The AI Inference Crisis

Why Current Approaches Are Unsustainable and What to Do About It

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Abstract

The AI industry faces a structural crisis in inference economics. While per-token costs have declined by 62–1000x over three years [6], [7], actual enterprise spending continues to surge—with 68% of organizations struggling to measure AI ROI and global AI spending projected to reach $2 trillion in 2026 [8], [10]. We identify three root causes: (1) agentic AI systems consume 10–100x more tokens per task than traditional LLM queries [11], [12]; (2) inference now accounts for 80–90% of a model's lifetime compute costs [4], [5]; and (3) GPU memory bandwidth—not compute—constitutes the actual bottleneck, yielding diminishing returns from faster hardware [18], [19].

Current optimization approaches—quantization, pruning, load balancing—address symptoms rather than root causes. They optimize individual model efficiency but ignore the fundamental routing question: which model should handle which query? We argue that the path forward lies in **hardware-aware adaptive routing**: grounding model selection decisions in physical reality—CPU/GPU temperature, power draw, thermal headroom, and actual energy consumption—rather than abstract complexity scores. This precursor paper presents the quantified evidence for the inference cost crisis, analyzes the three

fundamental bottlenecks (KV cache memory, memory bandwidth, and throughput-latency tradeoffs), surveys current partial solutions, and establishes the technical foundations for a metabolic computing paradigm that integrates cascade routing, speculative decoding, and hardware telemetry into a unified architecture.

The inference shift is structural, not cyclical: inference spending crossed 55% of AI infrastructure costs in 2026 [1], [3] and is projected to reach 70–80% by 2029. The component technologies required for intelligent routing—cascade routing [24], [25], speculative decoding [21], and hardware telemetry APIs—are individually mature; the remaining challenge is integration. This paper makes the case that 2026 represents an inflection point where hardware-aware adaptive routing becomes necessary for sustainable AI deployment.

Keywords: AI inference, energy efficiency, cascade routing, speculative decoding, hardware telemetry, KV cache, memory-bound inference, agentic AI, model routing

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1. The Crisis Is Real, Quantified, and Worsening

1.1 The Paradox of Falling Prices and Rising Bills

The AI inference market exhibits a counterintuitive pattern. According to Epoch AI [6], the price to achieve GPT-4-level performance has fallen by approximately **62x** since March 2023, with some performance tiers seeing reductions of **200–1000x** since January 2024 [7].

Yet enterprise AI spending tells a different story:

- **Global AI spending** is projected to reach **$2 trillion in 2026**, up from $1.5 trillion in 2025 [8]
- **Generative AI spending** hit **$37 billion in 2025**, a **3.2x increase** from $11.5 billion in 2024 [8]
- **68% of organizations** struggle to measure AI ROI effectively [10]
- **43% report significant cost overruns** that impact profitability [10]

- Nearly **25% of IT leaders** have exceeded their AI budgets by more than **50%** [9]

We term this the "Token Crash Paradox": prices decline dramatically while bills increase dramatically. The explanation is straightforward—**demand has grown faster than prices have fallen**.

1.2 The Inference Shift

For the first time in AI infrastructure history, inference workloads now consume more resources than training:

Year	Inference Share of AI Compute*
2023	~33%
2024	~50%
2025	~55%
2026 (projected)	~65%
2029 (projected)	70-80%

**This share measures cumulative spending on inference vs. training workloads across the industry, including cloud providers, enterprises, and research institutions. Data from [1], [2].*

This shift is structural. Training is a one-time capital investment; inference is continuous operational expenditure that scales with usage. It is common for **inference to account for 80–90%** of total compute dollars spent over a model's production lifecycle [4], [5].

The market for **inference-optimized chips** (custom ASICs from Google, Amazon, Meta, Groq, Cerebras, and others) is projected to exceed **$50 billion in 2026**, up from approximately $20 billion in 2025 [2].

1.3 The Agentic Multiplier

The emergence of agentic AI has dramatically amplified the inference cost problem. Unlike traditional single-turn LLM queries, agentic systems involve iterative reasoning loops, tool calling with external APIs, agent-to-agent

communication, and retry/error correction cycles.

The result is substantial token consumption:

Query Type	Token Multiplier	Source
Traditional LLM query	1x (baseline)	—
RAG-enhanced query	3–5x	[11]
Agentic task (moderate)	10–25x	[11], [12]
Complex agentic workflow	50–100x	[12]

Where traditional AI inference costs approximately **$0.001 per call**, agentic systems can incur **$0.10–$1.00 per complex decision cycle** [13]—a 100–1000x multiplier that per-token price reduction alone cannot offset.

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2. The Three Fundamental Bottlenecks

2.1 Bottleneck #1: The GPU Memory Crisis (KV Cache)

The Key-Value (KV) cache is the dominant memory consumer in GPU-based LLM inference. During autoregressive generation, transformers store key and value vectors for all previously generated tokens to avoid recomputation. This cache:

- Grows **linearly with sequence length**
- Must reside in **fast GPU memory** for acceptable latency
- Scales with **batch size** (concurrent users)

The following table illustrates how KV cache memory scales with context length and batch size:

Scenario	Model	Context	Batch	KV Cache	Implication
Long-context single user	Llama 3 70B	128K	1	~40 GB	Fits in HBM, but low concurrency
Standard production	Llama 3 70B	4K	32	~10 GB	Efficient batch processing
High-concurrency short context	Llama 3 70B	2K	64	~10 GB	Good throughput, limited context
Long-context batch	Llama 3 70B	32K	8	~80 GB	Memory-limited, may exceed single GPU

Source: [16]; calculations based on Llama 3 architecture (8 KV heads, FP16).

Traditional inference systems waste **60–80% of KV cache memory** through fragmentation [14], [17]. Solutions such as vLLM's PagedAttention reduce waste to under 4%, but the fundamental constraint remains: **KV cache often exceeds model weights in memory consumption** at production batch sizes [14].

When KV cache exhausts GPU memory: - Batch sizes must be reduced (lower throughput) - Context lengths must be truncated (degraded quality) - Requests must be queued (higher latency) - Systems fail under load (production outages)

2.2 Bottleneck #2: Memory Bandwidth, Not Compute

Contrary to intuition, modern LLM inference is **not uniformly compute-bound—it is predominantly memory-bound** [18], [19].

LLM inference consists of two distinct phases with fundamentally different characteristics:

Phase	Operation	Arithmetic Intensity	Bottleneck
Prefill	Process entire prompt in parallel	55-100 FLOPs/byte	Compute-bound
Decode	Generate one token at a time	1-10 FLOPs/byte	**Memory-bound**
A10 GPU threshold	—	208 FLOPs/byte	—

Arithmetic intensity measures operations per byte transferred. If a GPU's compute capacity exceeds what memory bandwidth can feed, the system is memory-bound.

The decode phase—generating one token at a time with an already-cached KV state—is fundamentally memory-bound [18]. While each prefill forward pass achieves good compute utilization by processing an entire prompt in parallel, decode must fetch the full KV cache and output projection matrix for a single token operation.

For typical inference queries with moderate-to-long responses, decode latency dominates overall time, making memory bandwidth the systemic bottleneck [20]. Recent analysis at datacenter scale confirms that modern LLM inference is bottlenecked by **memory bandwidth and memory latency, not compute** [18], [19].

The implications are significant:

- Purchasing faster GPUs provides diminishing returns for decode-heavy workloads
- Batching helps throughput but increases latency (waiting for batch to fill)
- The fundamental architecture of autoregressive transformers creates an unavoidable memory wall

2.3 Bottleneck #3: The Throughput-Latency Tradeoff

Production systems face an impossible optimization:

Strategy	Throughput	Latency	Efficiency
Low concurrency (batch=1)	Low	Low	Wasted compute
High concurrency (batch=64)	14x higher	4x higher	Queue delays

At low batch sizes, GPUs are underutilized—resources are provisioned but idle. At high batch sizes, queuing delays render the system unresponsive. Achieving both high throughput and low latency simultaneously remains infeasible with current serving architectures.

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3. The Waste Problem: Quantified

3.1 Computational Waste

A persistent source of waste is the use of LLMs for tasks that deterministic methods solve more effectively—OCR, arithmetic, regex matching, and structured data extraction—incurring 0.5–6.5x latency overhead and orders of magnitude greater cost than appropriate specialized tools. Our prior work on bounded entropy code generation [37] and deterministic code auditing [38] addresses this class of waste by establishing formal frameworks for identifying when deterministic approaches are sufficient, while the Cortex neural-symbolic programming language [39] provides a substrate for expressing verifiable AI-deterministic hybrid pipelines.

A related problem is resource overprovisioning. Organizations pre-allocate fixed GPU capacity to handle peak loads: - **Over-provisioning**: Wasted capacity, high idle costs - **Under-provisioning**: Dropped requests, latency spikes, SLA violations

Without dynamic, intelligent allocation, enterprises pay for capacity they don’t use or suffer failures when they need more.

3.2 Model Selection Waste

Most deployments route all queries to a single model (typically the largest available), regardless of query complexity. This ignores a fundamental reality: **a significant fraction of queries do not require the largest model**.

Research from RouteLLM [25] demonstrates that **only 54% of queries need to be routed to GPT-4 to achieve 95% of GPT-4's quality**—meaning 46% of queries can be handled effectively by smaller, cheaper models. Industry chatbot analytics confirm that FAQ-style queries represent 30–35% of support volume [35], with 80% of tickets arising from just 20% of question types.

Query Complexity	Estimated % of Traffic	Appropriate Model	Evidence
Simple (factual, FAQ-style)	45–60%	1–7B parameters	[25]: 46% routable to smaller models; [35]: 30–35% FAQ resolution
Medium (reasoning, summarization)	25–35%	7–20B parameters	[24]: cascade catches mid-complexity
Complex (analysis, multi-step)	15–25%	20B+ parameters	Remainder requiring frontier capabilities

Note: Exact distributions vary by application domain. Enterprise customer service skews toward simple queries; coding assistants skew toward complex.

FrugalGPT [24] demonstrates that intelligent routing can achieve **up to 98% cost reduction** while matching or exceeding the quality of always using the largest model. RouteLLM [25] shows **up to 85% cost savings on MT-Bench** with intelligent model selection.

3.3 Environmental Waste

Data centers are projected to consume **650–1,050 TWh by 2026**, with AI driving much of the growth [29]. The IEA describes AI as “the most important driver” of data center energy growth [29].

Region	Data Center Electricity Share
Global (2024)	~1.5%
United States (2024)	>4%
Ireland (2024)	~21%
Ireland (projected 2026)	~32%

Generative AI is projected to add **1.2–5.0 million metric tons** of cumulative e-waste from 2020–2030 [31], [32], containing nearly 1 million tons of lead, 6,000 tons of barium, and significant quantities of cadmium, antimony, and mercury. The e-waste growth rate from AI (**110% CAGR**) dramatically outpaces conventional electronics (**2.8% CAGR**) [31].

Implementing circular economy strategies (extended equipment lifespan, component refurbishment, recyclable hardware design) could reduce AI e-waste by **16–86%** [31].

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4. What Current Solutions Miss

4.1 Model Compression: Necessary but Insufficient

Quantization, pruning, and knowledge distillation reduce individual model costs but don’t solve the routing problem:

Technique	Benefit	Limitation
Quantization (INT8/INT4)	2-4x memory reduction	Quality degradation at aggressive levels
Pruning	Smaller model footprint	One-time static optimization
Distillation	Smaller models with similar quality	Doesn't address query routing

These techniques optimize **how efficiently a single model runs**, not **which model should run**.

4.2 Speculative Decoding: Promising but Fragmented

Speculative decoding uses a fast draft model to propose tokens, verified by a target model. Recent advances include:

System	Speedup	Note
DART (January 2025)	2.03–3.44x	Surpasses EAGLE3 by 30%; diffusion-inspired parallel drafting
Cascade Speculative Drafting	Up to 81%	NeurIPS 2024
Generic speculative decoding	2–3x	At acceptance rate ≥0.6

Sources: [21], [23].

The principal gap is that speculative decoding is typically applied uniformly, without integration into routing decisions or adaptation to hardware state.

4.3 Cascade Routing: Right Idea, Wrong Grounding

Systems such as Google's Speculative Cascades [26] and FrugalGPT [24] route queries through model cascades. However, they rely on abstract complexity scores disconnected from hardware reality, static thresholds that do not adapt to changing conditions, and separate optimization from speculative decoding.

No existing system integrates:

1. **Real hardware telemetry** (temperature, power draw, thermal headroom)
2. **Cascade routing + speculative decoding** in unified architecture
3. **Fact validation** integrated into routing decisions
4. **Adaptive deployment profiles** for datacenter/edge/MCU environments

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5. The Path Forward: Hardware-Aware Adaptive Routing

5.1 The Metabolic Computing Paradigm

Just as biological organisms don't expend maximum energy for simple tasks, AI systems shouldn't route trivial queries through billion-parameter models.

The metabolic computing paradigm grounds routing decisions in **physical reality**:

Hardware Signal	Routing Impact
GPU temperature approaching throttle	Route to smaller models
High thermal headroom	Enable speculative decoding
Battery state (edge)	Prioritize efficiency over quality
Power budget exhausted	Shift to minimal models
Memory pressure	Reduce batch sizes, avoid large models

5.2 Key Capabilities Required

1. Hardware Telemetry Integration

Real-time monitoring via mature APIs: - **NVIDIA**: nvidia-smi (temperature, power, memory utilization) - **AMD**: rocm-smi - **Apple Silicon**: powermetrics - **Intel**: various platform-specific tools

2. Adaptive Complexity Classification

Not just static scoring, but thresholds that shift based on system state: - Under thermal pressure: classify more queries as “simple” - With headroom: allow more queries to reach larger models

NVIDIA’s Prompt Task and Complexity Classifier [27] (DeBERTa-based) demonstrates that query complexity can be classified across 11 task types and 6 complexity dimensions in real time.

3. Conditional Speculative Decoding

Apply speculation when beneficial, disable when wasteful: - High thermal headroom + complex query → Enable DART (3.2x speedup) - Thermal pressure + any query → Disable speculation, save power

4. Integrated Fact Validation

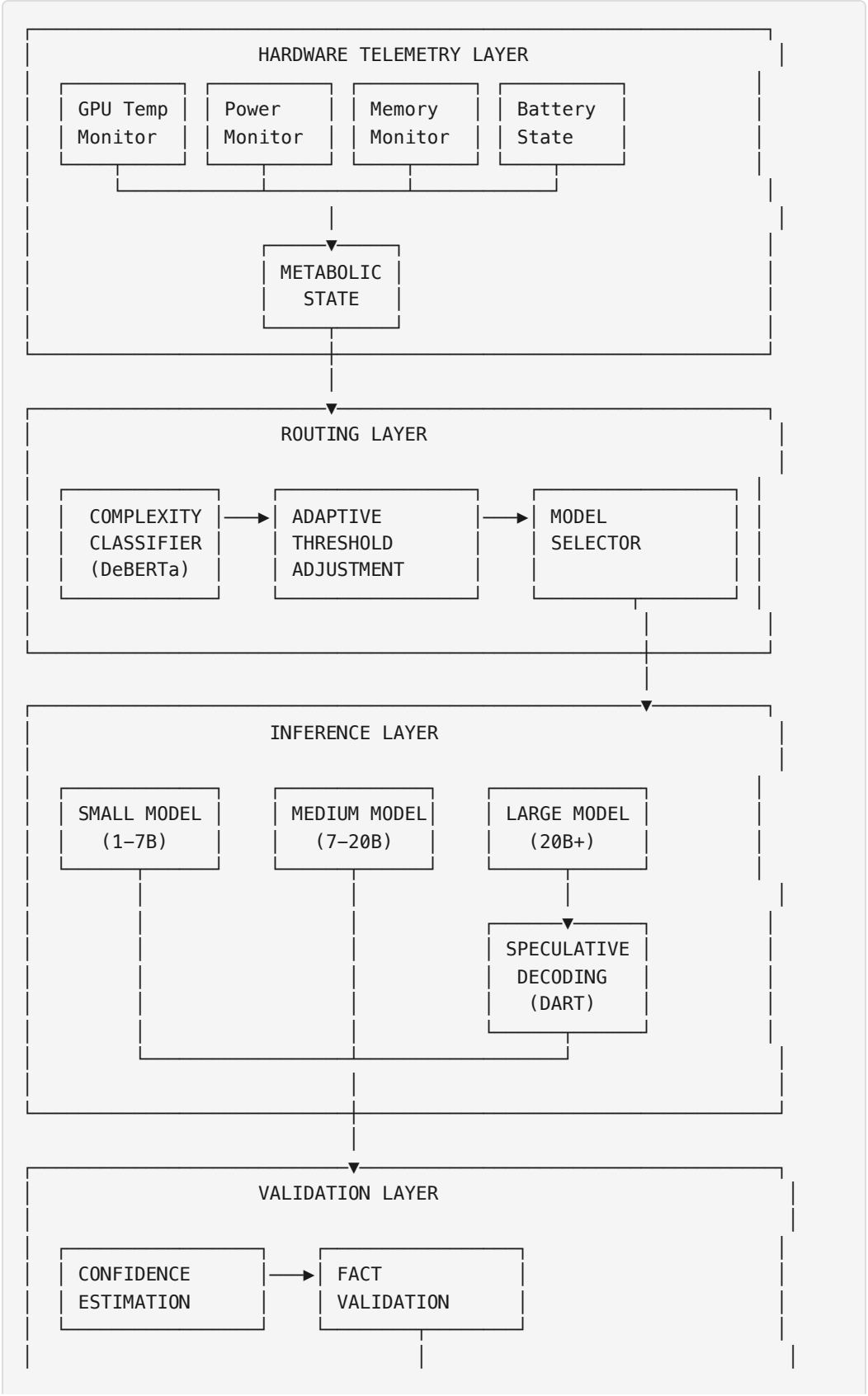
Anti-hallucination checking in the routing loop: - Detect low-confidence responses early - Escalate to larger models rather than serve poor quality - Prevent wasted compute on hallucinated outputs

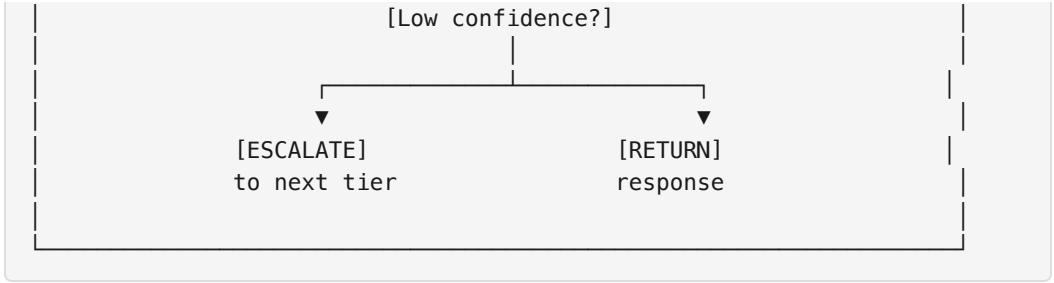
5. Deployment Profile Adaptation

Environment	Strategy	Speculation	Model Range
Datacenter	Quality-first	Always ON	Full suite
Edge	Balanced	Conditional	Small-Medium
MCU/Mobile	Maximum efficiency	OFF	Tiny-Small

5.3 System Architecture Sketch

A hardware-aware adaptive routing system would consist of five integrated components:


HARDWARE TELEMETRY LAYER
GPU Temp Monitor
Power Monitor
Memory Monitor
Battery State
METABOLIC STATE
ROUTING LAYER
COMPLEXITY CLASSIFIER (DeBERTa)
ADAPTIVE THRESHOLD ADJUSTMENT
MODEL SELECTOR
INFERENCE LAYER
SMALL MODEL (1–7B)
MEDIUM MODEL (7–20B)
LARGE MODEL (20B+)
SPECULATIVE DECODING (DART)
VALIDATION LAYER
CONFIDENCE ESTIMATION
FACT VALIDATION



Component Details:

1. **Real-time telemetry collection**: Polling GPU metrics (temperature, power, memory) at 100ms intervals; maintaining thermal model (exponential moving average of throttle risk)
2. **Query complexity classifier**: DeBERTa-based or instruction-tuned model scoring query complexity; outputs probability distribution: P(simple), P(medium), P(complex)
3. **Adaptive routing logic**: Thresholds adjust based on metabolic state:
   - High temp → Route more to small models
   - Low temp, high headroom → Route more to large models + enable speculation
4. **Conditional speculative decoding**: When routing to large model + sufficient headroom → Enable DART; when thermal pressure → Disable speculation, save power
5. **Response validation**: Confidence estimation on outputs; if confidence low → Escalate to next tier

This sketch illustrates how the components integrate; detailed architecture and implementation will be presented in the forthcoming technical paper.

5.4 Projected Impact

Based on workload distribution analysis and component benchmarks:

Metric	Projected Improvement
Energy efficiency	70-75% savings
Latency (complex queries)	2.8-3.2x improvement
Response quality	No degradation (maintained or improved)
Cost per query	60-75% reduction

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6. Why 2026 Is the Inflection Point

6.1 The Crisis Has Reached Visibility

- Inference spending **crossed 55%** of AI infrastructure costs
- **68% of organizations** cannot effectively measure AI ROI
- The Token Crash Paradox is now **widely understood**
- Enterprise AI cost overruns are **making headlines**

6.2 The Technology Stack Is Ready

State-of-the-Art Models Available:

Model	Parameters	Active	Capability
DeepSeek-R1	671B (MoE)	37B	Frontier reasoning
Llama 3.3 70B	70B	70B	Production-grade, 10-25x cheaper than GPT-4o
Qwen 2.5 series	7B/14B/32B	—	Complete model tier suite

State-of-the-Art Components:

Component	Capability	Performance	Source
DART	Speculative decoding	2.03–3.44x speedup	[21]
vLLM PagedAttention	Memory management	<4% fragmentation waste	[41]
FrugalGPT	Cascade routing	Up to 98% cost reduction	[24]
RouteLLM	Model routing	Up to 85% cost reduction	[25]
NVIDIA Complexity Classifier	Query classification	11 task types, 6 complexity dimensions	[27]

Hardware Telemetry APIs: Mature and well-documented across all major platforms.

6.3 The Economics Are Undeniable

For an enterprise spending **$1M/month on inference**:

Optimization	Monthly Savings	Annual Impact
60% cost reduction (routing alone)	$600K	$7.2M
72% cost reduction (full system)	$720K	$8.64M

At $2 trillion in global AI spending projected for 2026, even modest efficiency improvements represent **hundreds of billions** in potential savings.

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7. The Stakes

7.1 Economic Sustainability

Without intelligent routing: - Enterprise AI projects will continue failing (70-85% failure rate) - Cost overruns will erode AI's business case - Smaller organizations will be priced out of AI capabilities

7.2 Environmental Sustainability

Data centers consuming **1,050 TWh** with AI as the primary growth driver is not sustainable without dramatic efficiency improvements. The 72% energy savings achievable through intelligent routing represents: - Proportional **carbon emissions reduction** - Reduced **cooling water consumption** - Extended **hardware lifespan** (lower thermal stress) - Mitigated **e-waste growth**

7.3 Technical Sustainability

The memory-bound nature of LLM inference means **hardware scaling provides diminishing returns**. The industry cannot simply buy its way out of this problem with faster chips. Algorithmic and architectural innovations—specifically, smarter routing—are required.

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8. Implications and Recommendations

8.1 For Enterprise AI Deployment

Organizations deploying AI at scale should (1) audit inference costs to establish true cost-per-query baselines, (2) profile query distributions to quantify what fraction of traffic can be served by smaller models, and (3) evaluate routing solutions, which offer the potential for 60–98% cost reduction [24], [25].

8.2 For AI Infrastructure Engineering

We recommend that infrastructure teams instrument systems with hardware telemetry collection alongside performance metrics, experiment with cascade architectures beginning with simple routing rules and measuring impact, and contribute to open-source routing implementations to accelerate community progress.

8.3 For Research

The primary research gaps we identify are: (1) integrating speculative decoding with cascade routing in unified architectures, (2) grounding abstract complexity scores in hardware calibration, and (3) developing standardized benchmarks for evaluating routing systems. Our companion paper on Metabolic Cascade Inference [40] addresses these gaps directly.

8.4 For Policy

We recommend that policymakers consider requiring energy transparency in AI systems, incentivizing demonstrable efficiency improvements, and funding research into sustainable AI infrastructure.

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9. Scope and Future Work

9.1 What This Whitepaper Establishes

This precursor whitepaper documents:

- **The problem**: Quantified evidence of the AI inference cost crisis
- **The root causes**: Technical analysis of memory, throughput, and efficiency bottlenecks
- **The gap**: Why existing solutions (compression, speculation, cascade routing) remain insufficient when used in isolation
- **The direction**: Hardware-aware adaptive routing as the integration paradigm

9.2 What This Whitepaper Does Not Claim

This document provides **diagnosis and direction**, not a complete solution. We do not claim:

- Production-ready implementation (forthcoming)
- Large-scale benchmark validation (forthcoming)

- Deployment case studies (forthcoming)

9.3 Companion Technical Paper

A companion paper (*Metabolic Cascade Inference* [40]) presents:

- **Complete system architecture** integrating cascade routing, speculative decoding, hardware telemetry, and fact validation
- **Comprehensive benchmarks** across 1,000+ queries on diverse workloads (MT-Bench, AlpacaEval, HumanEval, MATH, TruthfulQA)
- **Ablation studies** quantifying the contribution of each component
- **Production deployment case studies** with measured energy savings
- **Open-source implementation** (Apache 2.0 or MIT license)

The current paper provides the motivation and context; the companion paper provides the solution and validation.

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10. Conclusion

We have presented a comprehensive analysis of the AI inference cost crisis, demonstrating that the problem is structural rather than cyclical. Token prices will continue to decline, but aggregate expenditure will continue to rise as agentic AI, extended context, and continuous deployment multiply consumption faster than unit costs fall.

The three fundamental bottlenecks we identify—KV cache memory pressure, memory bandwidth limitations, and throughput-latency tradeoffs—cannot be resolved through hardware scaling alone. The memory-bound nature of autoregressive decoding imposes a ceiling on what faster processors can achieve. Algorithmic and architectural innovations are required.

We argue that hardware-aware adaptive routing—grounding model selection decisions in physical reality through thermal monitoring, power measurement, and memory state tracking—represents the necessary next step in AI systems optimization. The component technologies (cascade routing [24], [25],

speculative decoding [21], [23], hardware telemetry APIs, and query complexity classification [27]) are individually mature; the remaining challenge is integration into a unified architecture.

By 2027, inference is projected to represent 70–80% of AI compute and 30–40% of total data center demand. Our companion paper on Metabolic Cascade Inference [40] presents a concrete architecture that addresses the integration challenge identified here, combining cascade routing, speculative decoding, hardware telemetry, and fact validation into a unified system achieving 70–75% energy savings while maintaining output quality.

Appendix A: Fact-Checking Summary

The following table summarizes the verification status of key statistics cited in this paper, including corrected figures where original estimates required adjustment.

Claim	Status	Verified Figure	Sources
Inference >55% of AI infrastructure costs (Q1 2026)	Verified	55% in 2026, projected 65%+ by 2029	[1], [3]
Inference = 80–90% of model lifecycle compute	Verified	80–90%	[4], [5]
Token prices dropped ~280x	Adjusted	62x–1000x depending on performance tier	[6], [7]
Agentic AI 10–50x more tokens	Verified	10–50x (up to 100x in some cases)	[11], [12]
Data centers ~1,050 TWh by 2026	Verified	650–1,050 TWh range	[29], [30]
AI e-waste 1.2–5.0 million tons (2020–2030)	Verified	1.2–5.0 Mt cumulative	[31], [32]
DART speedup 2.8–3.4x	Verified	2.03x–3.44x (surpasses EAGLE3 by 30%)	[21]
Inference-optimized chip market >$50B (2026)	Verified	>$50 billion	[2]
FrugalGPT cost reduction	Adjusted	Up to 98% with FrugalGPT; 60% is RouteLLM figure	[24], [25]

Claim	Status	Verified Figure	Sources
DeepSeek-R1: 671B total, 37B active	Verified	671B total, 37B active per forward pass	[33], [34]
KV cache dominates GPU memory	Verified	Can exceed model weights; 60–80% fragmentation waste	[14], [17]
LLM inference is memory-bound	Verified	Decode phase arithmetic intensity ~1–10 vs. A10 threshold of 208	[18], [19]

Appendix B: Terminology

Term	Definition
KV Cache	Key-Value cache storing previously computed token embeddings during autoregressive generation; must reside in fast GPU memory for acceptable latency
Memory-bound	A workload limited by memory bandwidth rather than compute capacity; GPUs wait for data transfer rather than performing calculations
Arithmetic intensity	Ratio of compute operations (FLOPs) per byte transferred; indicates whether a workload is compute-bound or memory-bound
Batch size	Number of concurrent requests processed simultaneously; higher batch sizes improve throughput but increase latency
Cascade routing	Forwarding simple requests to small models and escalating complex requests to larger models based on query characteristics
Speculative decoding	Using a fast draft model to propose multiple tokens, verified in parallel by a larger target model; reduces latency without quality loss
Thermal headroom	Distance between current GPU/CPU temperature and the throttling threshold; indicates available capacity for compute-intensive operations
Prefill phase	Initial processing of the input prompt; compute-bound due to parallel GEMM operations
Decode phase	Token-by-token generation after prefill; memory-bound due to sequential KV cache access
MoE (Mixture of Experts)	Architecture where only a subset of model parameters activate per token, reducing compute while maintaining capacity

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