Physical AI — the path to a beautiful tomorrow.



PRAVDA REPLIKANTA

THE REPLICANT TRUTH
A NEWSPAPER ABOUT PHYSICAL ARTIFICIAL INTELLIGENCE

BREUKELEN (Netherlands)
Forecast · 2026-11-02 · CET

MORNING · 09:00	9.8°	Cloudy Wind: N 2.9 m/s · 54%
MIDDAY · 12:00	12.4°	Clear Wind: N 5.3 m/s · 11%
EVENING · 18:00	11.1°	Cloudy Wind: N 4.1 m/s · 21%

Daily: 8.6–12.5 °C
Precipitation probability: 94%

All we can do is learn to be human while the rain falls.

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Weather source: Open-Meteo · Retrieved: 2026-11-01 20:51 CET

Pravda Replikanta — For curious readers

Robotics research, from training and touch to evaluating skills and practical limitations.

News

Drawing from instructions becomes a test of robot generalization

A robot repeating a familiar motion does not necessarily understand a new request. Xiangyu Xu and collaborators introduced BURGER, a benchmark where a robot arm receives a verbal description of a drawing and chooses a sequence of strokes. Starting from the same blank canvas, multiple drawings and stroke orders can be valid. This reveals more than reproducing one memorized trajectory.

The researchers generated 28,200 simulated demonstrations spanning 282 drawing tasks and evaluated five models connecting visual input, language and robot actions. They examined the effects of training scale, task diversity, spatial composition and the ability to combine familiar objects in unseen arrangements. The paper reports distinct failure patterns among models and examples of transfer to new compositions.

The team also deployed a trained policy on a physical Franka Panda arm and demonstrated drawing that reacts to human intervention. Yet drawing is a deliberately constrained task, not a complete proxy for kitchen or warehouse manipulation. A successful drawing does not demonstrate unrestricted autonomy, safety or reliability outside the tested setup.

The most revealing question is the difference between repeating a learned example and behaving well in a genuinely new situation. Generalization means coping with conditions that were not identical to the training examples. One striking video cannot tell us how many attempts failed. It helps to ask what the held-out tests looked like, whether objects and lighting changed, who selected the demonstrations and which baselines were compared. Those questions turn a fascinating result into a testable claim rather than a promise of a robot that can already do everything. The signal is not artistic beauty but whether familiar elements can form an unseen composition. Line accuracy and language understanding are separate abilities.

Sources

BURGER: Benchmarking and Understanding Robotic Generalization via Embodied Drawing · 2026-10-29

Coding agents build robot training worlds while frontier models struggle on new tests

Constructing a realistic virtual training environment can require extensive expert labor before a robot starts learning. Pranjal Aggarwal and Sean Welleck propose Gym-Anything, where coding agents build simulations and an adversarial audit checks whether their physics and tasks satisfy explicit criteria. The selection of physical work draws on US economic activity instead of focusing solely on familiar toy demonstrations.

RoboWorld contains 25 simulations, 175 training environments and 25 held-out test environments. According to the authors, even the strongest evaluated frontier models failed every test task, averaging 0.06 reward. Reward is a numerical simulator score, not a real-world robot success percentage. The paper also explores learning from repeated attempts, privileged teachers that can inspect simulator state, and demonstrations produced by code policies.

Several approaches improved the measured results, but transfer to physical hardware remains unproven. Automatically generated worlds can misrepresent friction, contact dynamics and unexpected events in actual industrial settings.

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Sources

Gym-Anything for Robotics: Scaling physical simulations with digital agents · 2026-10-29

A robot map estimates how doors and drawers respond to force

A conventional room map can show a robot where a door is without revealing which way it moves or how much force opening it requires. Dibyendu Ghosh proposes PhysVLMM, a map that stores probabilistic beliefs about articulated components. After a measured pull, the system updates its estimate, and a planner can ask whether an action is likely to succeed within a stated risk limit.

Watching a part move does not uniquely reveal its dynamics. Even a measured pull directly informs only the tested component and direction. The method therefore maintains a distribution of possible properties, shares relevant evidence with visually similar untested parts and can abstain when the evidence is inadequate.

In real doors and drawers across 18 homes, the method identified joint types in 86% of held-out pulls versus 48% for a single-view learned comparison. Its prediction error measured by CRPS was 0.323 versus 0.544 for differentiable simulation, while computation took 13 milliseconds versus 230 seconds per case. These are results for the studied objects, not a universal safety guarantee.

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Sources

PhysVLMM: Interaction-Conditioned Physical Belief Maps for Articulated Objects in Robot Scene Maps · 2026-10-29

Human fingertip contact becomes training data for robot hands

Human fingers and robotic fingers have different geometry, so copying a hand trajectory does not guarantee the same contact with an object. Haozhe Zhang and collaborators propose TouchBridge, a combined hardware-and-software system with a wearable human demonstration interface and a corresponding robotic interface. Both capture visual and fingertip tactile information to establish correspondence across different hand designs.

Its Tac-Retarget component aligns fingertip contact patches and their spatial relationships using measured touch. The authors report that this conversion does not require an object mesh, an object-pose estimate or a physics simulator. With visual synthesis and camera-anchored action conversion, the transformed examples are used to fine-tune a pretrained model that maps visual observations and instructions to robot actions.

Across four physical contact-rich tasks, policies trained solely on converted human demonstrations reached 72.5% average success. An equal number of robot demonstrations collected through direct teleoperation yielded 77.5%, while human data collection was seven times faster. These results are promising for collecting examples efficiently, but cover specific tasks, hands and training conditions, not every object or robotic platform.

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Sources

TouchBridge: Tactile-Conditioned Human-to-Robot Transfer for Dexterous Manipulation · 2026-10-29

One learning pipeline adapts coordinated manipulation to different robot hands

Robotic hands can have very different numbers of joints yet face similar problems: hold an object, turn it and coordinate both wrists and fingers. Xiaoyu Yang and Nan Wu propose AcrossDEX 1.0, a pipeline combining human-motion pretraining, simulation-based expert learning, robot demonstration collection and visual feedback during execution.

During pretraining, the system predicts one second of bimanual motion from five images and thirty annotated hand states recorded over the preceding second. Shared wrist representations are retained when adapting to robots, while finger control accounts for the mechanics of each hand. The researchers tested six-channel Inspire hands and sixteen-joint Allegro hands, with control predictions revised from new camera observations.

In their evaluations, direct regression achieved 40.6% success on opening and returning a lid, 100% on Inspire object reorientation and 93.3% on Allegro reorientation. Flow matching achieved 90% on Allegro reorientation. These figures describe different tasks and conditions, not an overall ranking of robotic hands. Constraining new plans with previous plans can improve continuity.

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Sources

AcrossDEX 1.0: From Human Motion Pretraining to Bimanual Dexterous Manipulation across Hand Embodiments · 2026-10-29

Analysis

Testable skills matter more than striking demonstrations

New research emphasizes structured data, measurements and testable results.

The next step is independent testing on different robots and real tasks.

Sources

BURGER: Benchmarking and Understanding Robotic Generalization via Embodied Drawing · 2026-10-29

Gym-Anything for Robotics: Scaling physical simulations with digital agents · 2026-10-29

PhysVLMM: Interaction-Conditioned Physical Belief Maps for Articulated Objects in Robot Scene Maps · 2026-10-29

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Issue glossary

Key terms in this issue.

01 **generalization**

Using a learned skill under conditions different from training.

02 **trajectory**

A sequence of positions and movements over time.

03 **tactile data**

Measurements of touch complementing camera images.

04 **simulation**

A virtual model of physical actions used for learning and tests.

05 **feedback**

Changing behavior after receiving new observations.

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