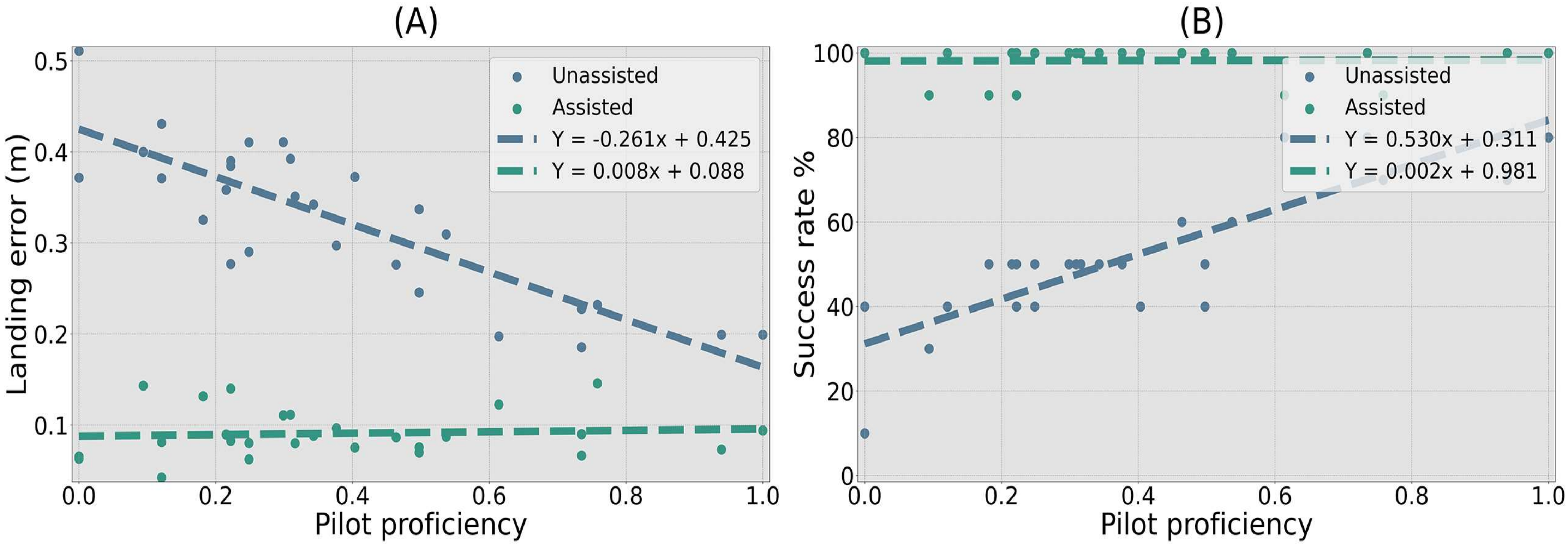
# RESULTS

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# Communications – Conveying Robot State

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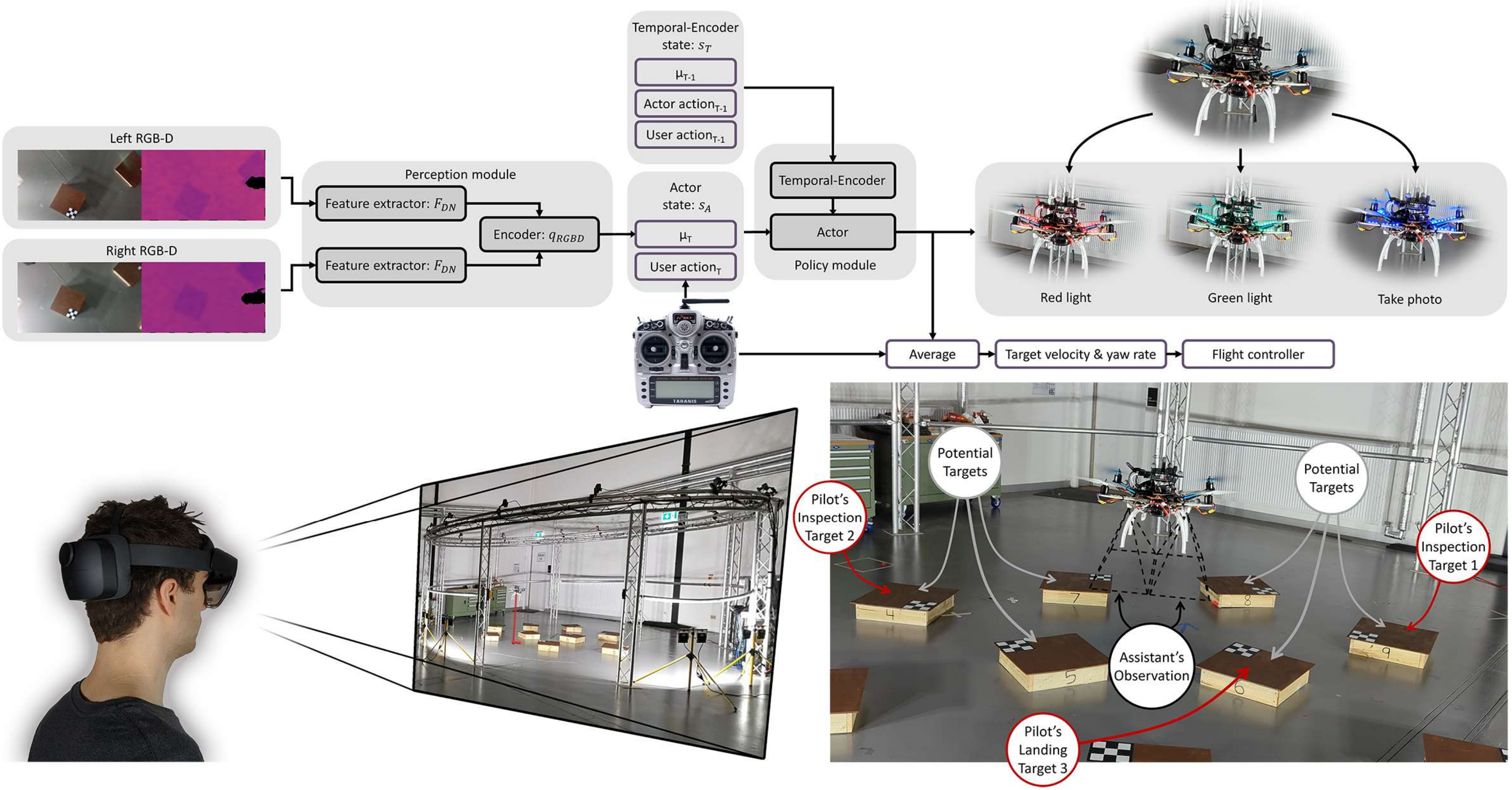
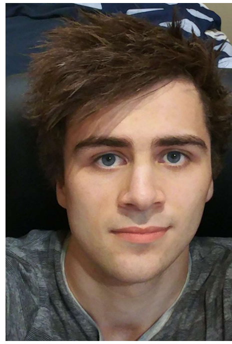
# Visual (on robot vs. AR)



Kal Backman

K. Backman, D. Kulić and H. Chung, Learning to Assist and Communicate with Novice Drone Pilots for Expert Level Performance, 2023, Submitted.

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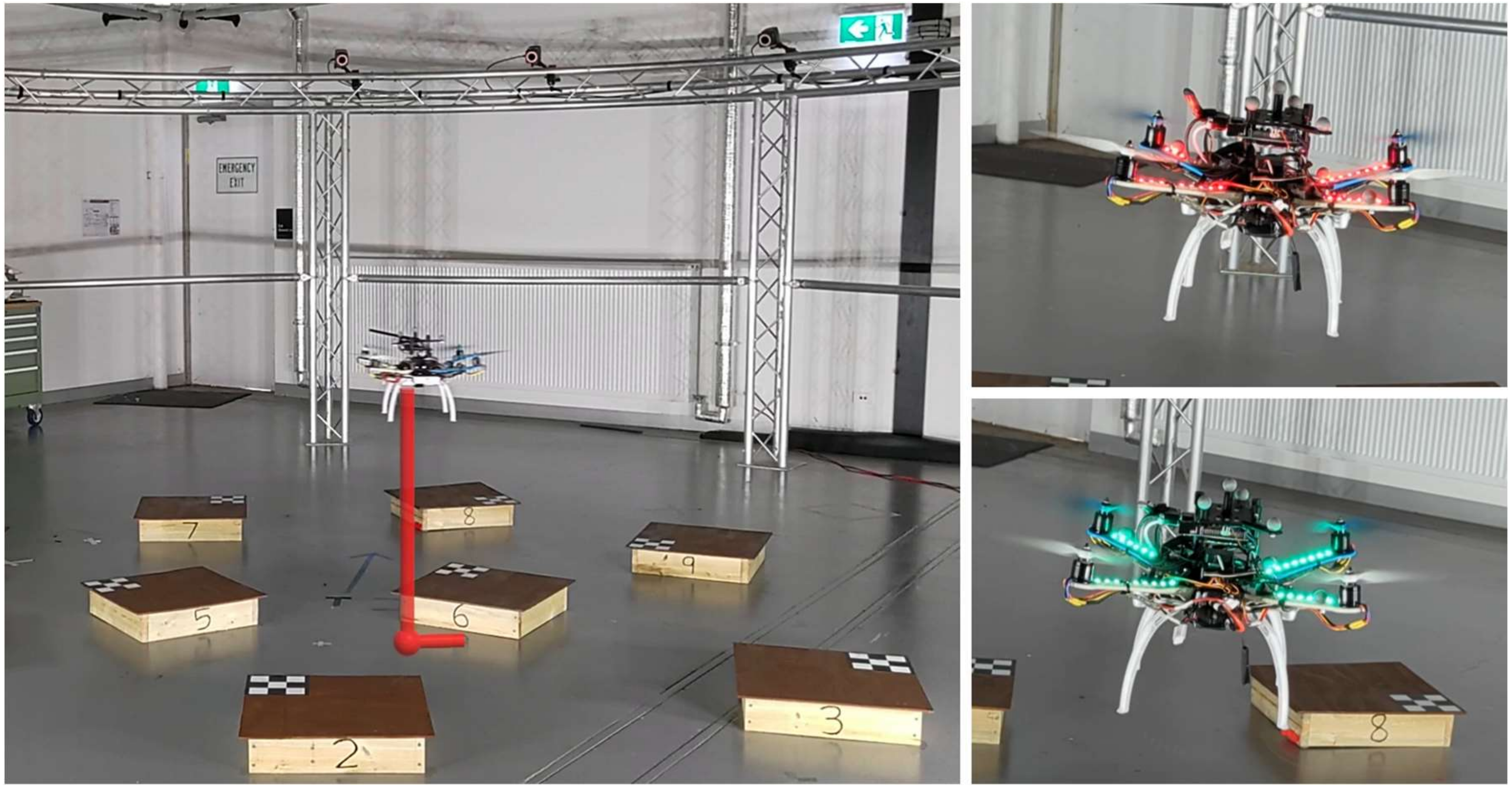
# Visual (on robot vs. AR)



# Learning to Assist and Communicate with Novice Drone Pilots for Expert Level Performance

Kal Backman, Dana Kulić and Hoam Chung

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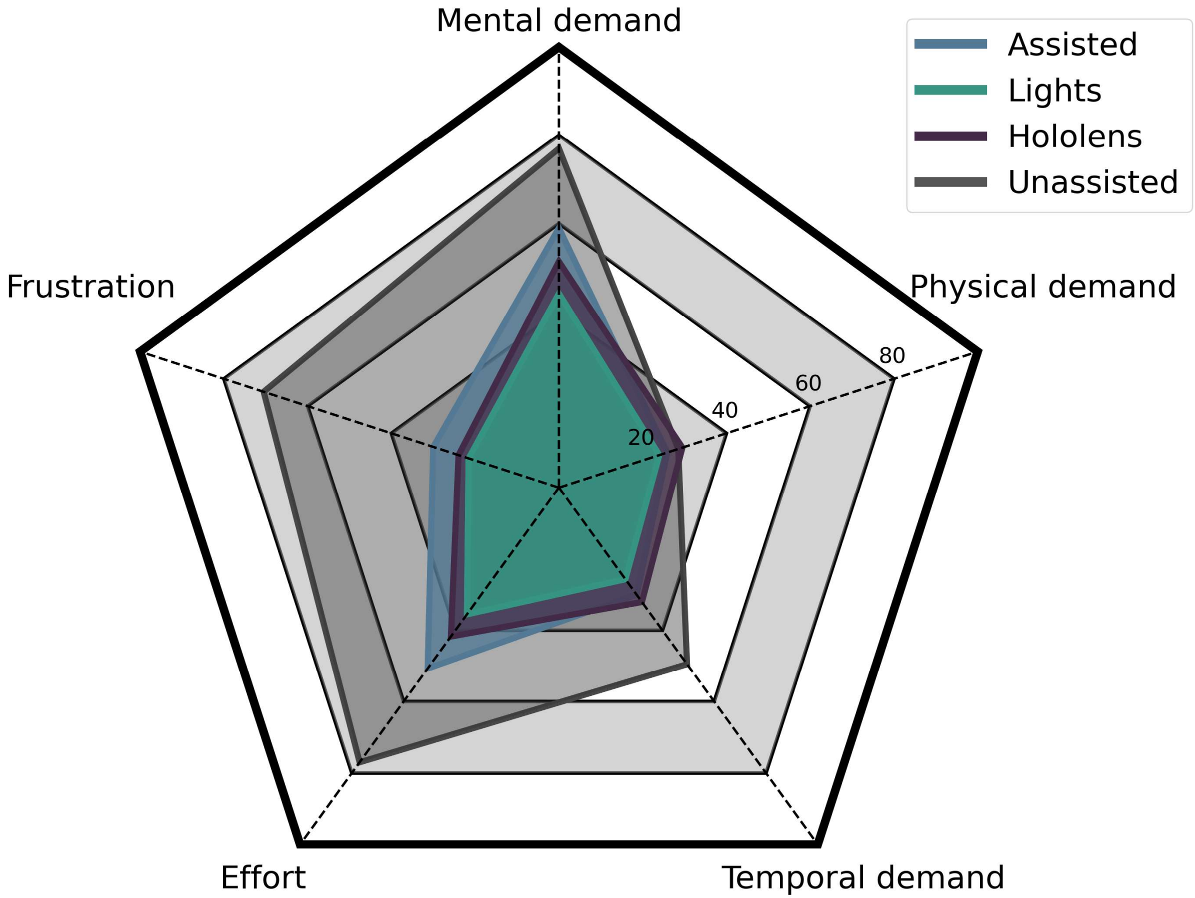
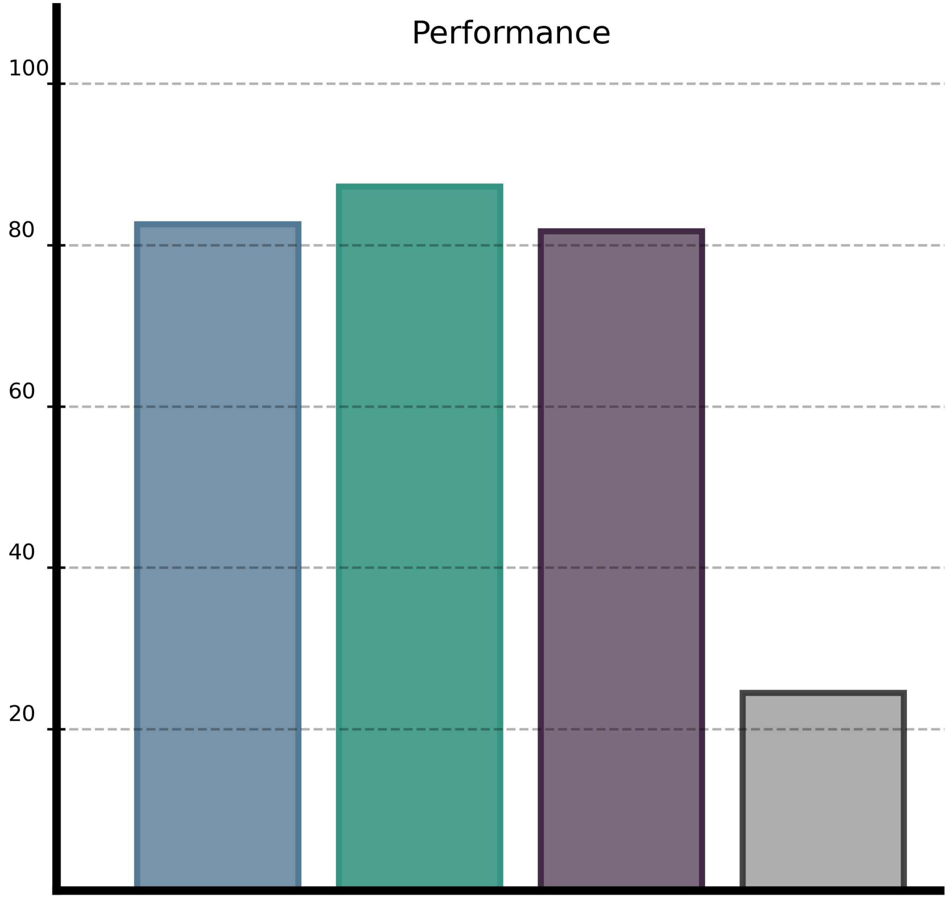
# Results

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# Learning during interaction

# Learning to provide feedback during gait rehab

**PARKINSON'S DISEASE GAIT THERAPY**

- A common symptom of PD includes Freezing of Gait (FoG)
- Can be alleviated by providing cues on where or when to step

Videos courtesy of Dr. A. Murphy and the Monash Health Movement Disorder Clinic

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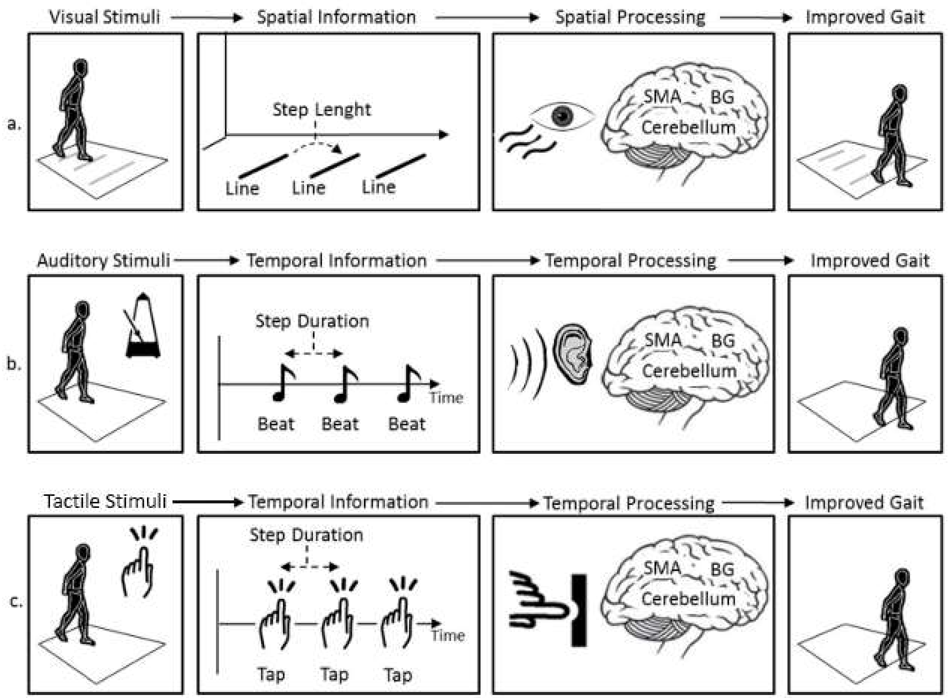
# Learning to provide feedback during gait rehab

Tina Wu

**PARKINSON'S DISEASE GAIT THERAPY**

- Cues can be visual, auditory or haptic
- Most existing approaches generate a fixed on-demand cueing strategy, with no adaptation to the user
- Inspired by human-in-the loop optimisation for gait rehab (Felt et al., 2015, Zhang et al., 2017, Kim et al., 2017), we want to develop an approach to on-line optimisation for cueing




(Sweeney et al., 2019)

T.L.Y. Wu, A. Murphy, C. Chen and D. Kulić, Human-in-the-loop Auditory Cueing Strategy for Gait Modification, RA-L 2021. https://arxiv.org/abs/2011.13516

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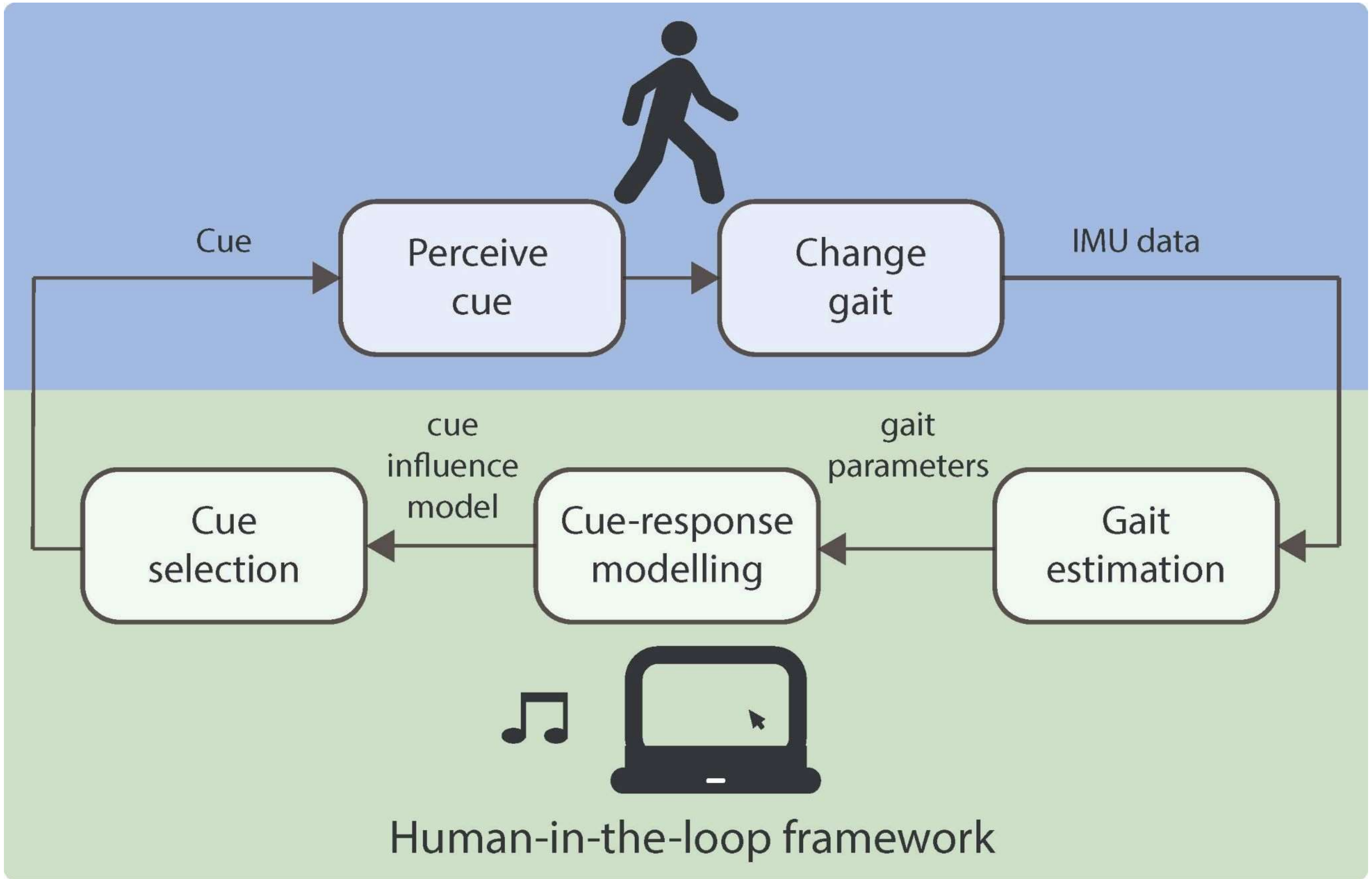
# Overview of the Proposed Approach

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# Modelling Approach

### GAIT MODEL

Model periodic gait as a weighted sum of sinusoids

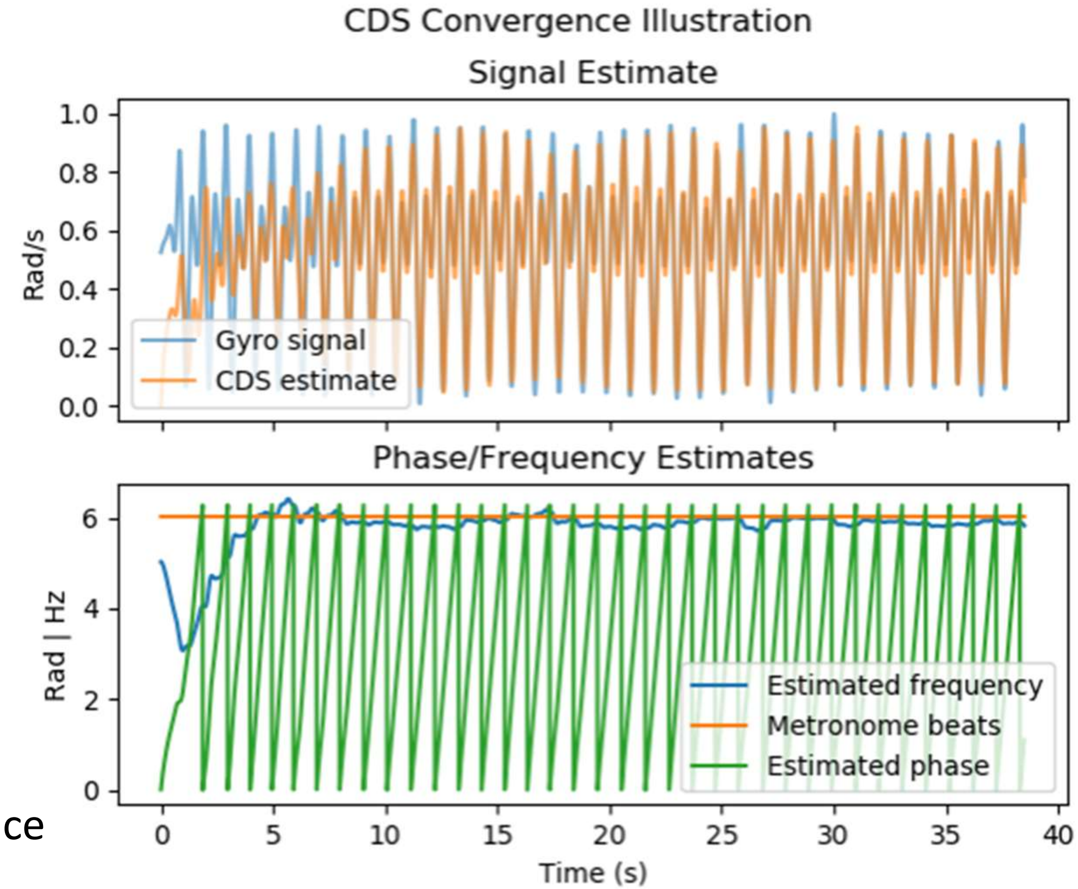
Learn the model parameters with incremental updates (Petric et al., 2011) from IMU signal data (Waugh et al., 2019)

### MODEL OF CUE-INFLUENCE ON GAIT

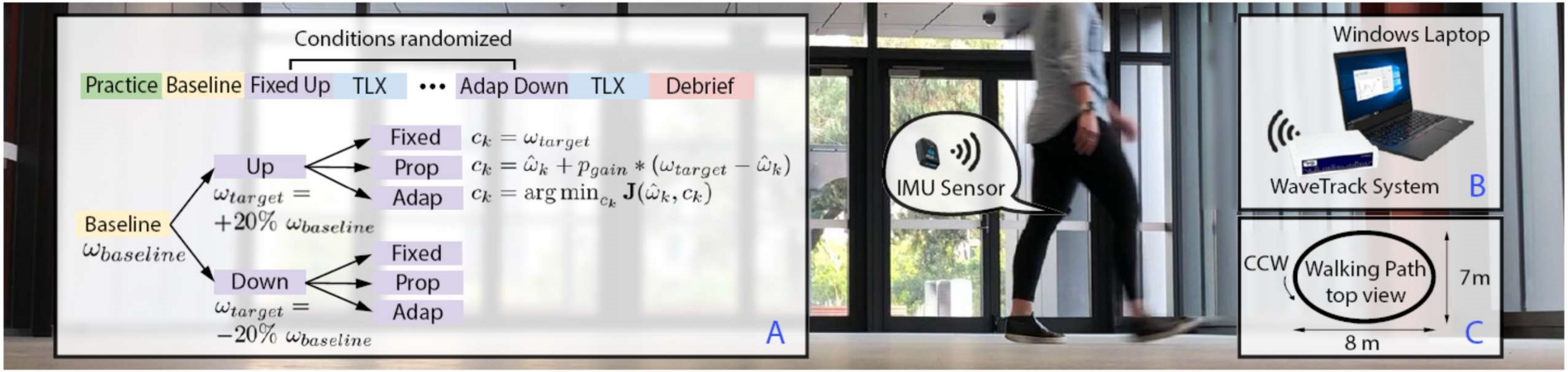
Gaussian Process (GP) model that learns the mapping between input cue frequency and resulting cadence

### NEXT CUE SELECTION

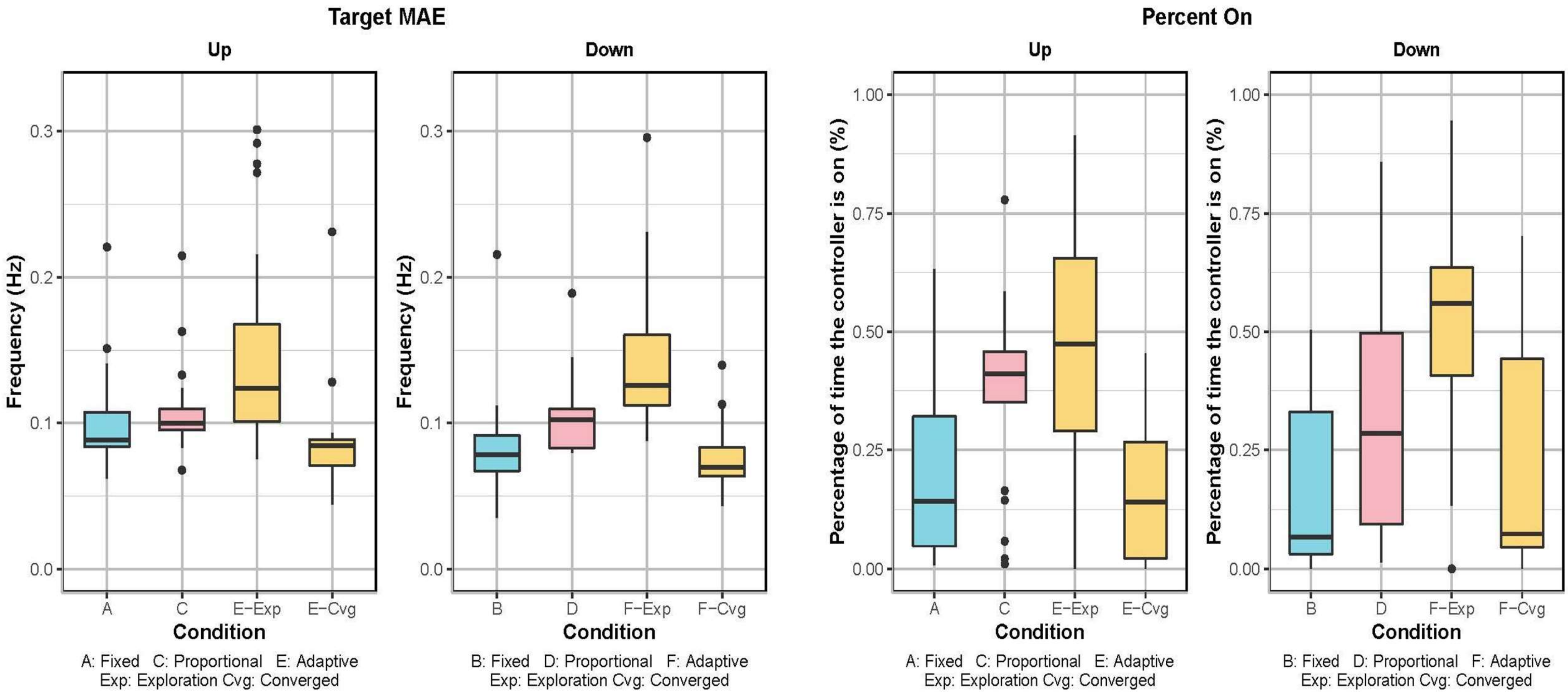
Using GP model, generate cue that minimises the difference between the target and the predicted cadence



# Experiments



# RESULTS




T.L.Y. Wu, A. Murphy, C. Chen and D. Kulić, Human-in-the-loop auditory strategy for gait modification, RA-L, 2021.

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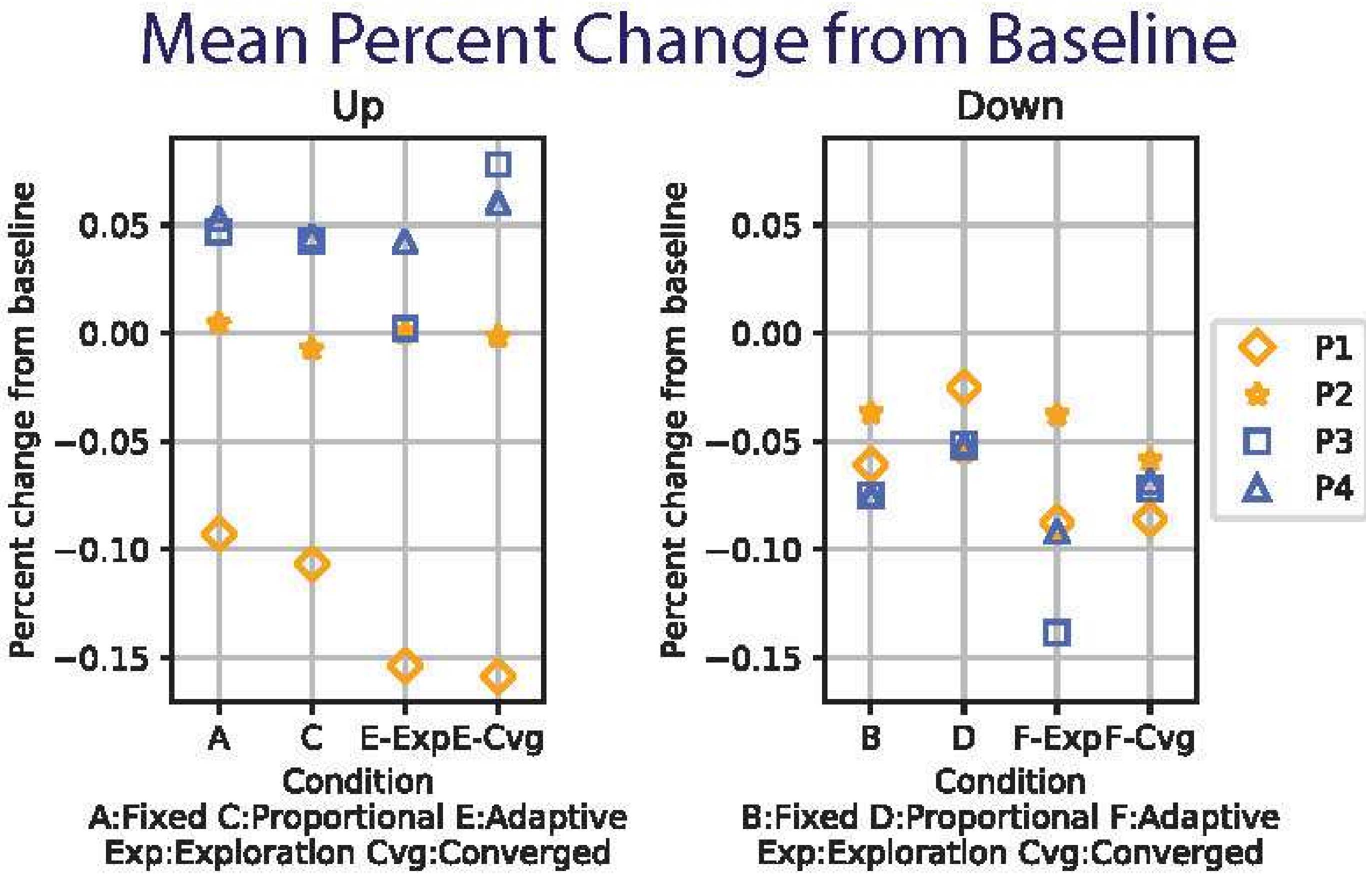
# First feasibility study with patients

- Choice of target is important:
  - Yellow data: want ±0.15
  - Blue data: want ±0.1




T.L.Y. Wu, A. Murphy, C. Chen and D. Kulić, Adaptive Auditory Cueing Strategy for Gait Modification: A Case Study, Frontiers in Neurorobotics, 2023.

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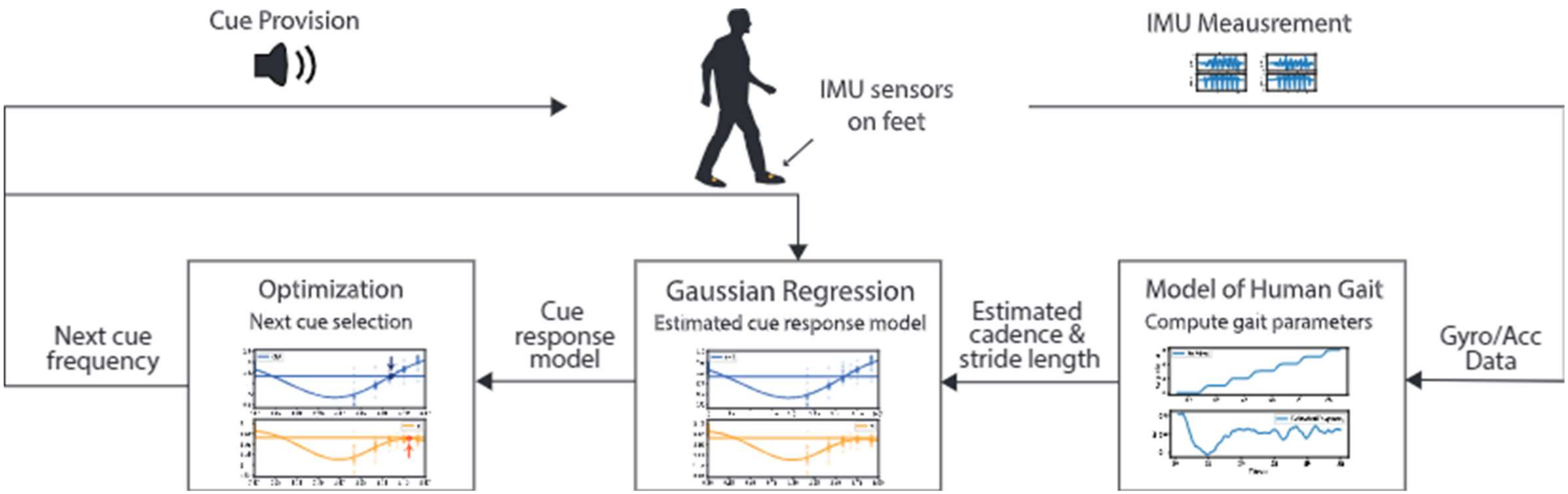
# Cueing cadence and stride length

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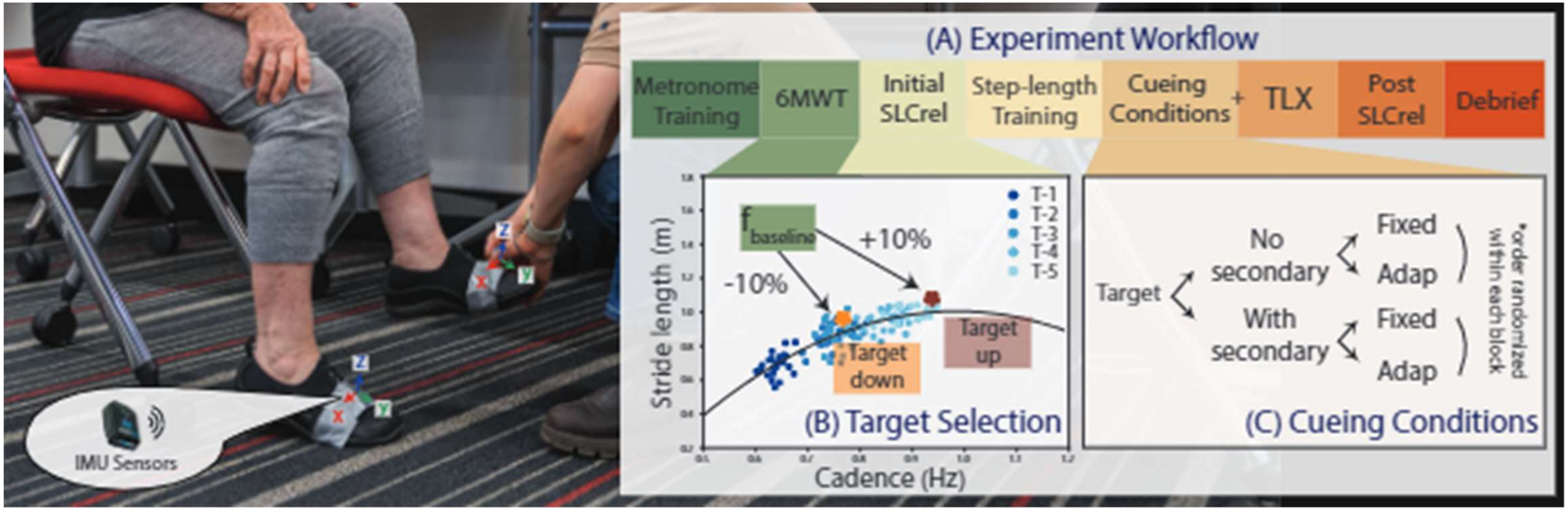
# Considering Distractors




T.L.Y. Wu, A. Murphy, C. Chen and D. Kulić, Auditory cueing strategy for stride length and cadence modification: a feasibility study with healthy adults, EMBC 2023.
T.L.Y. Wu, A. Murphy, C. Chen and D. Kulić, Adaptive auditory assistance for stride length cadence modification in older adults and people with Parkinson’s, 2024.

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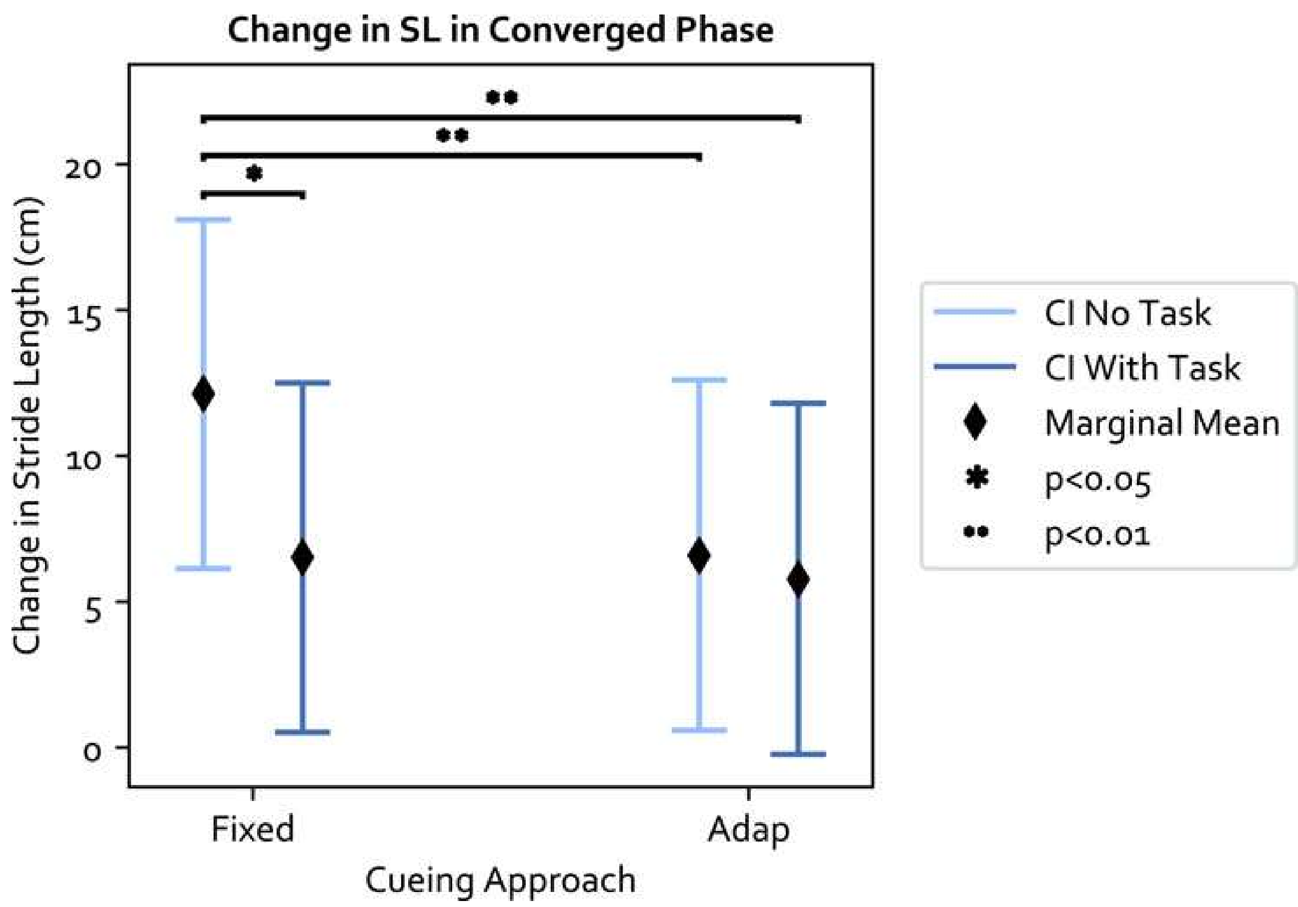
# Results


Change in SL in Converged Phase
**
**
*
20
15
10
5
0
Change in Stride Length (cm)
Fixed
Adap
Cueing Approach
CI No Task
CI With Task
Marginal Mean
p<0.05
p<0.01

# Current + Future Work

## BETTER MODELS FOR LEARNING

- Can we move towards more easily generalisable human models for policy training?
    - Identifying (time-varying) objectives
    - Modelling biases
    - Identifying the main dimensions of variation
    - Dealing with user adaptation

## BETTER TEAMS

- Understanding team dynamics
- Understanding situational awareness
- Errors + error recovery

Thanks to all my students, collaborators and sponsors!

Questions:

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