Interplay of Cognitive Fatigue and Trust in Human-Robot Collaboration

Aakash Yadav, Sarah K. Hopko, Ranjana K. Mehta
Texas A&M University

Background

At present

- Manufacturing encompasses 12% of US economy[1]
- Traditional assembly lines are either manual or completely automated

HRC allows for

- Improved team fluency with complementary skill set[2]
- New possible interaction modes and collaboration

Challenges

- Improved teaming requires human factors considerations such as trust and fatigue
- Operator safety is critical as robots are not 100% reliable[2]

Background

Strictly separated robot workspace

Part of the workspace is shared

Workspaces are full shared

Level of Human Robot Collaboration

Images adapted from Rizal et al. 2019

Trust and Fatigue

Trust

"the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability"[3] – Lee and See

Why?
Robots and other autonomy agents cannot be 100% reliable[3]. Unreliable behaviors cause distrust leading to lower efficiency and worker satisfaction.

Fatigue

Cognitive fatigue is defined as a decrease in cognitive resources developing over time on sustained cognitive demands.

Why?
Workers in industrial settings are subject to extended and erratic work hours leading to fatigue. Cognitive fatigue can impact attention, vigilance, and situation awareness[4].

Trust × Fatigue

Brain regions affected by fatigue[5] has been observed to be affected by trust[6]. However, this interplay is yet to be investigated in HRC.

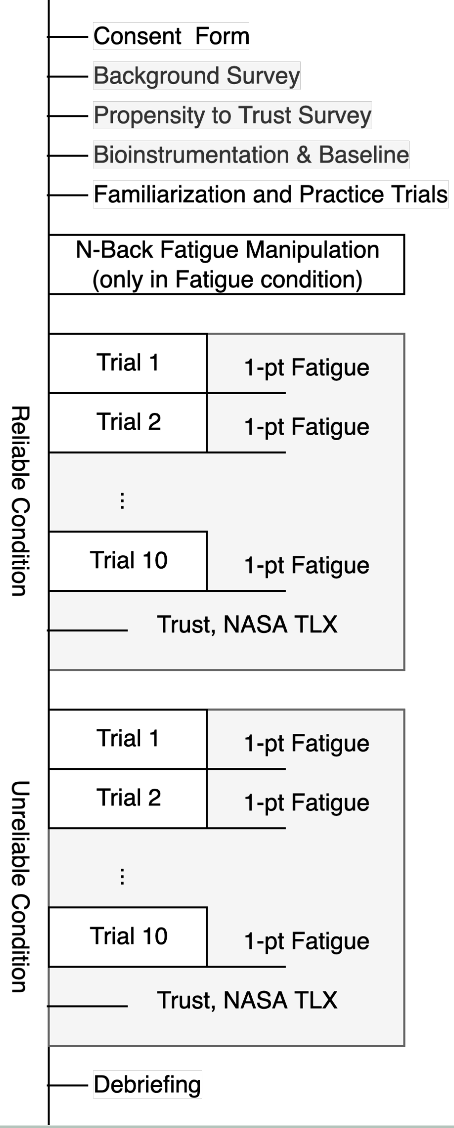
Why?
Industrial workers collaborating with robot are often exposed to the unreliable robot behavior under fatigue conditions.

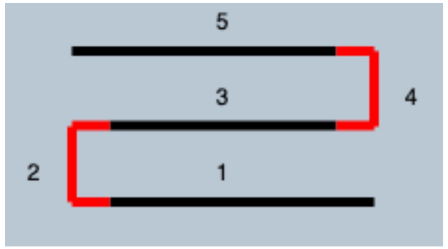
Objective and Hypothesis

Objective	Hypothesis
Understand the impact of reliability and fatigue manipulation on the human performance	Humans perform better in reliable and no-fatigue conditions.
Understand the impact of the reliability and fatigue manipulation on brain activation and connectivity	Higher activation and increase in connectivity is expected in unreliable conditions. Activation may decrease under fatigue
Understand the effect of robot reliability and fatigue manipulation on subjective measures	It is expected to observe higher trust in reliable condition and higher fatigue in fatigue condition

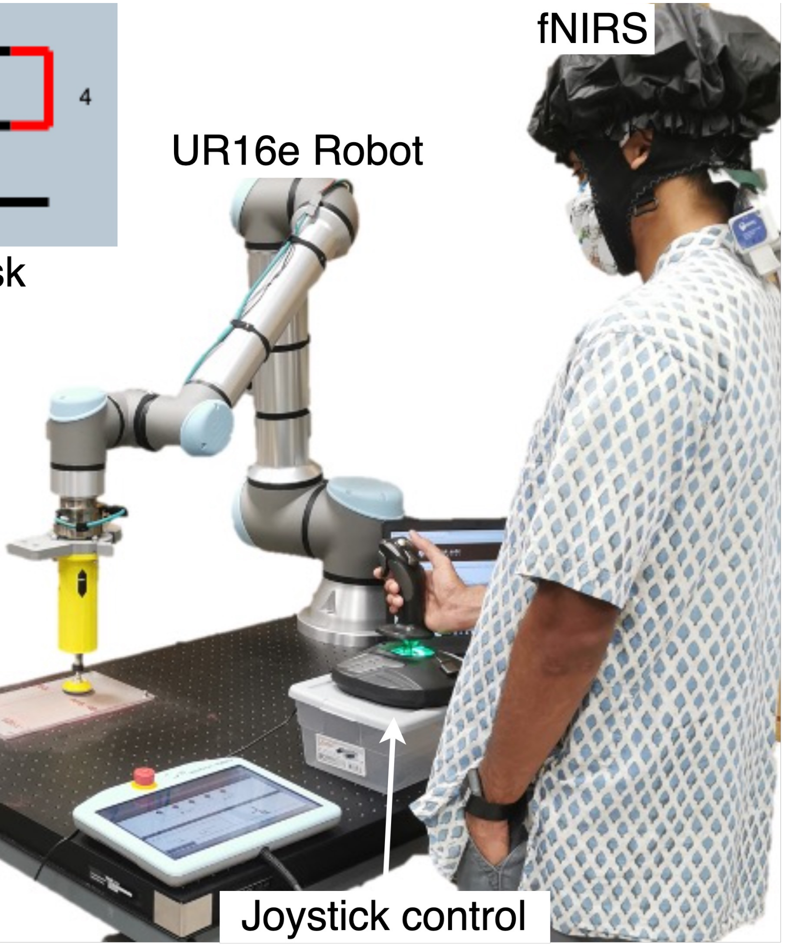
A closer look

- S-shaped metal surface polishing task where lateral trajectories are polished by participant and curved paths by the robot.
- Indicator lights on the end-effector inform control takeover
- 3-axis end effector control using joystick
- Sixteen participants aged 25.12 ± 3.31 years (IRB2020-0097DCR)





Polishing task



Manipulating trust and fatigue

Fatigue manipulation: 2-back task for 1h

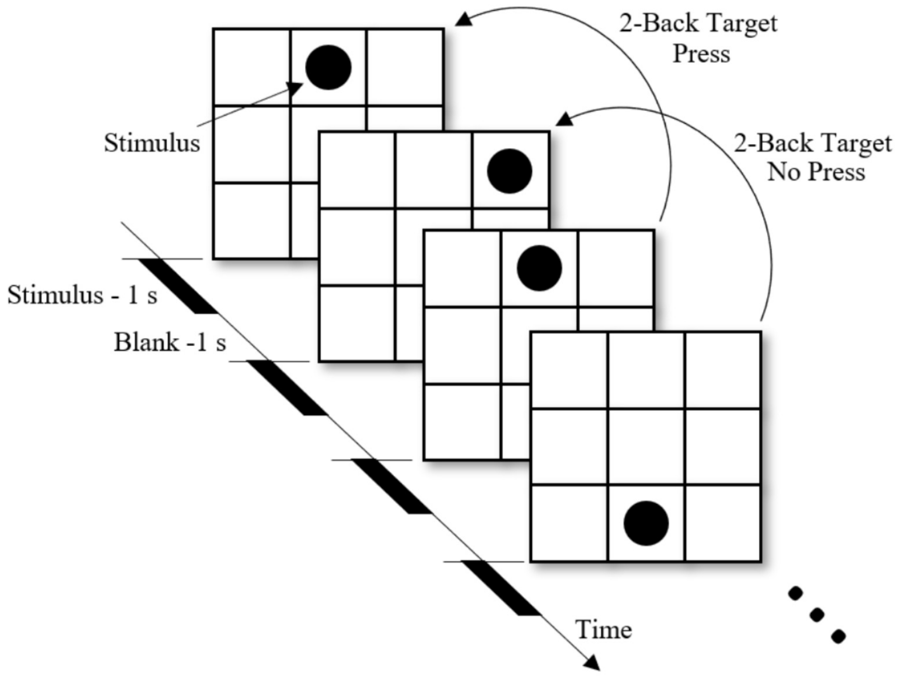


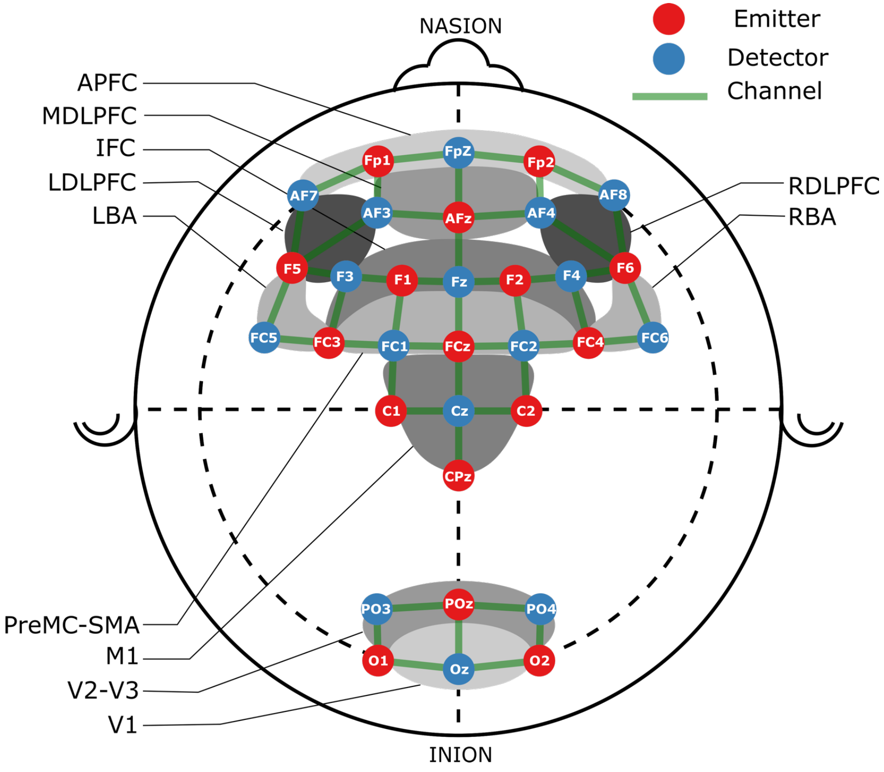
Image source: Hopko et al. 2021

Trust manipulation: 76% reliability[10,11]

- Reduction in speed for 2.5 cm;
- Loss of contact of end-effector with surface
- Late/early start of automatic control (2.5cm)
- Automatic control complete half turn
- Automatic control performs straight turn
- Joystick command stops suddenly for 2 seconds.

Measurements

- **Subjective**
  - Trust[7]
  - Fatigue: 1-point fatigue question (“What is your level of fatigue?”)
  - NASA TLX[8]
- **Objective**
  - Performance
    - Speed
    - Accuracy
    - Precision
  - Brain
    - Peak activation
    - Effective connectivity[9]: causal relation between brain regions



Placement of the optodes and regions of interests
46 channels, 11 regions

Brain data processing

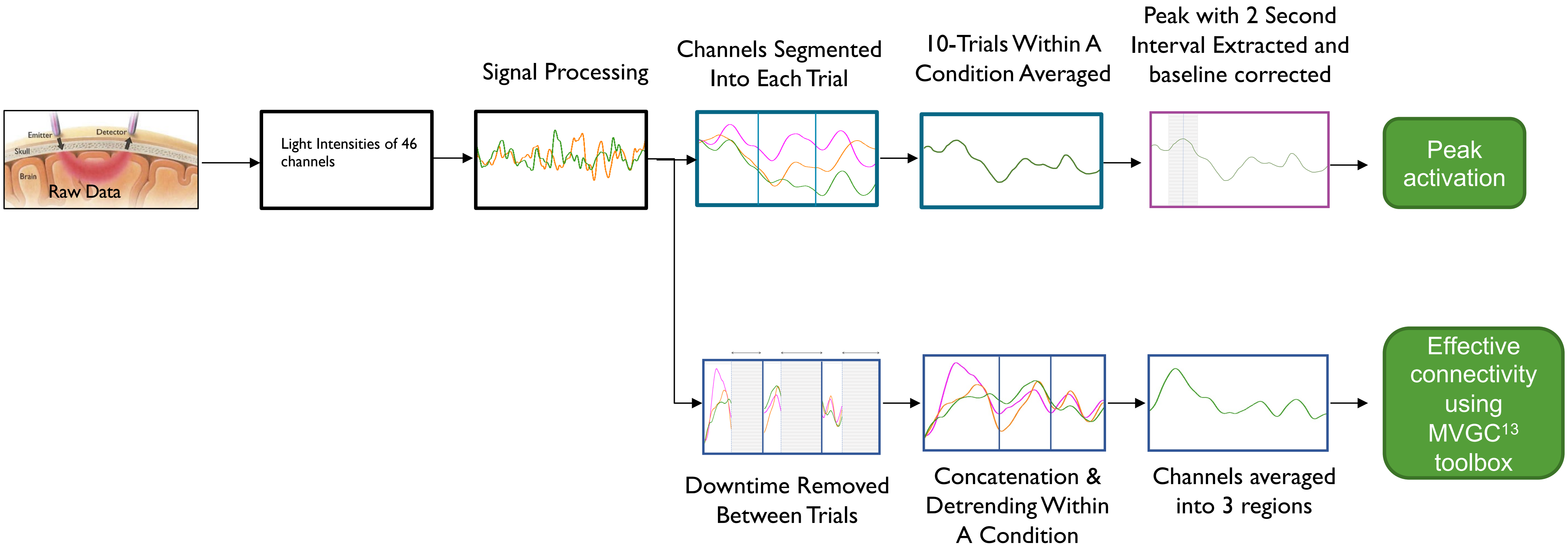
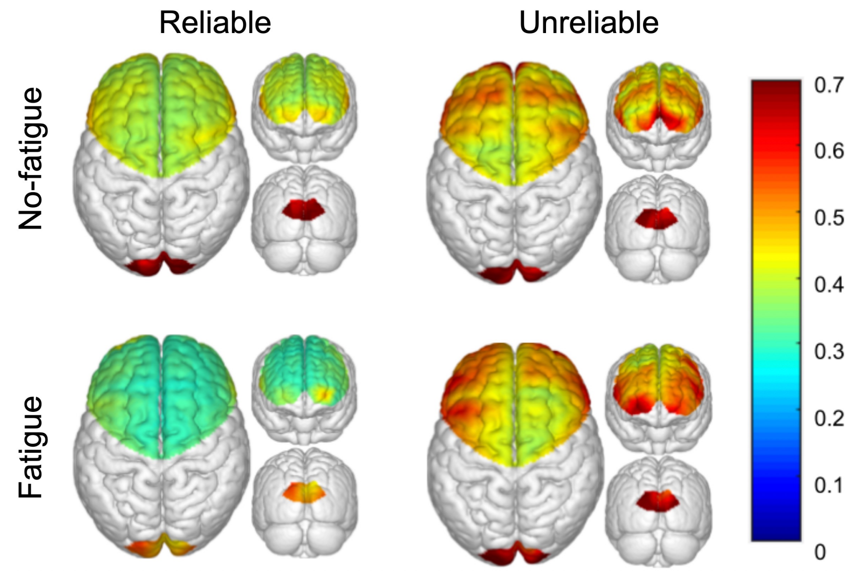


Figure adapted from: Hopko, S. K., & Mehta, R. K. (2022)

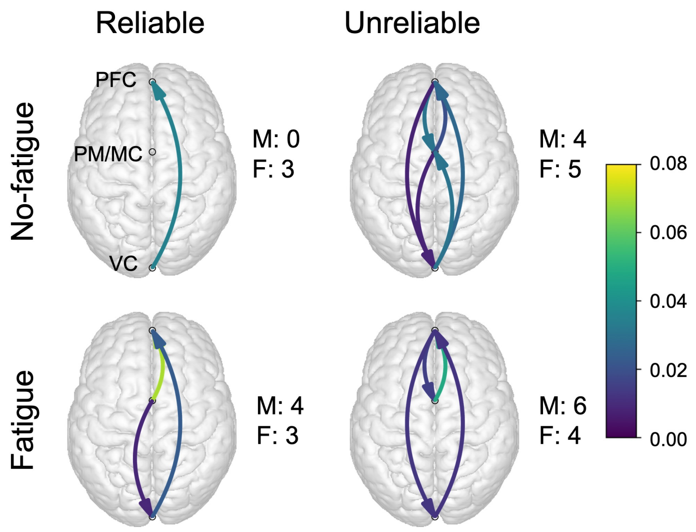
Results: brain activations and connectivity

Brain-activations across different conditions



- LBA, LDLPFC, MDLPFC, and RBA exhibited **higher activation in unreliable conditions** than reliable conditions.
- Fatigue led to **lower activation in MDLPFC**
- Fatigue × reliability interaction in M1 region

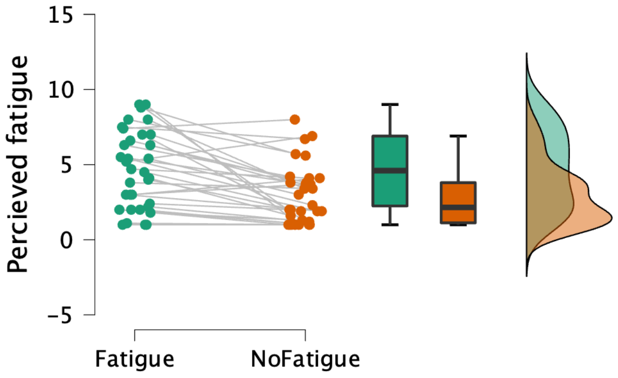
Effective connectivity between brain regions

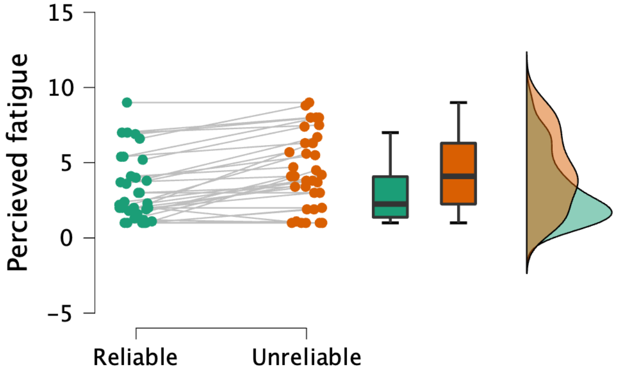


- Increase in number of connections in unreliable conditions
- Increase in connections from no-fatigue to fatigue under reliable conditions however opposite trend is observed in unreliable conditions

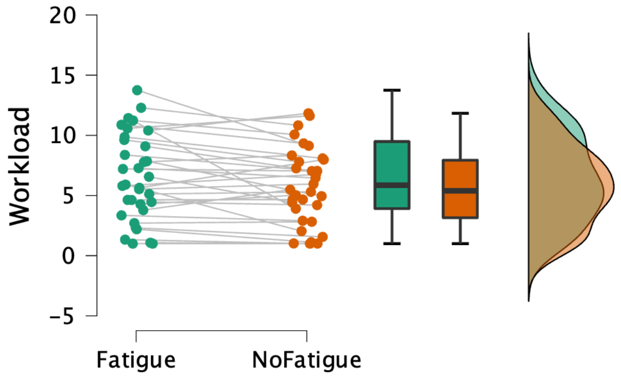
Results: Subjective responses

Perceived fatigue



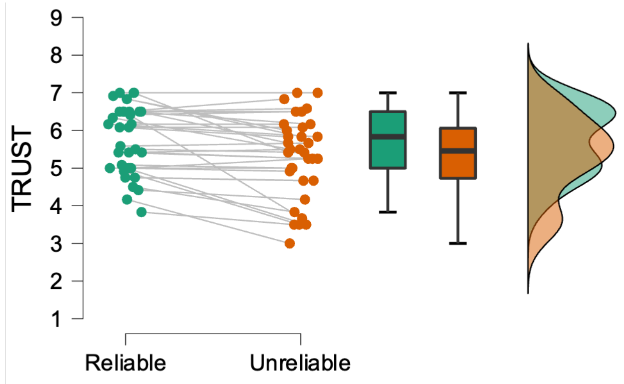


Workload



Trend: reliability × sex (p=0.071)

Trust

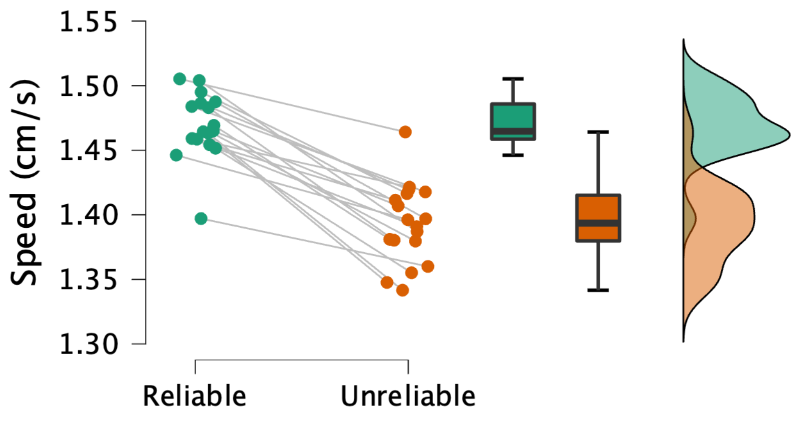


Trend: fatigue × reliability × sex (p=0.076)

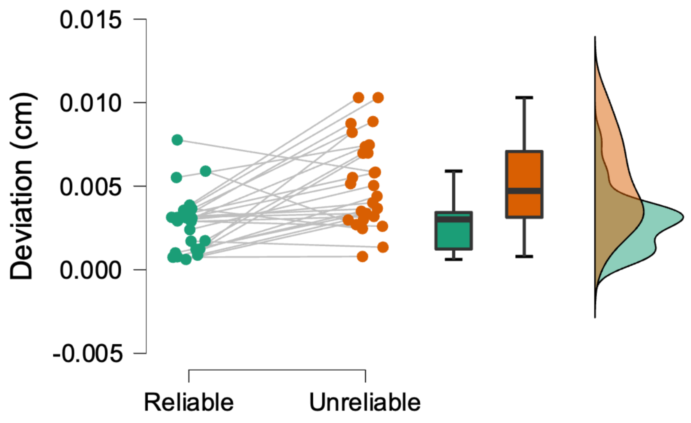
All other p’s<0.005

Results: Performance

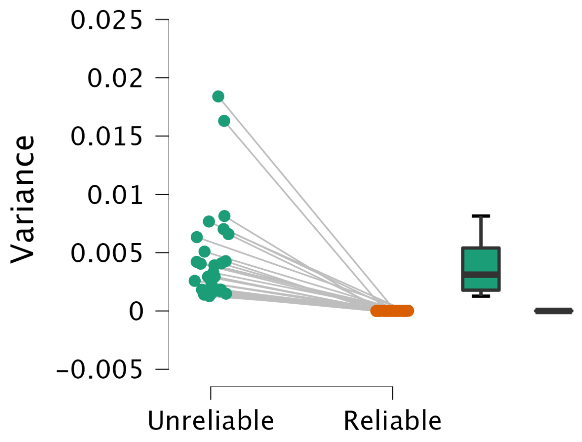
Speed



Accuracy



Precision



All p's<0.001

Graphic Source: https://www.praecis.com/blog/category/Science

Discussion

- Robot reliability and 2-back task successfully manipulated trust and cognitive fatigue as evident by the subjective measures.

- Reliability and cognitive fatigue alone and their interplay both affect the human brain and performance

- Increased activation suggest that increased task difficulty and mental effort causes an increase in oxygenated hemoglobin level in the PFC[14]
- Lower MDLPFC activation in fatigue is linked to decline in working memory[15]
- Increased complexity of causal connections suggest participants had to anticipate robot behavior during unreliability
- Effective connectivity showed different brain responses to fatigue and robot reliability manipulation in males and females.

Limitations

- Carefully controlled research setting may not represent or generalize real-world situations.
- Participants from engineering population not representative of the educational level or experience level of an industrial worker.
- Future studies should include a larger and more relevant sample size.

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