

Non-digital AI Compute Infrastructure

Cloud access to memristor-based neuromorphic hardware — a path toward low-energy, adaptive AI and European compute sovereignty.

Neuromorphic cloud

Organic memristors

Future compute



AI needs more than bigger GPUs

Future AI compute is becoming an energy, access and sovereignty question.



Digital AI bottleneck

Rapidly growing model size pushes compute demand, cost, power and infrastructure dependency.



Not every workload is matrix scale

Temporal, adaptive and bio-signal workloads need memory, dynamics and learning in hardware.



Europe needs options

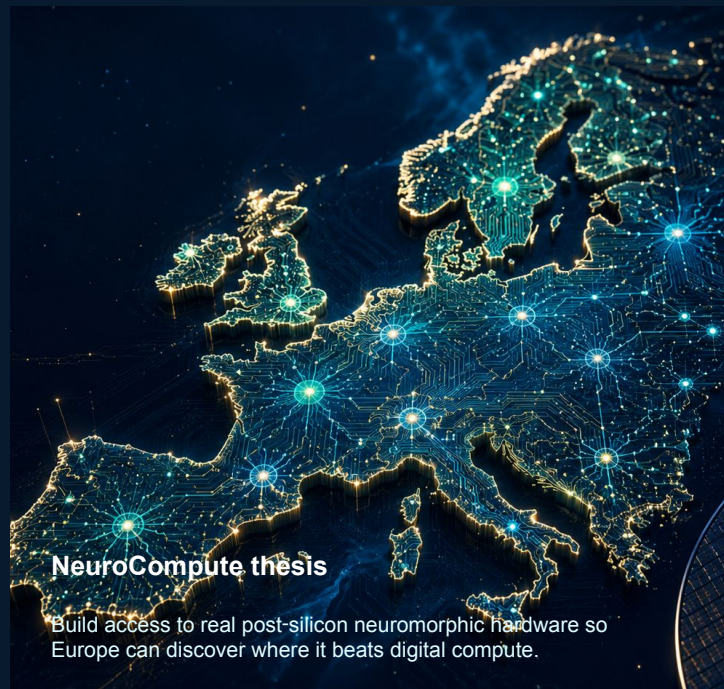
AI sovereignty needs alternative compute layers — not only imported GPU capacity.

Post-silicon compute layers

Memory + processing
In one physical element

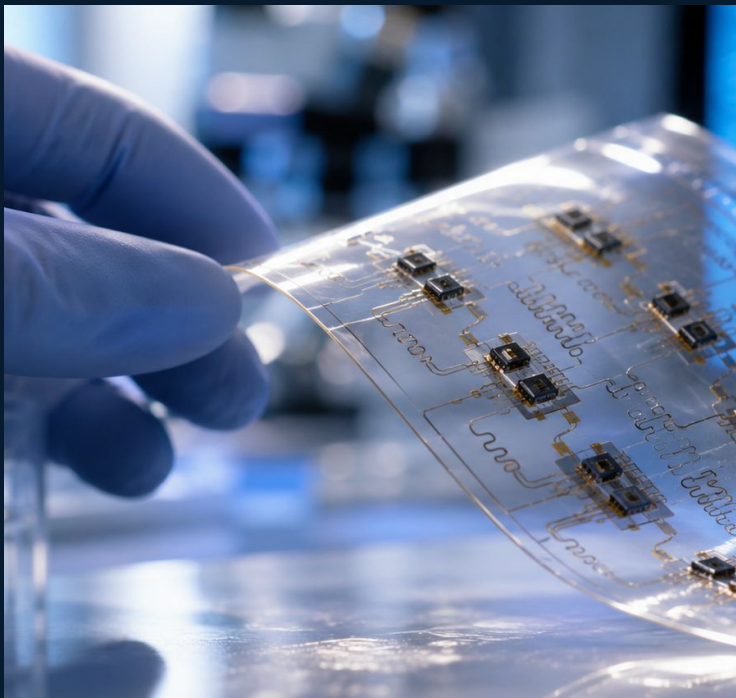
Event-driven dynamics
Sparse temporal signals

Adaptive state
Learning without full retraining



Organic memristors: why this substrate matters

A human-like, material-level compute primitive for selected adaptive and temporal AI workloads.



Energy efficiency

Event-driven and in-memory dynamics can reduce data movement and power for selected tasks **up to 10K times**.



Dynamic learning

Device state changes with signal history — a physical analogue of adaptive synapses.



Flexible devices

Organic materials support flexible, low-weight, bio-interface and wearable form factors.



3D / printed customization

Printing routes can reduce material waste and enable faster device iteration.

What makes it different

The device does not only store a bit. It behaves as a small dynamic system: memory, switching, timing and adaptation are part of the physical material.

Benchmarks for a spinal cord

Why Organic Memristors?

The same Spinal Cord model — orders of magnitude less energy

DIGITAL SIMULATION CPU CLUSTER



⌚ 6 hours
to simulate 2.5 seconds

💻 100 CPUs
200 GB RAM

⚡ Complex numerical
calculations

⚡ High power
consumption

Digital Spinal Cord Model

2,500 neurons

Simulate 2.5 seconds



ORGANIC MEMRISTOR SIMULATION



⌚ Real-time
2.5 seconds in 2.5 seconds

🌿 Energy consumption
in the milliwatt range

⚡ Natural dynamics
in hardware

🔋 Ultra-low power
operation

DIGITAL MODEL ENERGY ESTIMATE

$$\begin{array}{ccccccc} \text{CPU} & \times & \text{⚡} & \times & \text{⌚} & = & \sim 150,000 \text{ Wh} \\ 100 \text{ CPUs} & & \sim 250 \text{ W per CPU (avg.)} & & 6 \text{ hours} & & = \sim 150 \text{ kWh} \\ & & & & & & \text{(depending on exact system)} \end{array}$$

ORGANIC MEMRISTOR MODEL ENERGY ESTIMATE

$$\begin{array}{ccccccc} \text{Memristor hardware} & \times & \text{🌿} & \times & \text{⌚} & = & \sim 0.025 \text{ Wh} \\ & & \sim 10 \text{ mW power} & & 2.5 \text{ seconds} & & = \sim 0.000025 \text{ kWh} \end{array}$$



Long-term vision: **personal NeuroTwins for people worldwide**

Scalable low-energy neural digital twins for personalized rehabilitation and health.



Team and moat: the core investment case

World-class organic memristor expertise + a platform to translate it into infrastructure.



Victor Erokhin



Maxim Talanov



Konstantin Zhigunov



Oleg Pravdin

200+

research works in the field

10+

patents and IP assets

15+ yrs

organic memristor research

S

Scientific moat

Deep device know-how: materials, printing, characterization, dynamics, failure modes and repeatability.

P

Platform moat

Software layer, calibration logs, device health data, experiment templates, APIs and user workflows.

C

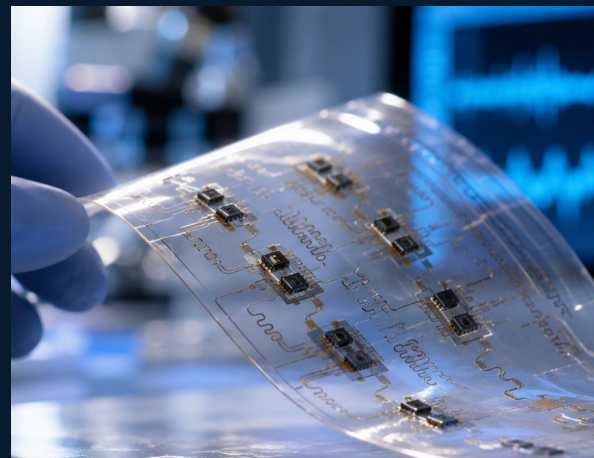
Commercial moat

Research network, clinic relationships, grant routes and early access to real-world demand.

E

Execution moat

Founders combine world-leading science with product, cloud, engineering and business development.



Investor message

The biggest de-risking asset is the team: rare hands-on expertise in a field that few companies can execute.

First step: find and prove the best applications for scaling

WHO USES IT



Deeptech startups



Research labs



Corporate R&D



Clinical research

NEUROCOMPUTE.CLOUD

Cloud access to memristive devices

MEMRISTIVE MODULE LIBRARY

READY TO USE

Spinal Cord



STDP Learning



IN PROGRESS

Reservoir Computing



Associative Learning



Bio-signal Processing



Wearable Synapses



More Modules



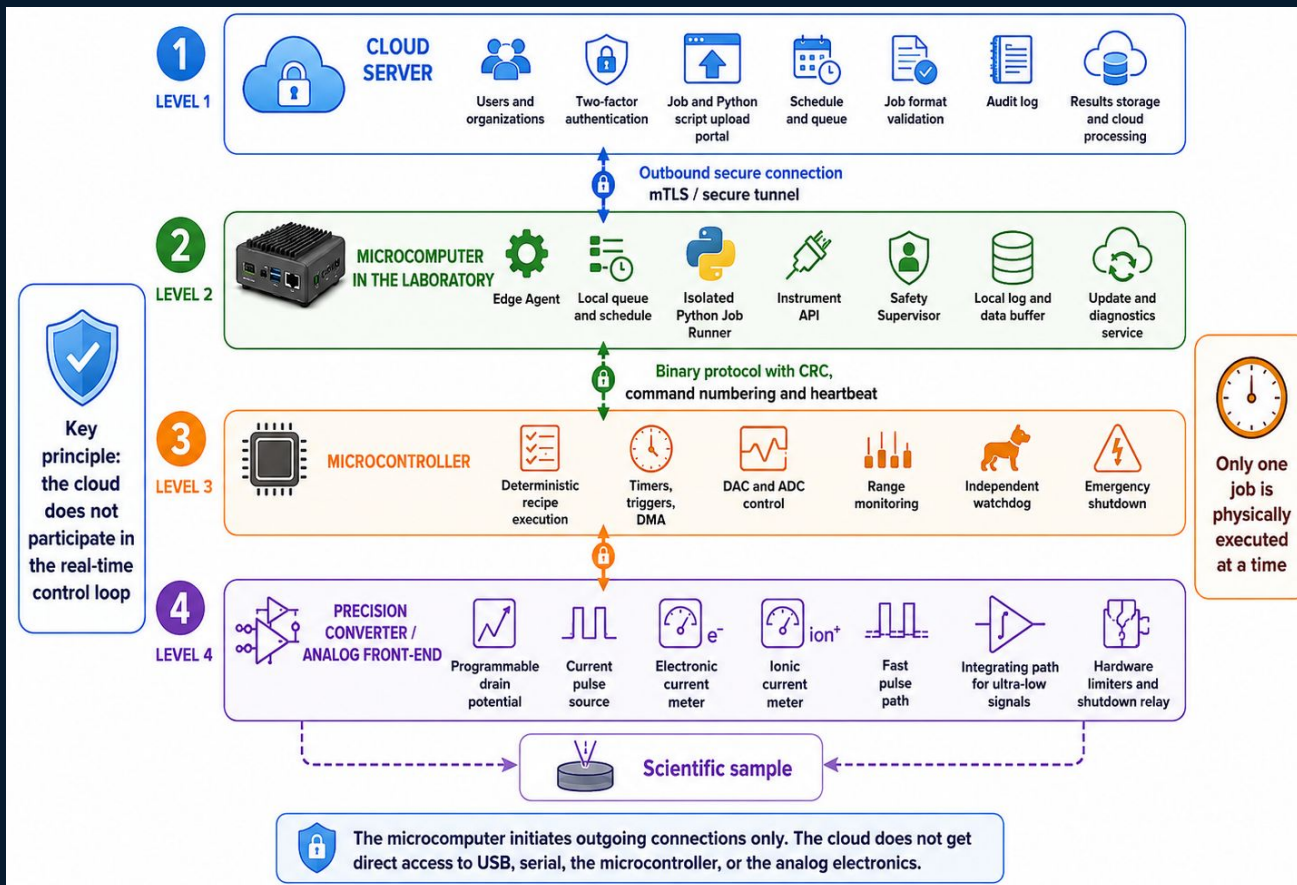
GOAL



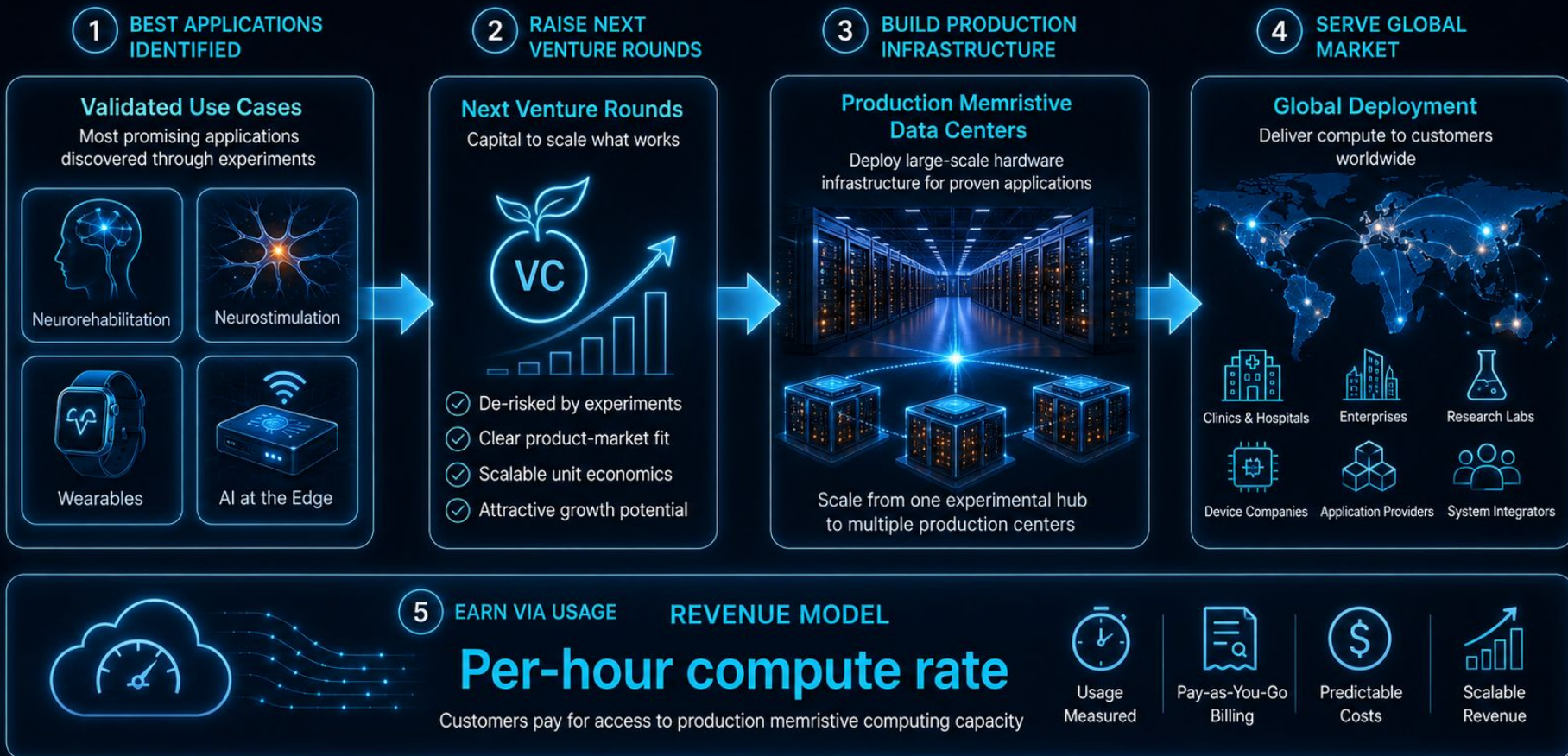
Find efficient use cases for further scaling

Run real hardware experiments, identify the highest-value applications, then scale the winning use cases.

NeuroCompute basic architecture



Next steps: scale best applications



Value for labs, researchers, startups, students & grant holders

The proposal is strongest when each party keeps its natural role and benefits from the shared network

