

Storage Class Memory is Dead, All Hail **Managed-Retention Memory**: Rethinking Memory for the AI Era

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AI Inference – The Dominant Cloud Workload

Generative AI has changed the game & inference demand is huge

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Data centres will use twice as much energy by 2030 – driven by AI

These facilities accounted for roughly 1.5% of global electricity consumption in 2024.

By [Sophia Chen](#)



AI EFFECT

Tech megacaps plan to spend more than \$300 billion in 2025 as AI race intensifies

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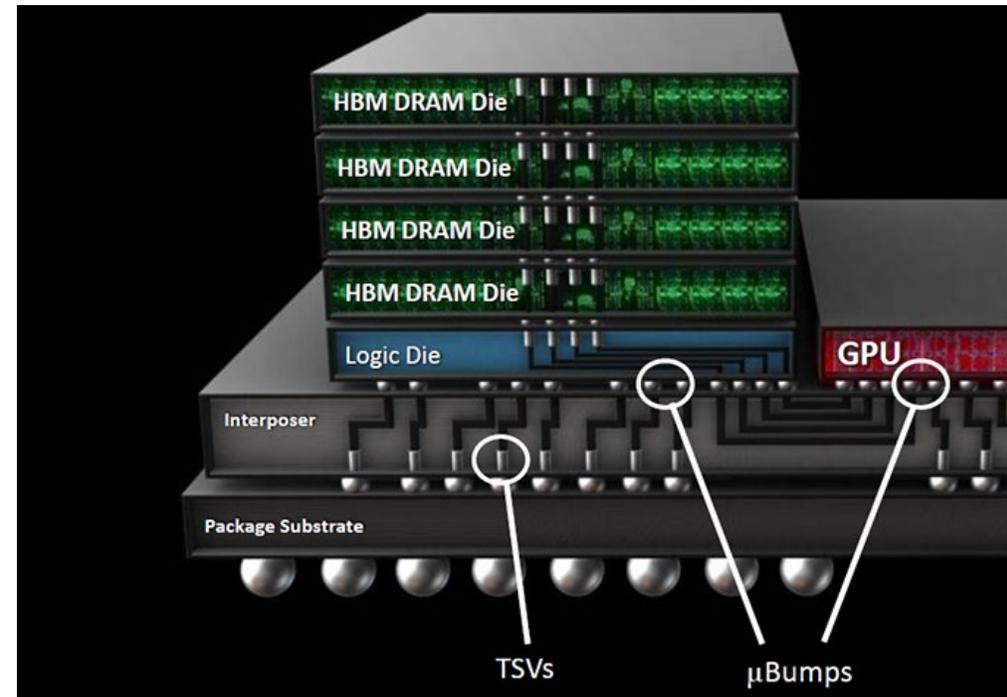
A great challenge and opportunity for the research community to rethink system hardware and software architectures

The Problem Today: The Curse of HBM

High **B**andwidth **M**emory is the **only** option today to achieve good bandwidth to AI data

But, a litany of problems...

- Complex manufacturing and packaging
- Unreliable
- Expensive: **significant** portion of GPU cost and power



(source: <https://www.anandtech.com/show/9969/jedec-publishes-hbm2-specification>)

What is HBM in *LLM Inference* Actually Used For?

LLM inference: the prominent workload

Two large data structures: model weights + KV cache

Model weights (~ 50% today)

Write: once

Read: each forward pass

KV-cache (~ 50% today):

Write: append-only

Read: in whole each forward pass

Observation: very large, predictable, block **Reads** dominate

- HBM is “overprovisioned” on write performance
- Small, random access of HBM not necessary

Can we leverage the specific properties of AI inference to design a better memory?

A New Class of Memory for AI Inference

- “New” memory technologies: STT-MRAM, ReRAM, PCM, FeRAM,...
 - Viewed through “Storage Class Memory” lens – long-term data *retention* was a goal
- For AI Inference:

Important Metrics	Less Important Metrics
Capacity / \$	Write performance
Read bandwidth	Small, random access
Energy	Long-term Retention

Key insight: possible to trade-off *write performance & retention time* for important metrics

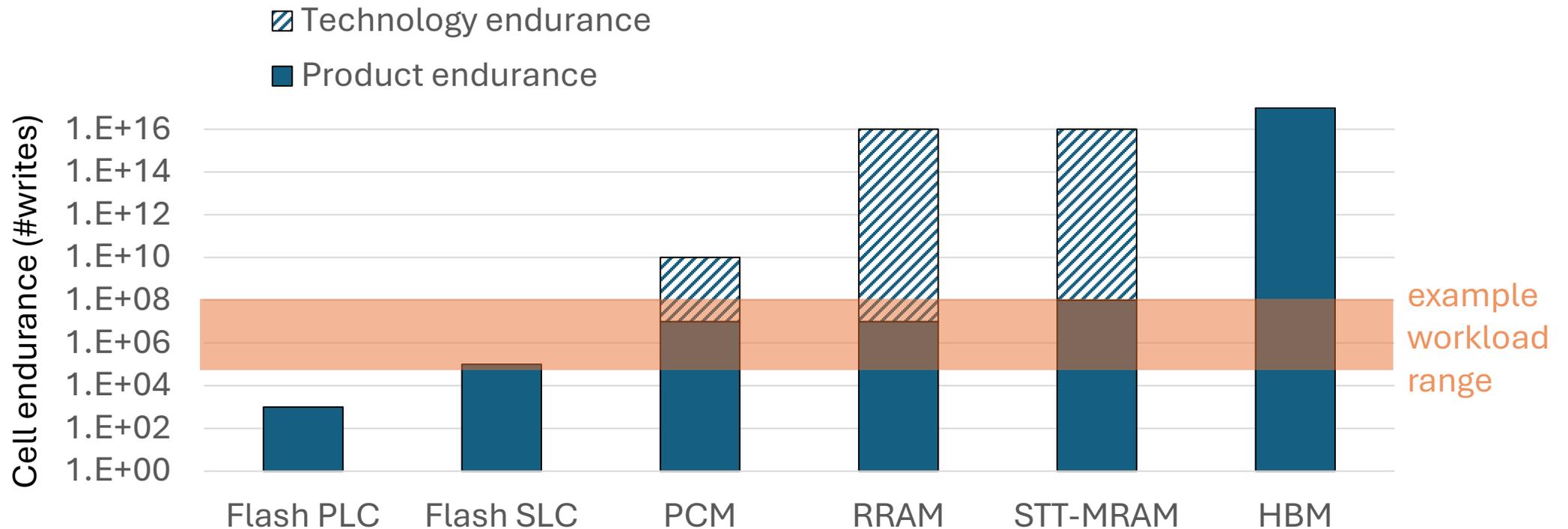
- Storage Class Memory non-volatility (10+ yr retention) is not required
- Hours-long retention time is sufficient and enables power advantage

Managed-Retention Memory: a new class of memory for AI inference

MRRM: A New Opportunity for SCM Technologies

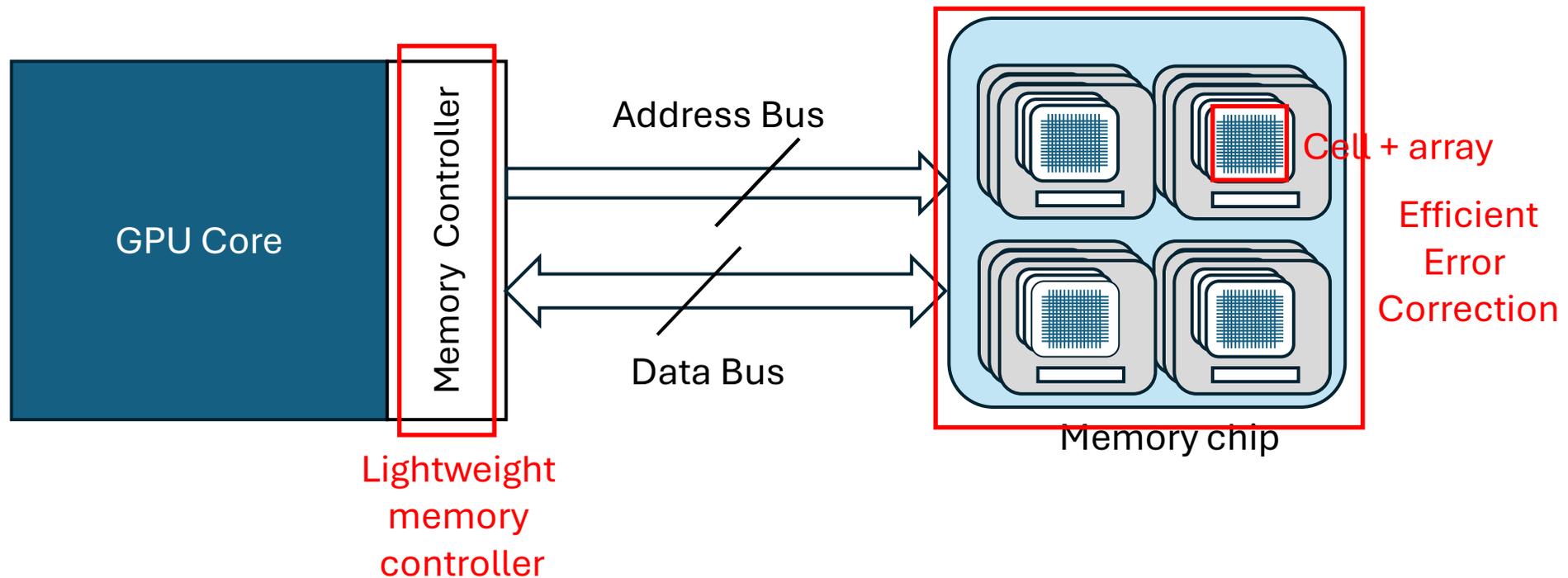
Existing memory technologies **can** inherently be optimised for MRRM

example trade-off: retention \uparrow endurance \downarrow



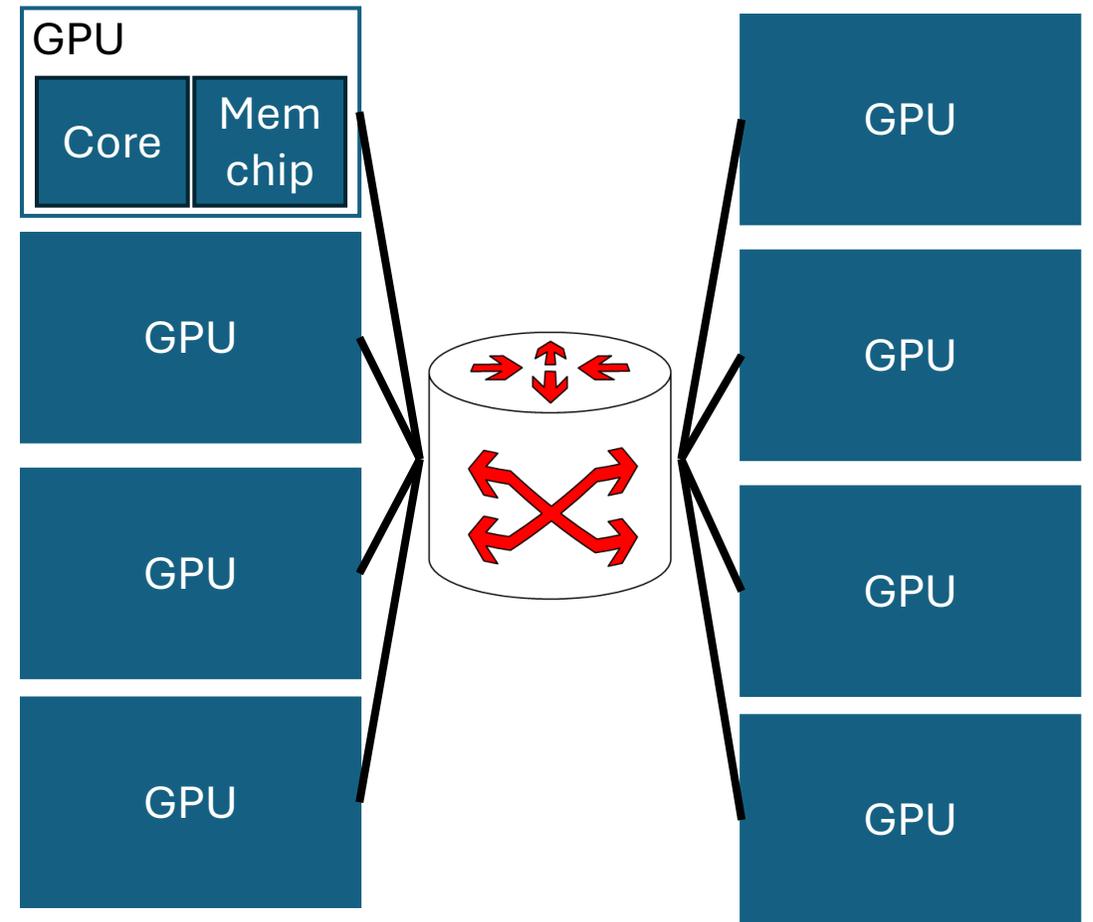
MRRM Research Opportunities

- Innovation across the HW/SW stack needed
- How do we leverage workload + cell properties?
 - lack of small random access, lack of refreshes



MRM Systems Research Opportunities

- MRM abstraction: how to expose MRM to systems?
- Dynamically configurable retention
 - Should software configure retention period per write?
- Retention-aware data placement & scheduling
 - Software-driven movement



MRRM: Rethinking Memory for the AI Era

- 1) Massive opportunity and need to disrupt HBM for AI inference
- 2) **Managed-Retention Memory**: a new class of memory that trades off retention and write performance for energy, read performance, and cost
- 3) Ripe for innovation across cells, arrays, controllers, system abstractions, and much more!