

#### Clustering Trust Dynamics in a Human-Robot Sequential Decision-Making Task

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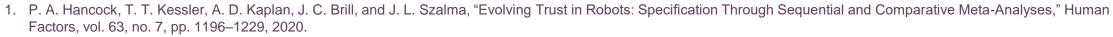






# Introduction

- Trust is a key factor for effective human-robot collaboration<sup>1</sup>
- A snapshot view of trust is not enough. Trust can be dynamic within the interaction period<sup>2</sup>
- With a human trust-behavior model, robotic agents can be given insights into human behavior while making their decisions



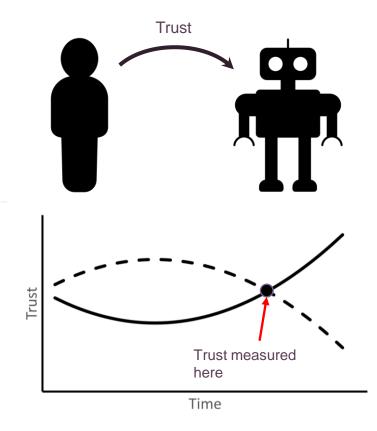
<sup>2.</sup> X. J. Yang, C. Schemanske, and C. Searle, "Toward Quantifying Trust Dynamics: How People Adjust Their Trust After Moment-to-Moment Interaction With Automation," Human Factors, p. 00187208211034716, 2021.





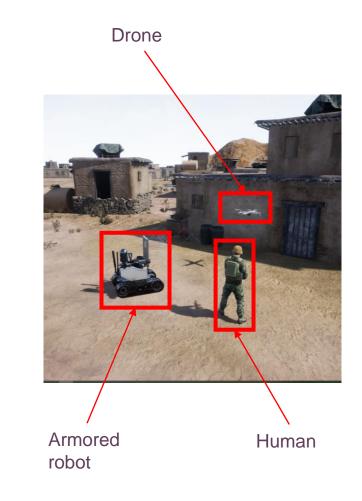


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# Human-Robot Teaming Task

- Intelligence, Surveillance, and Reconnaissance (ISR) Mission
- Human-Drone team searches through N sites for potential threats
- Drone recommends whether to use an armored robot to breach the building or not
- Team receives rewards associated with health remaining and time to complete mission









## **Problem Formulation**

• States:  $t_i \sim Beta(\alpha_i, \beta_i)$ 

• Human behavior model:

• Actions:  $a_r \in \{0,1\}$ 

$$\mathbb{P}(a_h = a_r) = t_i,$$
$$\mathbb{P}(a_h = 1 - a_r) = 1 - t_i$$

• Rewards: 
$$\mathbf{IR}_{i}^{a} = \underbrace{-w_{h}h(a_{h}^{i}) - w_{c}c(a_{h}^{i})}_{R_{i}(a = a_{h})} + \underbrace{\lambda_{i} \cdot \mathbb{1}(A)}_{\text{Trust gain reward}}$$
  
• Transition function:  $\alpha_{i} = \begin{cases} \alpha_{i-1} + w^{s}, & \text{if } P_{i} = 1, \\ \alpha_{i-1}, & \text{if } P_{i} = 0. \end{cases}$   
 $\beta_{i} = \begin{cases} \beta_{i-1}, & \text{if } P_{i} = 1, \\ \beta_{i-1} + w^{f}, & \text{if } P_{i} = 0. \end{cases}$   
 $P_{i} = \begin{cases} 1 & \text{if } R_{i}(a_{r}) \geq R_{i}(1 - a_{r}), \\ 0 & \text{otherwise.} \end{cases}$ 





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# Experiment

- 46 students from the University of Michigan participated
- Measures:
  - Big 5 Personality Traits
  - Perfect Automation Schema
  - Propensity to Trust
  - Trust after each site
  - Post-experiment Trust
  - Workload
- Participants searched through 100 sites sequentially





(a) No Threat, RARV Not Used

(b) No Threat, RARV Used



(c) Threat, RARV Not Used



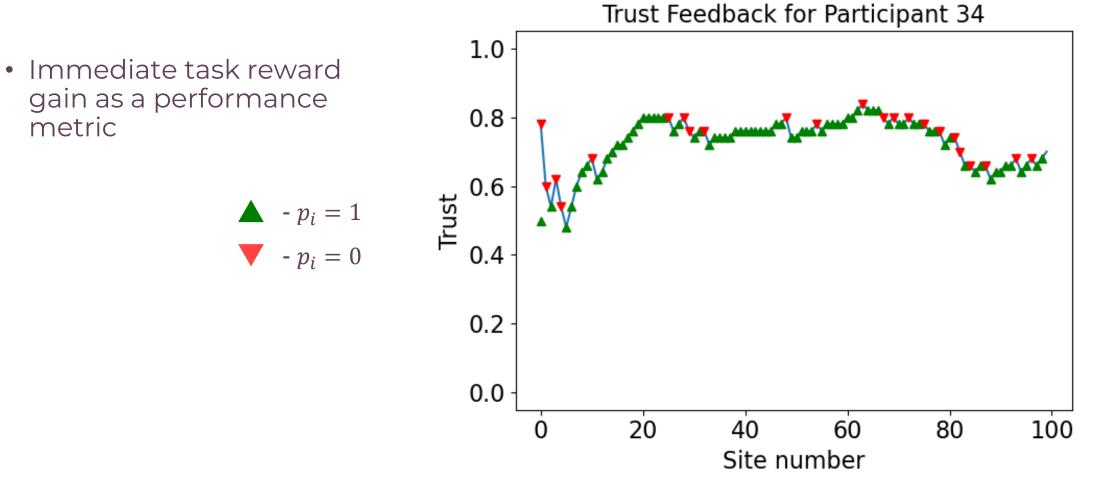
(d) Threat, RARV Used

Fig. 3. The four outcomes based on the presence of threat inside a site and the choice of action by the participant.







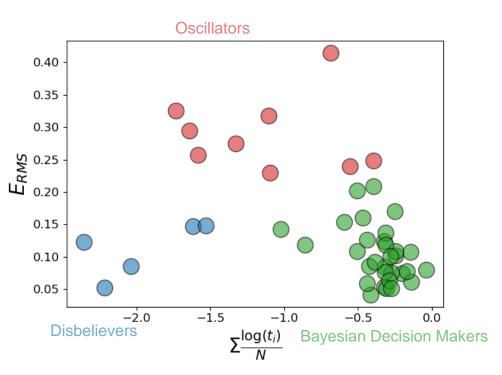








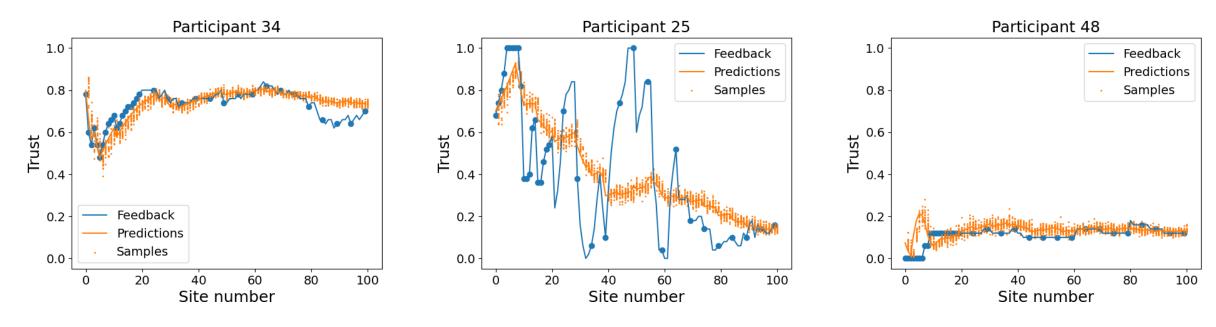
- K-means clustering analysis
- Features:
  - RMSE between feedback and predicted trust
  - Average log trust
- Elbow heuristic and silhouette scores indicate 3 significant clusters











**Bayesian Decision Maker** 

Oscillator



Type of trust dynamics	RMSE (SD)
Bayesian Decision Makers	$0.093\ (0.04)$
Oscillators	$0.26\ (0.05)$
Disbelievers	0.1  (0.04)







#### TABLE I

#### MEAN AND STANDARD DEVIATION (SD) OF PERSONAL CHARACTERISTICS BETWEEN THE THREE DIFFERENT TRUST DYNAMICS (BDM = BAYESIAN DECISION MAKER)

Personal Characteristic	BDM	Disbeliever	Oscillator
Extraversion (/20) *	9.5 (3.3)	5.8 (2.8)	11.3 (2.9)
Agreeableness (/20) *	13.5 (2.5)	10.4 (5.0)	14.1 (1.8)
Conscientiousness (/20)	13.1 (2.7)	12.4 (3.0)	12.1 (4.5)
Neuroticism (/20)	7.9 (2.7)	6.8 (3.6)	10.2 (4.7)
Intellect/Imagination (/20) <sup>†</sup>	11.7 (2.0)	9.8 (1.8)	12.2 (1.8)
High Expectations (/28) **	12.7 (3.9)	6.4 (2.8)	12.4 (4.2)
All or None Thinking (/21)	6.6 (2.9)	6.4 (3.4)	7.1 (3.1)
Trust Propensity (/30) †	20.2 (4.4)	17.2 (4.1)	22.8 (3.2)
++ $p < 0.01 + p < 0.05$	t = n < 0.1		

 $**-p < 0.01, *-p < 0.05, \dagger - p < 0.1$ 







#### TABLE II MEAN AND STANDARD DEVIATION (SD) OF POST EXPERIMENT METRICS BETWEEN THE THREE DIFFERENT TRUST DYNAMICS

Personal Characteristic	BDM	Disbeliever	Oscillator
Trust (Muir) (/100) ***	65.4 (13.5)	15.8 (9.9)	44.7 (26.1)
Trust (Lyons) (/7) ***	4.5 (0.54)	3.1 (0.6)	3.6 (0.9)
Mental Demand (/100)	39.6 (25.2)	42.0 (36.6)	50.3 (28.6)
Temporal Demand (/100)	50.8 (27.4)	62.0 (24.5)	42.9 (21.3)
Performance (/100)	58.6 (19.7)	50.8 (30.0)	46.2 (31.7)
Effort (/100)	34.3 (23.0)	34.4 (17.4)	49.8 (32.2)
Frustration (/100) *	45.8 (22.2)	58.4 (25.4)	68.1 (14.3)

\*\*\*-p < 0.001, \*-p < 0.05







### **Future Work**

- Inverse Reinforcement Learning<sup>1</sup> to learn personalized reward functions
- Using contextual information for trust prediction
- Creating more balanced datasets



1. A. Y. Ng and S. Russell, "Algorithms for inverse reinforcement learning," in Proc. 17th International Conf. on Machine Learning. Morgan Kaufmann, 2000, pp. 663–670.



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# Thank you

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