Evaluating Astronaut Training Algorithms in Virtual Reality for Long-Duration Exploration Missions

University of Colorado Boulder Bioastronautics

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TRINITY

Objective

Astronauts on deep space missions will require **automated** rather than facilitated training[1,2,3]. Virtual reality (VR) is immersive, low-cost, programmable, and effective for astronaut training[4,5].

Goal: Evaluate the feasibility of **automated**, personalized, and individually-adaptive training algorithms

Objective 1: Investigate the importance of **personalization**

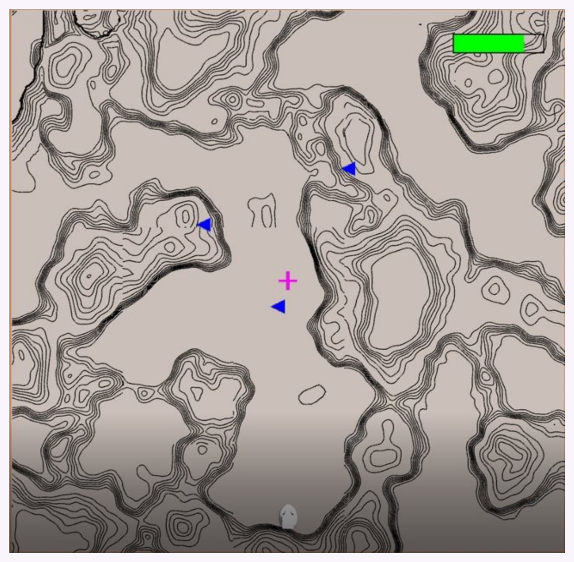
Objective 2: Investigate the importance of **responsiveness**

Credit: NASA

Methods: Training Simulator and Algorithms

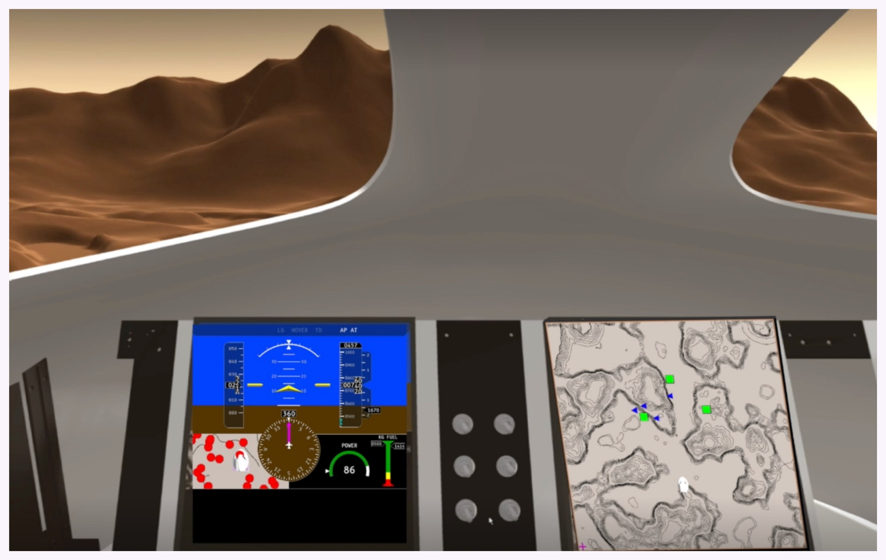
VIRTUAL TRAINING SIMULATOR

*Entry, descent, and landing (**EDL**) on Mars*



(**1**) Landing site selection

(**2**) Piloting and navigation



(**3**) Landing burn and touchdown

TRAINING ALGORITHMS

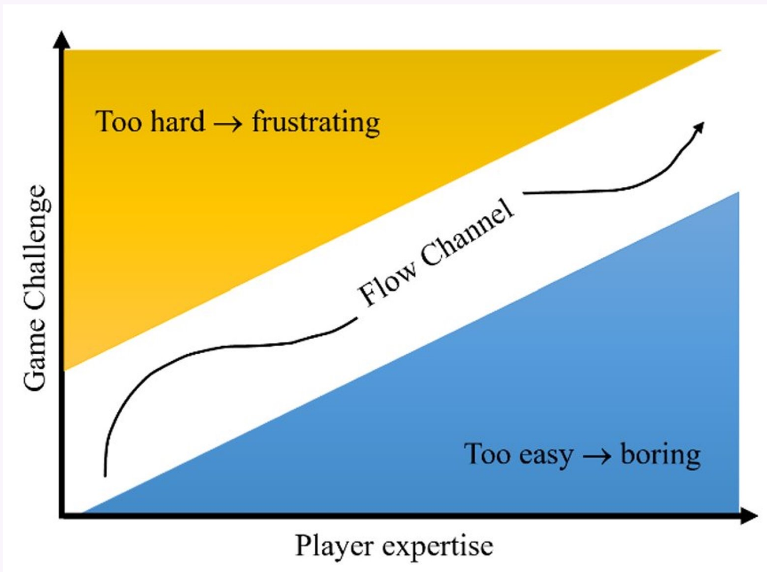
*Subtask difficulty modulated between **levels 1-24***

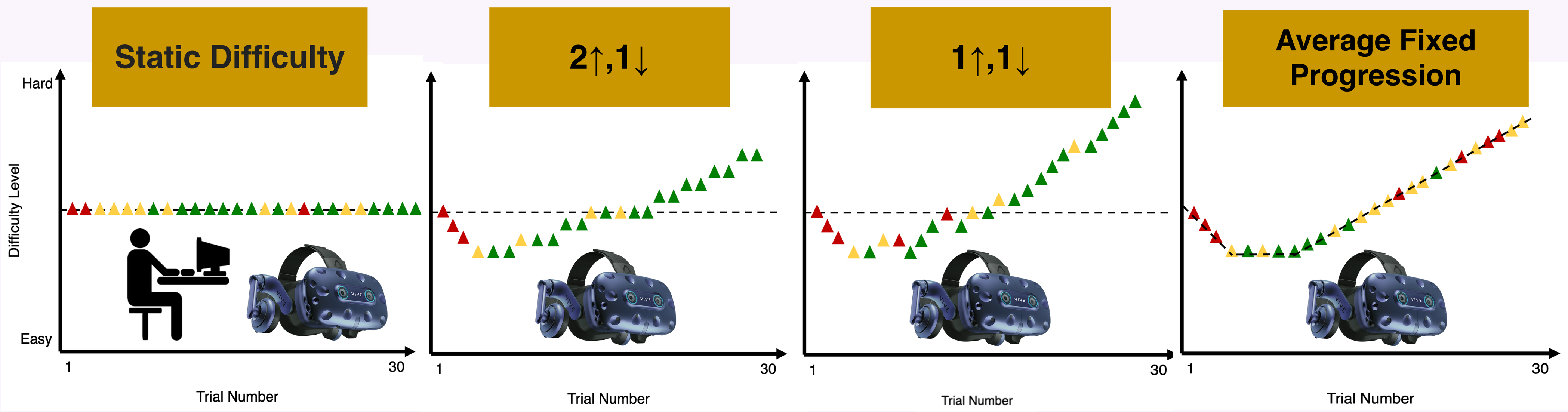
How can we modulate training algorithm adaptivity, sensitivity, and lockstep to maintain a **flow state**[6]?
Subject testing (n=48, 24M/24F) across **6 training algorithms**
VR training (30 trials over 3 sessions, 18-48 hours apart)

Variable 1: Adaptivity: Individually-adaptive vs. non-adaptive

Variable 2: Sensitivity: High vs. low threshold for progression

Variable 3: Lockstep: Unified vs. discrete difficulty modulation





References

[1] Gabay et al., 2019 [2] Kumar et al., 2018 [3] Wickens et al., 2013 [4] Saurav et al., 2018 [5] Summa et al., 2015 [6] Wightman et al., 1985

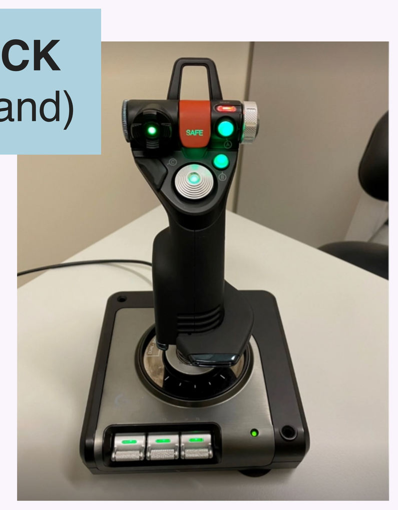
Methods: Cockpit Testing

COCKPIT MOCK-UP

Subjects put their training to the test in the Aerospace Research Simulator (ARES) **cockpit mock-up** to **test skill transfer** from virtual to physical environment (*fixed subtask difficulty, level 18, lockstep, 10 trials*)

THRUSTER (Left-Hand)

JOYSTICK (Right-Hand)



Preliminary Results

Characterization of logistic **"learning" curves** for initial 3 algorithms (n=15 subjects)

Method: Kruskal-Wallis hypothesis testing

RATE PARAMETER	**ASYMPTOTE**	**VARIANCE**
How *quickly* did subjects learn?	How *much* did subjects learn?	How *general* are training outcomes?
Goal 1: Analyze skill *acquisition*	**Goal 2**: Analyze skill *retention*	**Goal 3**: Analyze skill *transfer* (VR-Cockpit)

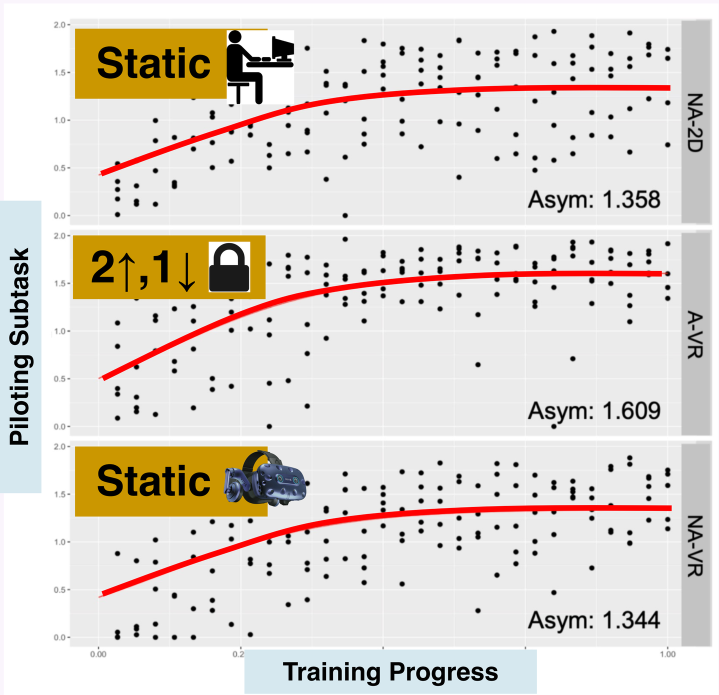
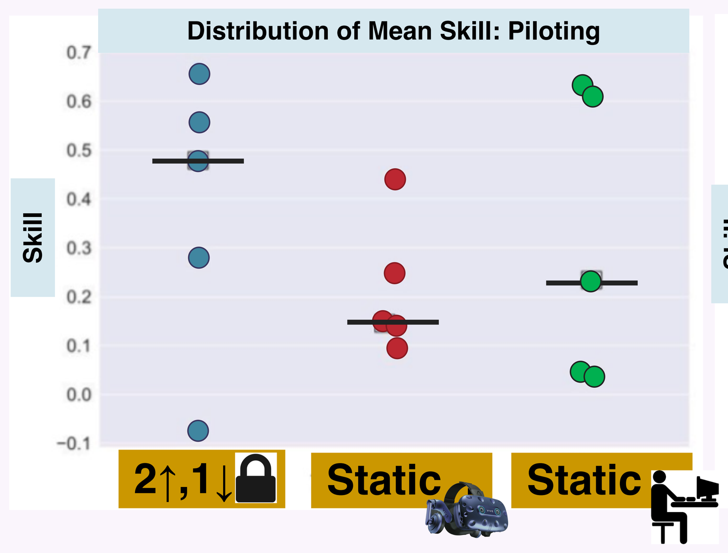
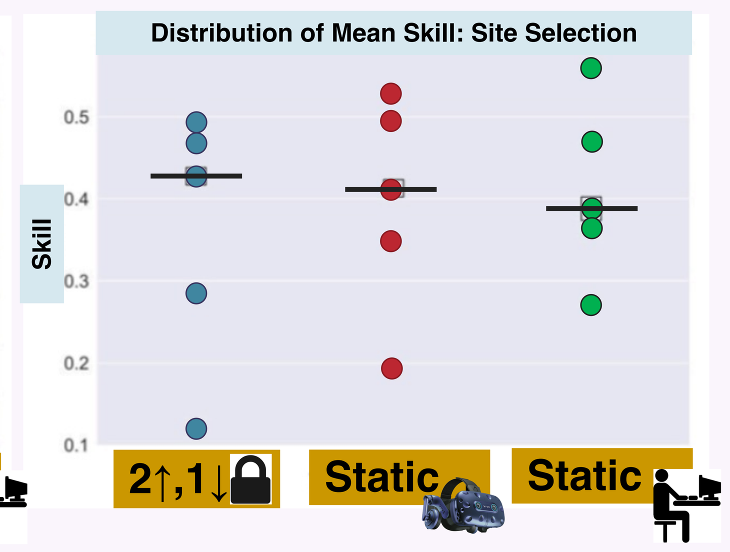


Fig 1: Composite learning curves (30 trials, 8 subjects, 3 conditions)
2↑,1↓ Locked has highest asymptote and steepest rate parameter





Figs 2-3: Mean skill distribution: piloting (2) and landing site selection (3)
2↑,1↓ Locked has highest average skill achievement for both subtasks

Preliminary Result: personalization and adaptivity lead to *improved training*

Conclusions

Personalized, individually-adaptive training algorithms lead to:

- Faster skill acquisition
- Increased learning retention between trials
- Improved cockpit performance

Low thresholds for progression (1↑,1↓) is hypothesized* to lead to:

- Faster learning rates
- Higher maximum performance
- Increased initial variability

**Data collection is ongoing*

Independently modulated difficulty across subtasks (🔒) is hypothesized* to lead to:

- Better performance outcomes
- Faster learning progression

**Data collection is ongoing*

Future Work

Run-dependence: dynamically switching between 2↑,1↓ and 1↑,1↓ after "runs" of consecutive excellent performance to incentivize progression

Scaled-response: Dynamic scaling of difficulty up or down by *variable* rather than fixed (i.e. +/- 1) amounts for rapid response to subject learning needs

Probabilistic estimation: Using a Bayesian approach to predict the optimal difficulty of subtasks using past subject performance data

Learn More

Immersive and Adaptive Training With Virtual Reality for LDEM
Presented by: Esther Putman
4DZ40809DK in Poster Session B

TRINITY: Multi-Environment Virtual Trainer For Long-Duration Exploration Missions
Presented by: Dr. Allison P. Anderson
0BQQ909VBW in Poster Session B

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