



Sentrix Robotics Pvt. Ltd.

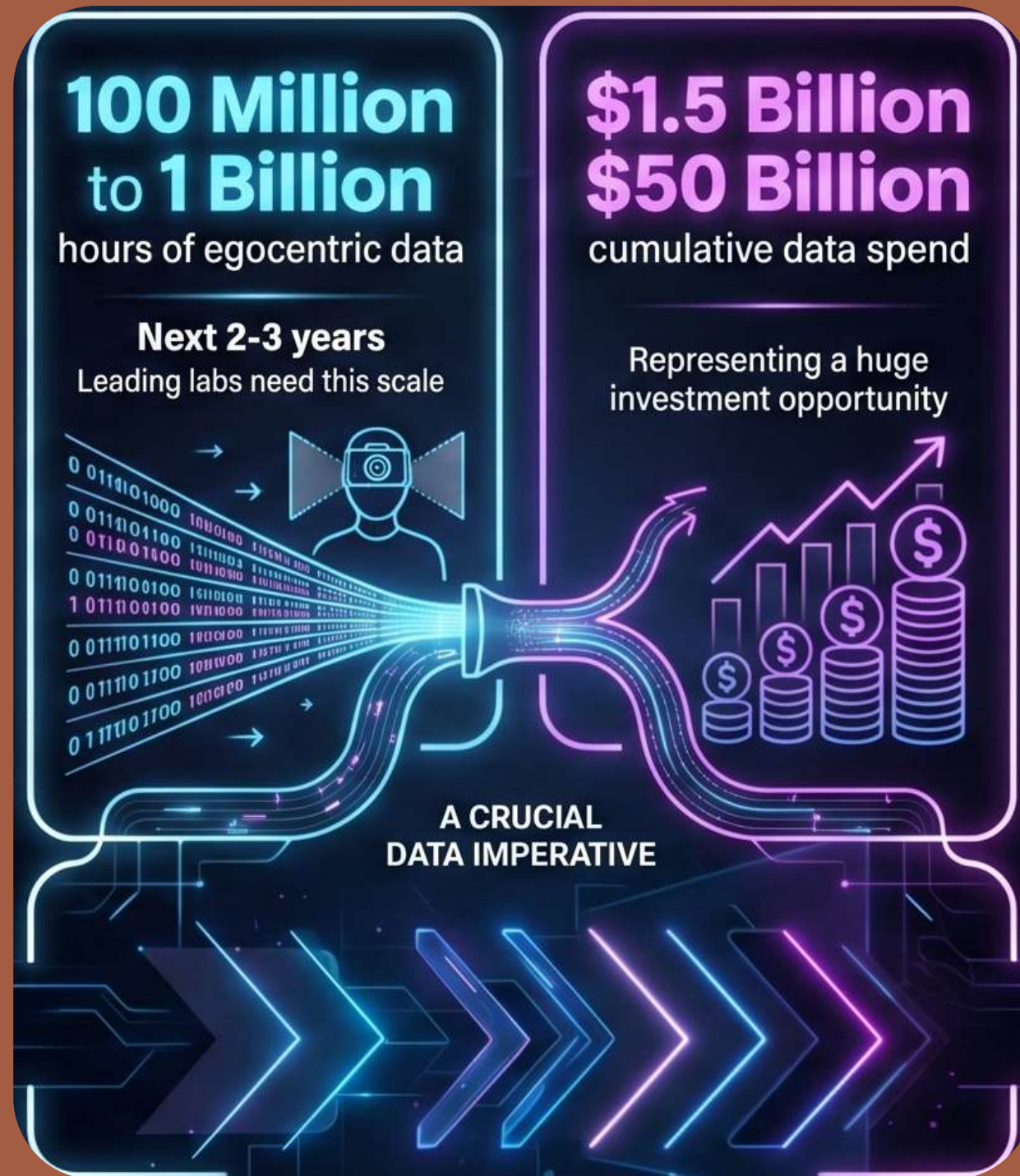
BROCHURE

The ground truth for physical AI.
Digitizing touch to scale autonomy.





Problem?



Source: Stellaris Venture Partners Blog: Physical AI Has a Massive Data Problem

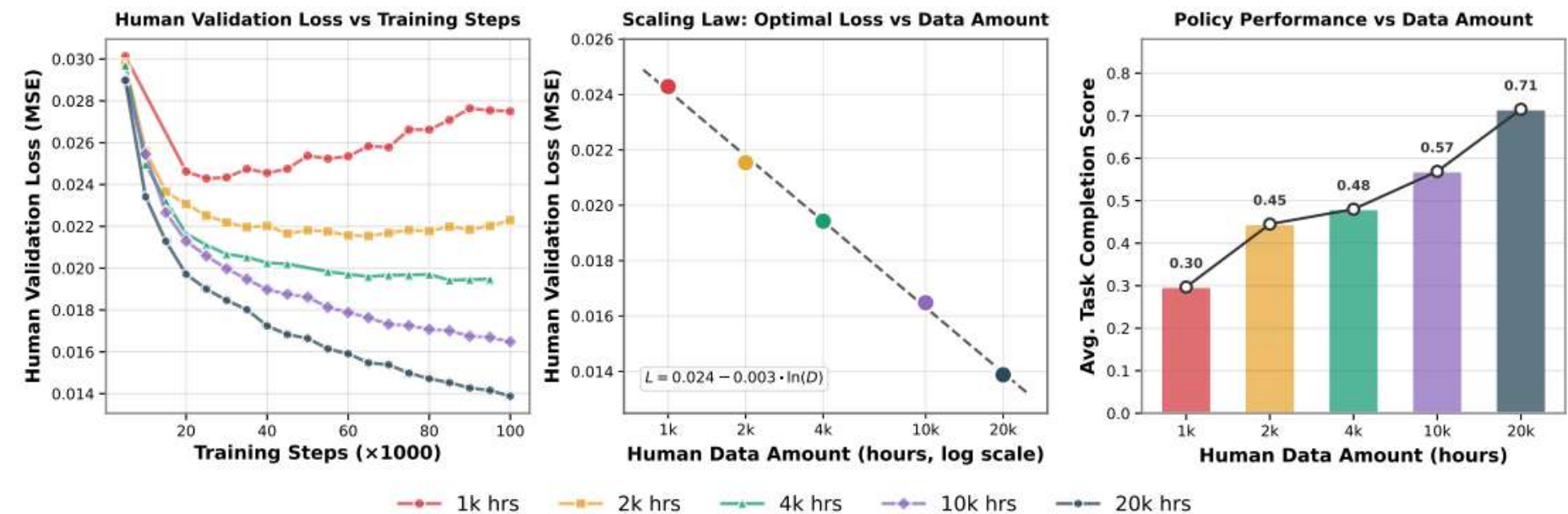


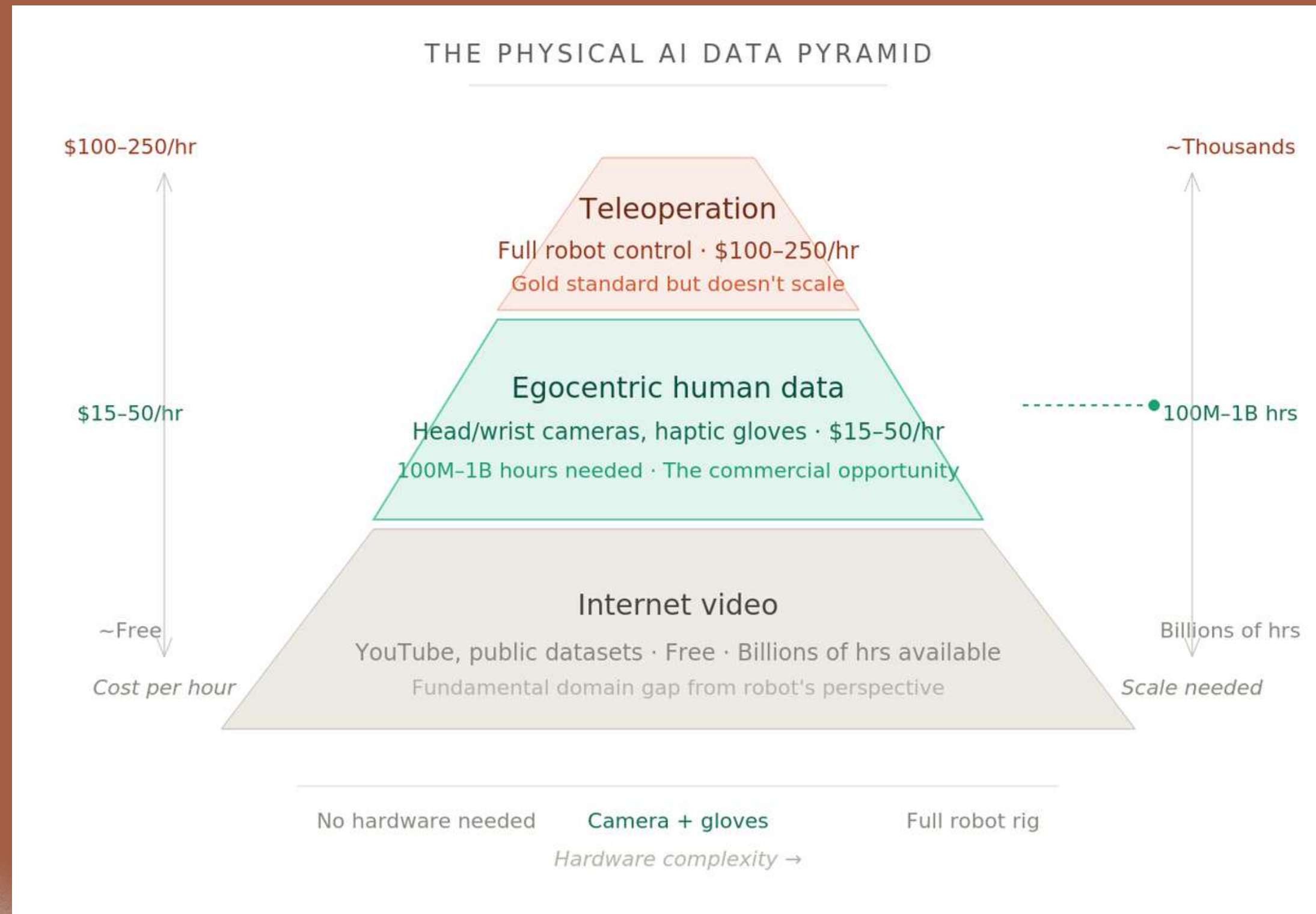
Figure 5: **Scaling behavior of human pretraining.** *Left:* Human validation loss versus training steps for models pretrained with increasing amounts of egocentric human data (1k–20k hours). Larger datasets yield stable, monotonic improvements, while smaller datasets exhibit early overfitting. *Center:* Optimal validation loss at convergence as a function of human data scale, revealing a near-perfect log-linear scaling law ($R^2 = 0.9983$). *Right:* Downstream robot performance after post-training, measured by average task completion score, improves consistently with increased human data scale. Together, these results demonstrate predictable scaling of learned action representations and their direct translation to improved dexterous manipulation performance.

Source: EgoScale: Scaling Dexterous Manipulation with Diverse Egocentric Human Data

100-1000X MORE DATA REQUIRED TO TRAIN AUTONOMOUS PHYSICAL AI!



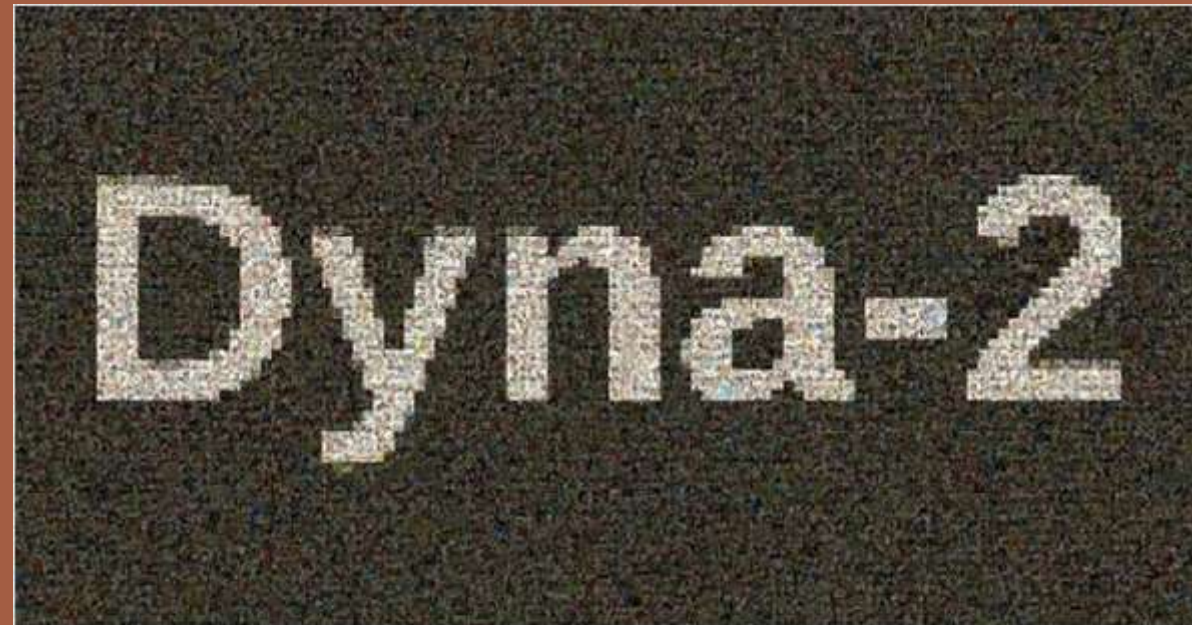
What kind of data is used?



Source: Stellaris Venture Partners Blog: Physical
AI Has a Massive Data Problem



Links embedded in the images



2: A 1-Million-Hour Scaling Law for World-Action Models

A world-action model pre-trained on more than one million hours of egocentric human video. It exhibits a scaling law on held-out human data and, for the first time, a human-to-robot transfer scaling law.

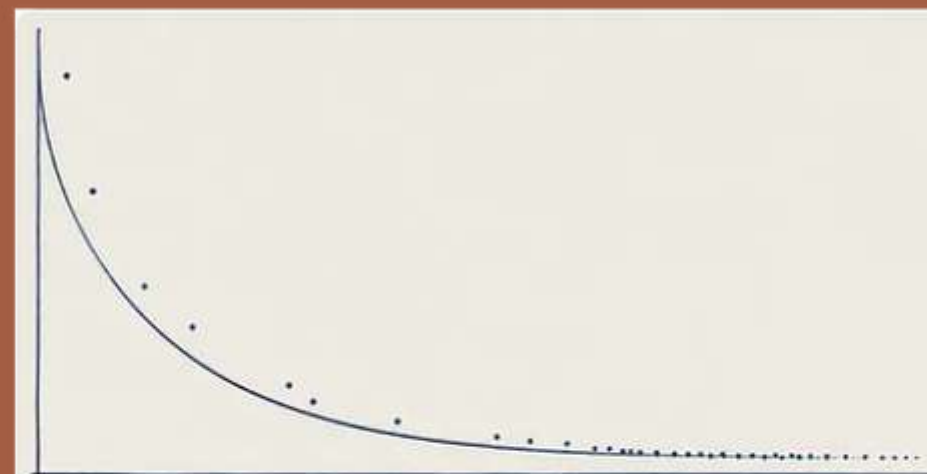
DYNA



<https://robotics.xiaomi.com/xiaomi-robotics-1.html>

Research has shown that real world human demonstration data collection is both scalable and cost-effective way to train (marginal utility per dollar of data) over teleoperation (for real world deployment)

Xiaomi Robotics and DYNA robotics have shown how promising this data can be.



Moneyball for Physical AI

A Scaling Law Perspective for Marginal Utility per Dollar

In 2002, the Oakland Athletics won 103 games despite maintaining the third-lowest payroll in Major League Baseball. This advantage emerged because the market for player assets was mispriced: legacy scouts favored subjective aesthetics, stolen bases, and batting averages, whereas forward-looking management mathematically isolated on-base percentage, the ...

Question is: how do we collect data which helps robots learn to do dexterous and intricate tasks, while being economical, by optimizing for marginal utility of data?

Answer: Egocentric Vision + Tactile Glove data!



The Sentrrix Solution



Our glove!

> FPV Stereo Camera + Tactile Gloves

GloveXR with 27-DoF kinematics layered with Proprietary Artificial Skin Sensors captures precise tactile and motion data in real-time.
(more than 10 datapoints captured by the skin!)

> Synchronization

Proprietary middleware synchronizes FPV vision with tactile feedback, filtered and annotated, creating unified multi-modal data streams.

> Data processing & export

Formatted, scalable cloud data pipeline for accessible tactile-vision infrastructure.



How much better is Vision + Tactile

Tactile Sensors Highlights:

For humanoids, the benefit is immediate:

- More stable grasps
- Better slip recovery
- Useful contact feedback without anthropomorphic complexity

For Physical AI labs, the impact compounds over time:

- Higher data throughput per robot
- More consistent learning signals
- Faster iteration cycles

We present FEELTHEFORCE (FTF): a robot learning system that models human tactile behavior to learn force-sensitive manipulation. Using a tactile glove to measure contact forces and a vision-based model to estimate hand pose, we train a closed-loop policy that continuously predicts the forces needed for manipulation.

Our approach grounds robust lowlevel force control in scalable human supervision, achieving a **77% success rate** across 5 force-sensitive manipulation tasks

Source: Feel the Force: Contact-Driven Learning from Humans

Our results show that the inclusion of force matching **raises average policy success rates by 62.5%**, visuotactile mode switching by 30.3%, and visuotactile data as a policy input by 42.5%, emphasizing the value of seethrough tactile sensing for IL, both for data collection to allow force matching, and for policy execution to enable accurate task feedback.

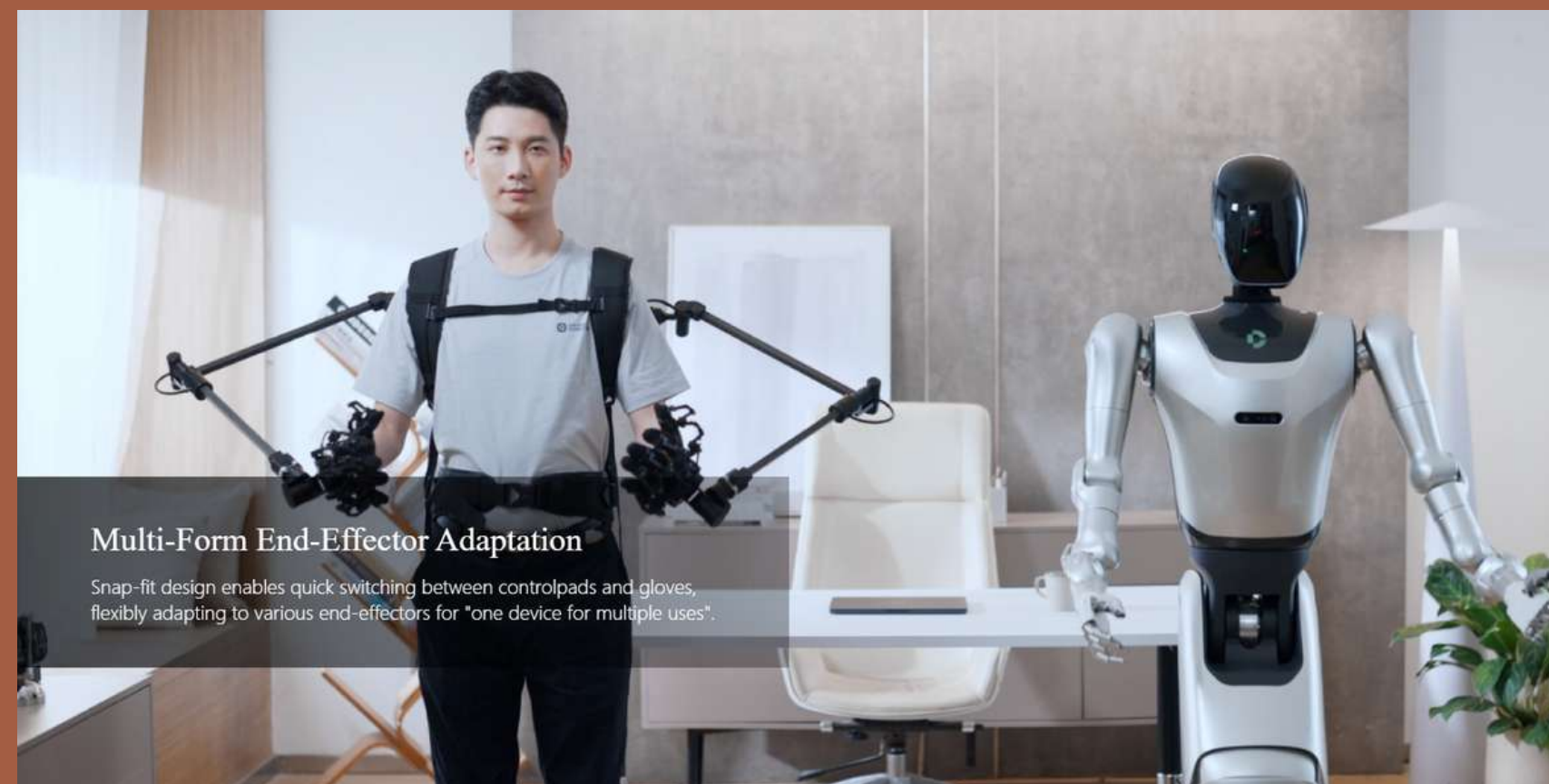
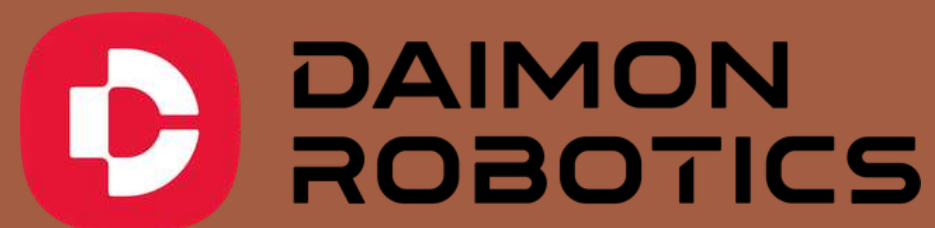
Source: Multimodal and Force-Matched Imitation Learning with a See-Through Visuotactile Sensor

Our experiments show that visuo-tactile pre-training **improved performance on a USB cable plugging task by up to 65% with vision-only inference**. Additionally, on a longerhorizon drawer pick-and-place task, pre-training — whether on a similar, dissimilar, or identical task — consistently improved performance, highlighting the potential for a large-scale visuotactile pre-trained encoder.

Source: Low-Fidelity Visuo-Tactile Pre-Training Improves Vision-Only Manipulation Performance



Who has done it before?



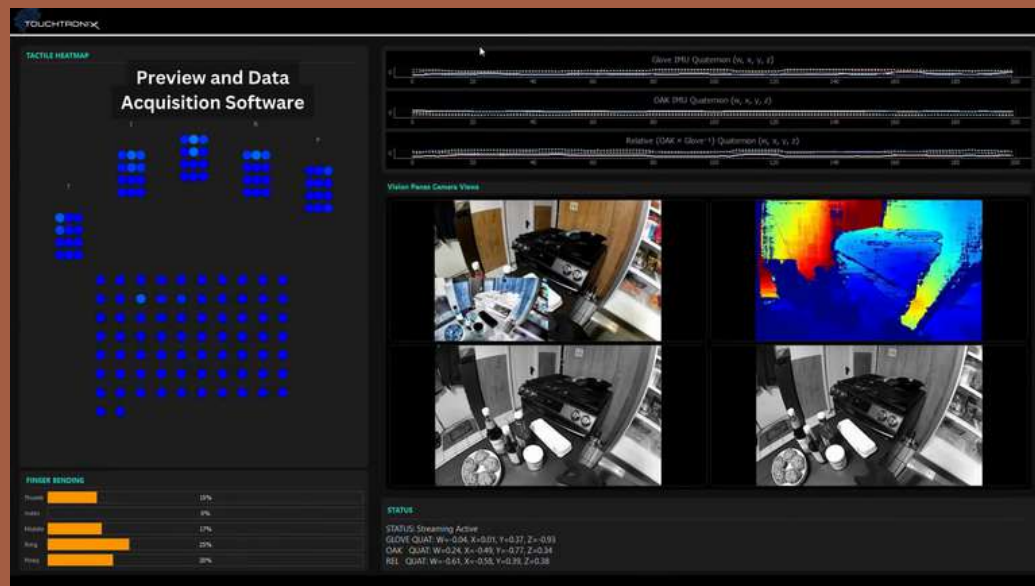
Tried and tested to work before!

SUNDAY α





Existing innovations?



Source: Touchtronix Robotics



Source: mimic Robotics



Source: 6thsense



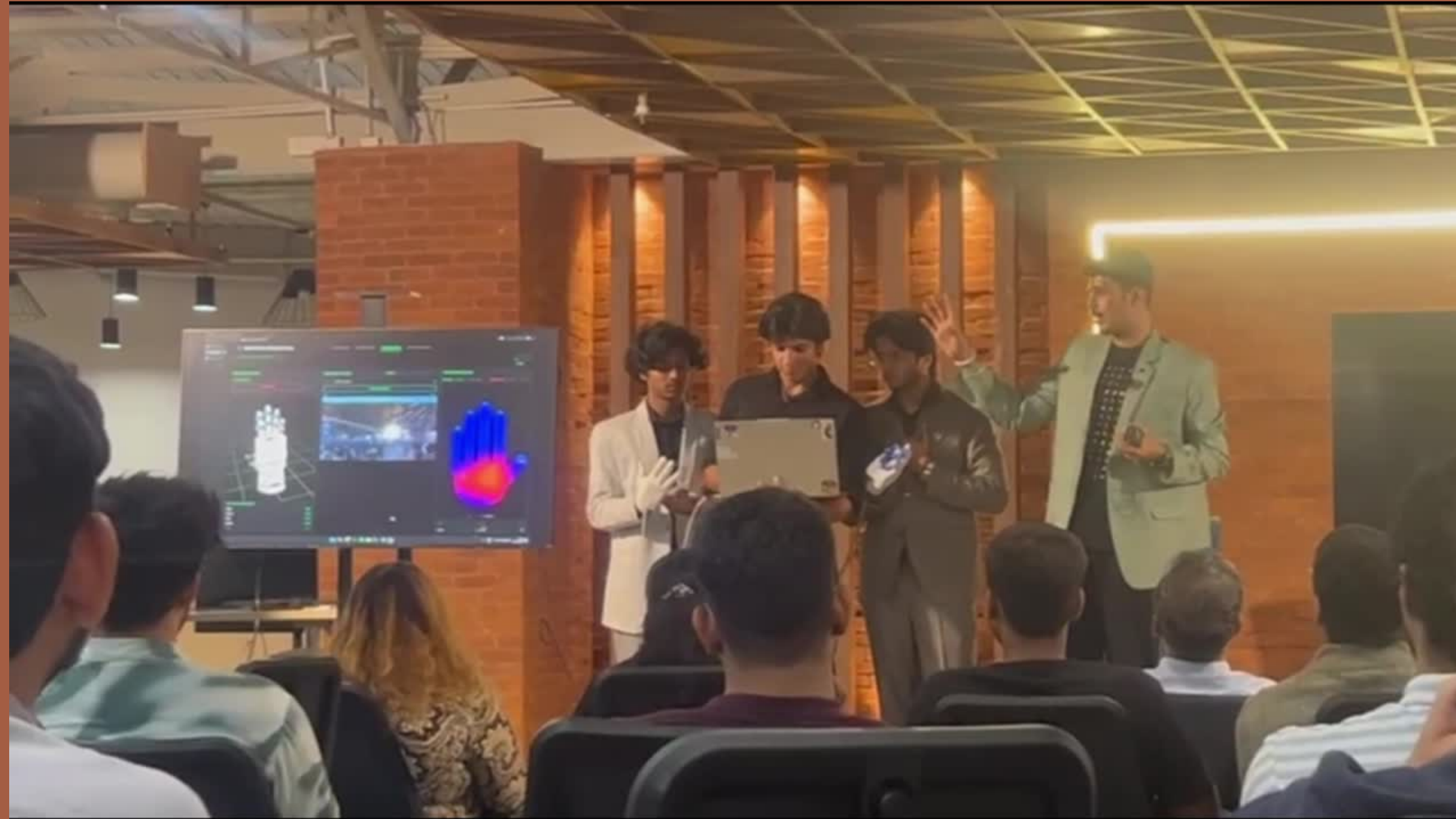
What distinguishes our Product then?

Tactile Sensing Capabilities Comparison						
Key tactile and motion parameters across popular sensing gloves						
Parameter	Sentrix	OSMO	ART-Glove	6th Sense	OpenGraph	PPS
 Normal pressure / contact	✓	✓	✓	✓	✓	✓
 3-Axis Force (X/Y/Z)	✓	✓	—	?	—	—
 Shear Force	✓	✓	—	?	—	—
 Contact location / map	✓	✓	✓	✓*	✓	✓
 Slip / vibration	✓	—	—	?	—	—
 Finger bending	✓	—	✓	?	✓	—
 Joint-level configuration	✓	—	✓	?	—	—
 Global hand orientation	✓	—	—	?	✓	—
 Global hand motion	✓	—	—	?	✓	—
 Local contact dynamics	✓	—	—	?	—	—
 RGB / Depth synchronization	✓	✓	✓	✓	✓	—
 Tactile + proprioception	✓	—	✓	?	✓	—
✓ Directly captured ⚠ Not publicly established — Not provided by the glove * 6th Sense publicly describes contact/pressure proxies but does not disclose enough detail to establish several rows.						

We provide the best data among all existing hardware to train robots for intricate tasks!



Product Demonstration



Our product pitch at Bharatl.ai, in front of MIT Professors and VCs (got PwC India interested for deployment!)



Progress & Traction Till Now

Where we are at:

- Got capital support of 10 Lakhs from IIMA Ventures
- Part of NVIDIA's Inception Program
- Pilots starting with 2 humanoid robotics companies
- A working MVP of the glove & egocentric vision headset
- A validated problem (validated by engineer at Google DeepMind, Humanoid robotics companies etc)
- LOIs with factories for deployment (3 factories confirmed)
- A team of 6 people working fulltime on the product

USE CASES TARGETED:

- 1) CNC Machining
- 2) Electronic Assembly
- 3) Garment/Textile Manufacturing
- 4) Packaging

and more as per customer demand!





**We're creating our own hand as well for
best translation & execution of this vision
+ tactile data**

What we're looking forward to?

**A pilot test for industrial robotic
automation use cases (humanoids and
robotic arms both) using our data!**

Team



Jyotishman Das
CEO & Co-Founder



Hardware Technology and R&D



Saideep Keshri
COO & Co-Founder



Operations, Sales & GTM



Pranav Prashant Shewale
CTO & Co-Founder



Data Curation & Processing