CALL FOR PROPOSALS · FALL 2026

Trace Labs Research Partner Program

Unrestricted research gifts of up to $100,000 for faculty-led robot learning research

About Trace

Trace Labs builds data and infrastructure for real-world robot learning. We capture how people perform everyday physical work in real homes and workplaces through synchronized first-person video, motion, hand and body pose, depth, and language annotation, and we build the perception and quality pipelines that make such data usable for training robots. We believe the richest source of experience for robots is the real-world activity, and that turning that activity into robot capability raises open questions no single team can address alone. This program exists to support the academic research that addresses them.

Program at a Glance

Award	Up to $100,000 per project, paid as a one-time **unrestricted research gift** to the PI's institution. The final amount is set case by case based on proposed scope and available budget. We anticipate multiple awards to different teams.
Duration	Up to 12 months. Awards are one-time; recipients may apply to future cycles.
Who may apply	Faculty, including research faculty, eligible to serve as the PI at an accredited college or university.
Proposal	One PDF file (up to 10 MB): research narrative, budget and justification, and PI/Co-PIs' CVs.
Submission deadline	**November 20, 2026, 11:59 PM Eastern Time.** Proposals will be reviewed on a rolling basis as they are received, and early submissions are strongly encouraged. Funding decisions may be made before the submission deadline for particularly strong proposals. Proposals submitted after the deadline may still be considered, subject to the availability of remaining funds.
Submission portal	tracelabs.ai/research-partner-program
Questions	Please send any questions to research-partner@tracelabs.ai.

1. Program Overview

The Trace Labs Research Partner Program funds PI-led research on how robots learn from, and work alongside, people in the physical world. We are especially interested in research that uses, improves, or

explains learning from egocentric human data: what can be learned from observing people, how it transfers to robots, which data matter and why, and how to evaluate the result rigorously. We also welcome adjacent work in multimodal and contact-rich learning, policy learning and adaptation, safe and generalizable robot learning, and human-robot interaction/collaboration. We welcome theory, algorithms, empirical studies, data and evaluation methods, and research systems. A focused contribution to one well-posed question is sufficient. Both foundational and application-driven research are eligible.

2. Research Themes

The research themes below indicate the breadth of our interest. The bullets are examples, not a checklist; a proposal may address one bullet, cut across themes, or propose a new direction under the Open Topics. *Proposals should name one primary theme (A-H).*

A. Learning from human experience and egocentric data

How can robots acquire skills and physical knowledge from the breadth of everyday human activity, including observations without robot actions or task labels?

- Learning representations, behaviors, and task knowledge from unstructured or weakly labeled egocentric video, including imperfect and unsegmented demonstrations
- Human-to-robot and cross-embodiment transfer, including object-centric and contact-centric action representations and the conditions under which transfer fails
- Latent actions, reusable skills, and task structure discovered without complete action annotation
- Egocentric perception: viewpoint change, camera motion, hand-object interaction, and grounding across egocentric, external, and robot views
- Learning from many demonstrators, expertise levels, and human-human interaction without overfitting to one person or scene

B. Data-centric robot learning: quality, scale, and evaluation

Which data improve which robot capabilities, and how do we know?

- Data valuation, scaling behavior, and mixture design across human and robot experience; learning under fixed collection or compute budgets
- Data quality for robot learning: synchronization, calibration, pose and annotation accuracy, and how processing choices affect downstream policies
- Curation and filtering that preserve rare but important events (contact, failure, recovery) rather than removing them
- Methods for understanding what a dataset teaches a policy: attribution of capabilities to data, diagnosis of failure modes, and targeted acquisition

C. Multimodal and contact-rich physical intelligence

How should vision combine with touch, force, proprioception, and language to learn physical interaction?

- Visual-tactile learning: representations that connect what is seen with what is felt, including contact geometry, deformation, slip, and material properties, and that transfer across tactile sensors and embodiments; no particular sensor is required
- Contact-aware policies and world models that fuse modalities at different time scales and remain useful when a modality is missing or noisy
- Learning contact from human demonstration, including wearable or sparse sensing, and deciding when touch is worth collecting
- Active sensing and fast feedback: when to touch, how to react to slip or disturbance, and how prediction error should change the next action

D. Policy learning, world models, and adaptation

How do learned policies and predictive models become capable, efficient, and adaptable?

- Generalist and compositional policies, including vision-language-action models and structured or modular alternatives
- Policy improvement through offline, online, model-based, or human-in-the-loop reinforcement learning; learning from failures and interventions
- Reward, progress, and success models learned from observation, language, or preferences, and whether they reliably support improvement
- Action-conditioned world models, memory, and long-horizon reasoning for partially observed, multi-stage tasks
- Few-shot, continual, and test-time adaptation to new objects, users, scenes, and embodiments; efficient training and real-time inference

E. Safety, robustness, and generalization

What are the limits of learned robot behavior, and how can its capabilities and risks be made predictable?

- Generalization and distribution shift: transfer to unseen tasks, objects, materials, users, scenes, and embodiments, and rigorous characterization of where transfer breaks down
- Uncertainty quantification and calibrated decisions, including when to ask for help or abstain
- Safe learning and runtime assurance that state their assumptions; robustness to imperfect sensing and execution
- Failure detection, recovery, and dependable operation over extended use
- Learning theory for physical intelligence: sample and interaction complexity, identifiability, and the value of demonstrations or additional modalities

F. Simulation, evaluation, and open research infrastructure

Better evidence and better tools are research contributions in their own right.

- Simulation, digital twins, and synthetic experience for physical interaction, including contact and tactile simulation and methods that identify or reduce simulation-to-reality gaps
- Generalization benchmarks and evaluation integrity: held-out splits by scene, person, object, sensor, or contact sequence; leakage detection; fair comparison across data and compute budgets
- Affordable, repeatable real-world and human-centered evaluation, including cross-laboratory protocols and measures of safety, intervention burden, and sustained reliability
- Open tools, data schemas, low-cost capture systems, and reusable experimental infrastructure that address a clear research need

G. Human-robot interaction and collaboration

Robots should learn not only from people but with and for them.

- Intent and behavior prediction connected to robot decisions: when to act, wait, ask, or hand back control
- Interactive teaching through language, demonstration, correction, and feedback; preference learning and personalization that respect user agency
- Shared autonomy, teleoperation, and learning from joint human-robot execution
- Physical collaboration, assistive behavior, and socially aware navigation, evaluated on human outcomes as well as task success

H. Open Topics

Proposals that do not fit the themes above are welcome when they make a clear contribution to robot learning. Select “Open Topics” as the primary theme and state the connection in the abstract.

3. How to Apply

Submit one PDF file (up to 10 MB) through the submission portal by **November 20, 2026, 11:59 PM ET**. Use US letter paper, 11-point font, and 1-inch margins. No contact with Trace, letter of support, or institutional nomination is required. There is no limit on the number of proposals a PI or institution may submit.

Required documents

- **Research narrative (3-4 pages, excluding references).** Project title; PI name, title, department, and institution; co-PIs, if any; one primary theme (A-H); a project abstract (around 200 words); and the narrative. Please refer to Appendix A for the detailed proposal guidelines.
- **Budget (up to 1 page).** Categories and amounts in US dollars with a justification.
- **CVs.** Up to 2 pages for each PI and co-PI.

Collaborating teams designate one lead institution to receive the gift. Multi-institution arrangements will be made by the institutions, not by Trace Labs.

Review criteria

Proposals are reviewed based on the following criteria.

- **Scientific merit and originality.** A well-posed question, clear key ideas, and a credible argument for why it is novel and unique.
- **Relevance.** A clear connection to the research themes listed in Section 2 or, for Open Topics, to broader robot learning.
- **Rigor of evidence.** A validation plan matched to the type of contribution: analysis for theory, user or behavioral studies for HRI, learning utility for data and sensing work, and appropriate comparisons for policies. There is no required benchmark or success threshold.
- **Feasibility and fit.** A realistic, up to 12-month plan for the requested amount, with the team, data, and infrastructure to carry it out. Trace Labs may be able to offer data or help with data collection.

Appendix A. Research Narrative Guideline (3-4 pages)

Header	Project title; PI and co-PI name(s), title(s), and institution(s); primary research theme (A-H); requested funding amount (USD); project duration.
Abstract (around 200 words)	Concisely summarize the research problem, its significance, the proposed approach and key technical innovations, expected scientific contributions, and potential impact on robot learning and embodied intelligence.
1. Motivation, Relevance, and Significance	Clearly define the research problem and the fundamental scientific or technical challenges it addresses. Explain the limitations of existing approaches, why these challenges remain unresolved, and why solving them matters. Describe the project's relevance to the CFP research themes and its potential to advance robot learning, embodied intelligence, or related foundational capabilities. Articulate the broader scientific significance and potential long-term impact, and how the proposed research could benefit Trace Labs.
2. Research Objectives, Key Ideas, and Novelty	State the primary research objectives, hypotheses, or research questions. Describe the central technical ideas, scientific insights, and anticipated innovations. Discuss the most relevant prior work, identify important gaps or limitations, and clearly explain how the proposed research differs from and advances the state of the art. Highlight what is fundamentally new, and identify the key expected scientific contributions.
3. Technical Approach and Methodology	Provide a concrete, technically rigorous description of the proposed methods, algorithms, models, theoretical frameworks, or experimental methodologies. Explain the underlying principles, technical rationale, major research components, and how they address the identified challenges. Describe the anticipated technical difficulties and proposed solutions. Include sufficient technical detail to assess the originality, soundness, and feasibility of the proposed research. Preliminary results or supporting evidence may be included where available.
4. Evaluation and Validation Plan	Present a rigorous and feasible plan to validate the research hypotheses, technical approaches, and expected contributions. Identify appropriate benchmarks, datasets, experimental platforms, baselines, evaluation metrics, and comparison methods, as applicable. Describe experiments, ablation studies, theoretical analyses, or human-subject evaluations appropriate to the research. Explain how results will demonstrate scientific advances, assess generalization and robustness where relevant, and distinguish the proposed contributions from existing methods. Discuss potential limitations, failure cases, and how unexpected or negative results would be interpreted.

5. Research Plan, Team, and Resources	Provide an up to 12-month research plan with major activities, intermediate milestones, and expected research outcomes. Identify key technical risks, dependencies, and mitigation strategies. Describe the PI's and team members' relevant expertise and responsibilities, as well as available datasets, experimental platforms, hardware, and computational resources. If access to Trace Labs' data or other research resources would be beneficial, specify the requested data types, modalities, approximate scale, annotation requirements, intended uses, and any critical dependencies. Such resources are subject to availability and separate arrangements.