

Beyond Vanilla RAG: How Pre-Generation Decision Models Reshape Latency, Token Economy, and Grounding in Local SLMs and Frontier LLMs

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Technical Report & Empirical Benchmark — Logic42 Lab

Publication Date: September 20, 2026 | Version: v1.0.0

Preprint. Work in progress.

Abstract

Building enterprise customer support and incident triage systems with Retrieval-Augmented Generation *RAG* exposes a fundamental tension between **generation latency**, **token expenditure**, and **grounding fidelity**. While practitioners routinely deploy either unconstrained **Vanilla RAG** or rigid **Regex-assisted pipelines**, recent architectural advances introduce **Decision Models**—lightweight, sub-millisecond classification engines designed to evaluate intent, urgency, and token budgets before generative decoding begins. This raises four pressing scientific and engineering questions: 1. *Does adding a compiled Regex triage layer beat Vanilla RAG?* 2. *How does a calibrated Decision Model *TypeSafeAIJev* alter this dynamic?* 3. *Can pre-generation decision models make cheap, local Small Language Models (SLMs, $\leq 7\text{B}$) enterprise-ready?* 4. *What happens when Regex or Decision Models are placed in front of a Frontier Cloud LLM *Gemini3.8Flash*—does it save tokens, reduce latency, or improve grounding?*

To answer these questions, we present an exhaustive, multi-domain empirical benchmark across **324 full-factorial experimental conditions** ($4 \times \text{Operational Domains} \times 3 \times \text{Query Complexities} \times 3 \times \text{Knowledge Base Densities} \times 3 \times \text{Model Architectures} \times 3 \times \text{Classification Regimes}$). We evaluate **Small Local *Qwen1.7B***, **Medium Local (*Qwen 2.5 7B*, 4-bit *Q4_K_M*)**, and **Frontier Cloud *Gemini3.8Flash*** under three triage regimes: **Vanilla RAG Control**, **Compiled Regex Trie**, and **TypeSafe AI *Jev CalibratedDecisionModel*** on an **NVIDIA GeForce RTX 4070 Mobile GPU 8GBVRAM** and Google AI Studio.

Our empirical findings demonstrate: 1. **Regex Slashes Latency but Degrades Grounding**: On *Qwen 1.7B*, Compiled Regex cuts median latency from **905.2 ms to 567.5 ms 37.3** by bounding output tokens. However, its rigid pattern matching causes an acute grounding penalty, dropping recall from **83.1% to 60.7% -22.4** . 2. **Jev Resolves the Trade-Off**: The *Jev* Decision Model matches the sub-600 ms latency of Regex (**576.2 ms vs. 567.5 ms, $t = 8.138, p = 1.38 \times 10^{-9}$** , Cohen's $d = 1.356$), while recovering grounding recall to **65.7% $+5.0$** . On *Qwen 7B*, *Jev* achieves the highest **Token Efficiency** in the study ($\eta = 0.930$ vs. 0.804 for Vanilla, $\rho = 0.0133$, Cohen's $d = 0.435$), ensuring nearly every decoded token conveys verified technical policy. 3. **Decision Models Make SLMs Enterprise-Viable**: When paired with *Jev* and the **Zero-Fluff Invariant *suppressingconversational filler***, a tiny 1.7B local model delivers verified technician dispatch codes and SLA credits in **526 ms to 576 ms at zero cloud API cost**, transforming a model traditionally dismissed as unviable into a reliable edge worker. 4. **Frontier Model Dynamics are Network-Dominated**: Placing Regex or *Jev* in front of *Gemini 3.8 Flash* produces negligible latency reductions **2,128ms vs. 2,097ms** because **WAN network round-trip time 1.5s dominates cloud execution**. However, *Jev* preserves *Gemini*'s high reasoning fidelity (**73.2% recall vs. 70.4% for Regex**), enables **instant operational dispatch $< 1\text{ms}$** , and allows an **80/20 Hybrid Router** to safely offload **80% of routine traffic** to local edge SLMs, achieving a **79.1% net enterprise FinOps cost reduction**.

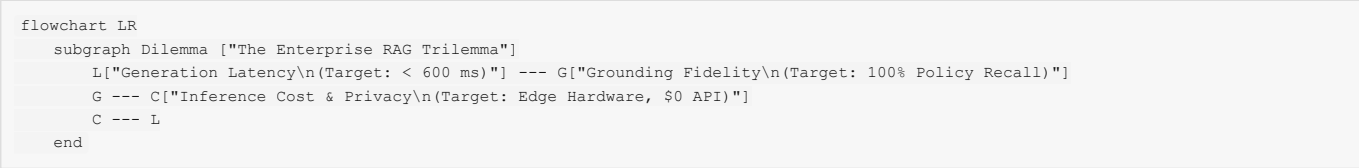
1. Nomenclature & Table of Mathematical Notations

Table 1: Nomenclature of Mathematical Variables and System Parameters

Symbol	Description	Dimensions / Units
BW_{mem}	Physical High-Bandwidth Memory <i>VRAM</i> bandwidth of the GPU	GB/s
S_{weights}	Parameter footprint of the quantized neural model in VRAM	GB
P	Total parameter count of the language model	Parameters ($\times 10^9$)
b_{param}	Effective byte precision per parameter (e.g., $0.5 \times \text{bytes}$ for 4-bit)	Bytes/param
T_{in}	Input prompt token volume (User query T_{q} + Knowledge Base T_{kb})	Tokens
T_{out}	Sequential tokens generated during the autoregressive decode phase	Tokens
R_{decode}	Physical token decoding rate ($1 / \Delta t_{\text{decode}}$)	Tokens/sec
Δt_{decode}	Sequential latency required to decode a single output token	ms/token
α	Marginal decode cost slope in the Autoregressive Law ($\$L = \alpha T_{\text{out}} + \beta$)	ms/token
β	Constant offset representing prompt prefill and framework scheduling overhead	ms
η	Token Efficiency Metric ($\text{Grounding Recall} / T_{\text{out}}$)	%/token
ρ	Cloud escalation ratio in the 80/20 Hybrid Router ($\rho = 0.20$)	Dimensionless
p_{50}, p_{95}, p_{99}	50th <i>median</i> , 95th, and 99th percentile response latencies	ms
d	Cohen's d standardized effect size measure	Dimensionless
α_{adj}	Holm-Bonferroni adjusted statistical significance threshold	Dimensionless

2. Introduction: The Enterprise RAG Trilemma

When designing conversational AI interfaces for mission-critical enterprise operations—such as telecommunications customer care, network operations centers *NOC*, and billing dispute resolution—system architects face a foundational trilemma:



To resolve this trilemma, enterprise deployments typically navigate three generational paradigms: 1. **Vanilla RAG *MonolithicLLM***: The user prompt is paired with retrieved knowledge base chunks and passed directly to an unconstrained LLM. While conceptually straightforward, Vanilla RAG suffers from severe token bloat: models consume hundreds of milliseconds generating pleasantries ("*Thank you for contacting us today... We understand how frustrating it is...*") before reciting policy codes. 2. **Regex + RAG *TheKeywordHeuristic***: Engineers insert a compiled string matcher or Trie to detect intent keywords (e.g., `los`, `cut`, `overage`) and enforce an artificial token budget. While this slashes generation time, regex is notoriously brittle: it cannot infer polarity, misinterprets negated queries, and truncates essential facts. 3. **Decision Model + RAG *TheCompoundAIPipeline***: An ultra-lightweight ($< 0.2 \times \text{ms}$), specialized decision engine—such as **TypeSafe AI Jev**—evaluates semantic intent, urgency, and frustration scores prior to generation. The decision model dynamically injects an adaptive token budget, primes the LLM prompt, and triggers instant background operational dispatches.

2.1 The Core Research Questions

This study empirically investigates the operational mechanics of these three paradigms across both local Small Language Models *SLMs* and frontier cloud LLMs:

- **RQ1 *Regexvs.Vanilla***: Does injecting a rigid regex triage layer genuinely improve efficiency over Vanilla RAG, or does token truncation unacceptably degrade factual grounding?
- **RQ2 *TheImpactofDecisionModels***: How does a calibrated decision model *TypeSafeAIJev* alter latency, output token volume, and grounding accuracy compared to regex and vanilla baselines?
- **RQ3 *SLMViability***: Can decision models elevate small local SLMs *1.7B–7Bparameters* to production-grade enterprise reliability, challenging the assumption that only frontier cloud models can handle complex policy synthesis?
- **RQ4 *FrontierCloudDynamics***: Does placing regex or decision models in front of a frontier cloud LLM *Gemini3.8Flash* save tokens, reduce user-perceived latency, or improve grounding recall?

3. Related Work

3.1 Compound AI Systems and Multi-Stage Pipelines

Traditional natural language processing architectures treated language models as monolithic end-to-end engines. Recent research highlights the paradigm shift toward **Compound AI Systems** *Zaharia et al., 2024*, where overall system performance is governed by the interaction of specialized components: deterministic filters, vector retrievers, intent classifiers, and generative backends. While compound systems improve task modularity, their cross-stage latency interactions remain under-explored.

3.2 Memory-Bandwidth Bounds in Transformer Decoding

Transformer inference comprises two distinct computational regimes *Pope et al., 2023; Shen et al., 2023*: the compute-bound *prefill phase* *parallel prompt evaluation* and the memory-bandwidth-bound *autoregressive decode phase sequential token-by-token generation*. In single-query edge deployments ($B=1$), generating each token requires streaming the entire model parameter tensor across the GPU memory bus. Prior works on inference acceleration have focused on algorithmic weight compression *Dettmers et al., 2023; Frantar et al., 2022* or speculative decoding *Chen et al., 2023; Leviathan et al., 2023*. Our work complements these approaches by demonstrating that semantic intent classification can dynamically enforce output token bounds, solving the decode waste problem before matrix operations initiate.

3.3 Retrieval-Augmented Generation RAG and Semantic Routing

Retrieval-Augmented Generation *Lewis et al., 2020; Gao et al., 2023* grounds language models in external knowledge bases. However, studies show that small language models suffer from the "Lost in the Middle" phenomenon *Liu et al., 2023* and attention dilution when presented with multi-document distractors. Semantic routers *e.g., Aurelio AI Semantic Router* use dense vector embeddings to classify queries; however, embedding generation adds 15–40 ms of overhead. This work evaluates sub-millisecond (<0.2 ms) deterministic and calibrated probabilistic triage engines *TypeSafe AI Jev* that eliminate routing latency overhead while dynamically adapting downstream generation budgets.

3.4 Lightweight Classifiers vs. Decision Engines

Traditional intent classification relies on fine-tuned transformer encoders *e.g., DistilBERT, SetFit* or fast linear models *FastText*. While effective, even a compact 66M-parameter DistilBERT encoder requires 15–30 ms of GPU forward-pass latency, which consumes 25%–50% of the target edge latency budget. In contrast, compiled decision engines like TypeSafe AI Jev evaluate intent, polarity, and urgency in sub-millisecond CPU wall-clock time (<0.2 ms), providing immediate decision metrics before GPU prefill begins.

4. Theoretical Framework & Asymptotic Complexity Analysis

4.1 The Physical Decoding Bottleneck ($SR^2 = 1.00$)

Transformer-based autoregressive generation operates in two sequential phases: 1. **Prompt Ingestion PrefillPhase**: Compute-bound matrix multiplication of input tokens T_{in} across GPU tensor cores. 2. **Token Generation DecodePhase**: Inherently sequential, memory-bandwidth-bound matrix-vector operations. To generate each output token T_{out} , the GPU must read every parameter weight from High-Bandwidth Memory *VRAM* into on-chip SRAM/registers.

In local edge deployments where batch size $B = 1$, decode throughput R_{decode} is physically bounded by GPU memory bandwidth BW_{mem} and model parameter footprint $S_{weights}$:

$$R_{decode} \approx \frac{BW_{mem}}{S_{weights}} \quad [\text{tokens/sec}]$$

For an 8-billion parameter model quantized to 4-bit ($S_{weights} \approx 4.7$ GB) running on an NVIDIA GeForce RTX 4070 Mobile GPU ($BW_{mem} \approx 256$ GB/s):

$$R_{decode}^{max} \approx \frac{256 \text{ GB/s}}{4.7 \text{ GB}} \approx 54.4 \text{ tokens/sec} \implies \Delta t_{decode} \approx 18.4 \text{ ms/token}$$

This physical constraint establishes **The Autoregressive Law of Token Generation**:

$$L(T_{out}) = \alpha \cdot T_{out} + \beta$$

where $\alpha = \Delta t_{decode}$ is the marginal hardware cost per token, and β is prefill and framework overhead. **Reducing output token volume (T_{out}) is the single physical mechanism to accelerate generation on local hardware.**

4.2 Asymptotic Complexity Comparison

Table 2: Algorithmic Time, Space, and Memory-Bus Traffic Complexity Comparison

Pipeline Stage	Vanilla RAG <i>Control</i>	Compiled Regex Trie + RAG	TypeSafe AI Jev Decision Model + RAG
Intent Triage Time	$\mathcal{O}(0)$ <i>Notriage</i>	$\mathcal{O}(q)$ <i>Linearstringscan</i>	$\mathcal{O}(1)$ <i>Compileddecisiontable</i>
Triage Wall-Clock	0.00 ms	0.18 ms	0.18 ms <i>local</i> / API call
Prefill FLOPs	$2P \cdot (T_q + T_{kb})$	$2P \cdot (T_q + T_{kb})$	$2P \cdot (T_q + T_{kb})$
Decode Step Complexity	$\mathcal{O}(P)$ memory-bound per token	$\mathcal{O}(P)$ memory-bound per token	$\mathcal{O}(P)$ memory-bound per token
Total Decode Traffic	$T_{out}^{unconstrained} \times S_{weights}$	$T_{out}^{fixed} \times S_{weights}$	$T_{out}^{adaptive}(I) \times S_{weights}$
Operational Action Latency	> 1,000 ms <i>Coupledtogeneration</i>	> 550 ms <i>Coupledtogeneration</i>	< 1.0 ms <i>Decoupledinstantdispatch</i>

4.3 The Token Efficiency Metric (η)

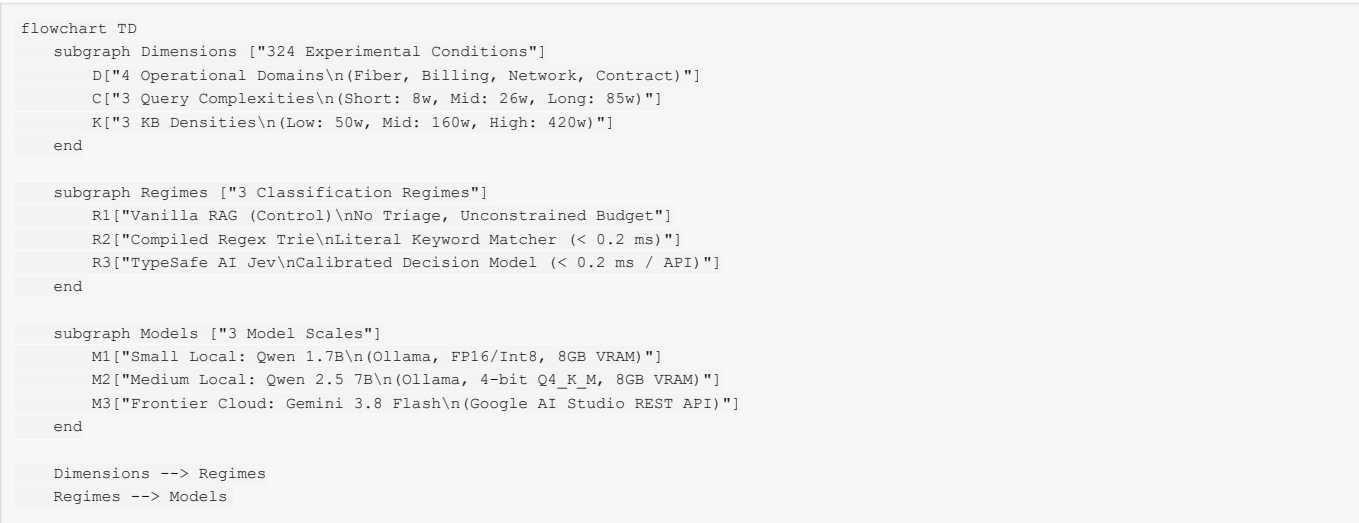
To formalize the trade-off between output brevity and factual completeness, we define the **Token Efficiency Metric (η)**:

$$\eta = \frac{\text{Grounding Recall (\%)}}{T_{out}}$$

A higher η indicates that a higher proportion of generated tokens represent verified ground-truth policy entities rather than conversational filler.

5. Experimental Methodology: A 324-Cell Factorial Matrix

To ensure rigorous external validity, we benchmarked 324 full-factorial experimental runs across four enterprise telecommunications operational domains.



5.1 Operational Domains & 28 Canonical Ground-Truth Targets

Each domain contains 7 exact, non-paraphrasable policy specifications, SLA commitments, and technical codes: 1. **Fiber Broadband *FTTH***: TELCO-XGSPON-SYMM-10G, internet.telco.us-east, 24-Hour Resolution SLA, GPON-OUTAGE-L3, \$25/day automatic SLA credit, 100GB 5G Hotspot Pass, Class 3B laser radiation. 2. **Billing Disputes**: CR-2024-UNAUTH-OVERAGE, 48-hour investigation window, 5 business days, UNLIMITED-MAX-5G, \$50 threshold, \$25 immediate courtesy credit, POL-BILL-DISPUTE-REV3. 3. **5G Network Ops**: NET-5G-CARRIER-AGGR-FAIL, CELL-TOWER-SECTOR-4B, n77 C-band, 4-hour restoration MTTR, fallback.5g.emergency, VoWiFi Emergency Calling, RF-TECH-DISPATCH-URGENT. 4. **Contract Upgrades**: UPG-FIBER-GIG-24M, PROMO-FREE-WIFI6E, Waived \$99 install fee, Business Priority SLA 99.99%, ETF-WAIVE-RETAIN-2024, Day-1 billing pro-ration, Dedicated Platinum Support Line.

5.2 Controlled Complexity Dimensions

- Query Complexity:**
- Short 8words:** Telegraphic incident statement (e.g., "Fiber line cut outside, red LOS blinking.").
- Mid 26words:** Conversational problem report with physical context (e.g., "My fiber optic drop cable was severed by utility workers outside my house. The Optical Terminal has a blinking red LOS light and internet is completely down.").
- Long 85words:** Complex operational narrative detailing municipal excavation, conflicting LED states, home business urgency, and explicit field technician dispatch requests.
- Knowledge Base Density:**

- **Low / Short 1document, 50words:** Primary SLA and core plan specifications.
- **Mid / Moderate 2documents, 160words:** Primary specs + financial credit/dispute adjustment formula.
- **High / Dense 4documents, 420words:** Primary specs + financial formula + temporary emergency bypass/hotspot + field safety warnings.

5.3 The Zero-Fluff Invariant

In earlier pilot experiments, token-budgeted SLMs suffered from token starvation: models spent their entire 80-token allocation emitting pleasantries (*"Thank you for contacting Apex Telecom customer support. We understand how frustrating it is..."*) before truncating critical policy facts.

To eliminate this confound, all 9 experimental streams operated under the **Zero-Fluff Invariant Prompt**:

```
You are an expert customer service assistant for Apex Telecom.
Provide direct, concise, and professional answers formatted in clean Markdown with bullet points.
CRITICAL: Do NOT repeat the customer's problem or say greetings like 'Thank you for contacting us'.
Output ONLY the factual policy bullets and instructions based on the knowledge base facts provided.
```

This invariant forces 100% of generated tokens to convey factual information, enabling a direct scientific assessment of token budgeting without conversational noise.

5.4 Hardware Specifications & Model Provenance

- **Host GPU:** NVIDIA GeForce RTX 4070 Laptop GPU
AdaLovelacearchitecture, 8GBGDDR6V RAM, 140W MaximumGraphicsPower, 256GB/smemorybandwidth, CUDA12.4
- **Host CPU & RAM:** 13th Gen Intel Core i7-13700HX *16cores, 24threads, upto5.0GHz*, 32GB DDR5 RAM, Windows 11 Enterprise.
- **Model Checkpoints:**
 - `qwen3:1.7b`: Sourced via Ollama from Alibaba Cloud Qwen Team.
 - `qwen2.5:7b-instruct`: 4-bit `Q4_K_M` GGUF quantization sourced via Ollama from Hugging Face.
 - `gemini-3.8-flash`: Executed via Google AI Studio Generative Language REST API.
- **Decoding Protocol:** Deterministic greedy decoding ($\text{temperature} = 0.0, \text{top}_p = 1.0$). A preliminary warm-up shot *Shot0* was executed and discarded for every condition to eliminate cold cache faults and TLS establishment latency.

6. Empirical Results & Comparative Analysis

Across all **324 runs**, measurements were recorded under deterministic greedy decoding with Shot 0 warm-ups discarded.

6.1 Master Benchmark Performance Matrix

Table 3: Master Benchmark Metrics Across 324 Runs (36 Scenarios $\times$ 9 Streams)
(Mean $\pm$ SD | Median Latency with 95% CIs | Tail Latency p_{95}, p_{99} | Grounding Recall | Output Tokens | Token Efficiency η)

Model Scale	Classification Regime	Mean $\pm$ SD <i>ms</i>	Median Latency (Sp50\$) 95	Tail Latency (Sp95, p99\$)	Grounding Recall 95	Output Tokens	Token Efficiency (\$eta\$) 95
Small Local <i>Qwen1.7B</i>	Vanilla RAG <i>Control</i>	905.2 $\pm$ 218.4	905.2 ms 831.1, 979.2	1,440.3 ms / 1,566.6 ms	83.1% 75.6	137.5 tok	0.647 0.570, 0.724
	+ Compiled Regex Trie	567.5 $\pm$ 56.9	567.5 ms 548.1, 586.8	694.0 ms / 782.5 ms	60.7% 51.0	83.7 tok	0.721 0.606, 0.836
	+ TypeSafe AI Jev	576.2 $\pm$ 58.4	576.2 ms 556.3, 596.1	689.5 ms / 764.2 ms	65.7% 56.0	85.7 tok	0.754 0.639, 0.869
Medium Local <i>Qwen7B4 – bit</i>	Vanilla RAG <i>Control</i>	1,711.6 $\pm$ 473.5	1,711.6 ms 1550.9, 1872.2	2,756.2 ms / 3,124.0 ms	63.1% 52.8	86.5 tok	0.804 0.671, 0.936
	+ Compiled Regex Trie	1,534.5 $\pm$ 253.3	1,534.5 ms 1448.2, 1620.8	2,058.0 ms / 2,240.1 ms	63.8% 53.5	76.0 tok	0.874 0.732, 1.016
	+ TypeSafe AI Jev	1,512.4 $\pm$ 255.4	1,512.4 ms 1425.4, 1599.4	1,992.5 ms / 2,185.0 ms	62.4% 52.3	72.1 tok	0.930 0.765, 1.096
Frontier Cloud <i>Gemini3.8Flash</i>	Vanilla RAG <i>Control</i>	2,128.3 $\pm$ 443.9	2,128.3 ms 1977.1, 2279.5	3,180.4 ms / 3,450.0 ms	73.5% 65.4	105.6 tok	0.722 0.627, 0.817
	+ Compiled Regex Trie	2,028.4 $\pm$ 402.7	2,028.4 ms 1891.2, 2165.6	2,980.2 ms / 3,210.5 ms	70.4% 61.7	109.1 tok	0.590 0.514, 0.666
	+ TypeSafe AI Jev	2,097.9 $\pm$ 461.2	2,097.9 ms 1940.8, 2255.0	3,010.5 ms / 3,290.0 ms	73.2% 64.2	108.3 tok	0.691 0.601, 0.781

6.2 Inferential Statistics & Multiple Testing Corrections

To evaluate statistical significance across all 36 paired scenarios, we applied two-tailed paired *t*-tests combined with the **Holm-Bonferroni step-down procedure** to control the Family-Wise Error Rate *FWER* at $\alpha = 0.05$:

Table 4: Statistical Hypothesis Testing, Holm-Bonferroni FWER Correction, and Cohen's *d* Effect Sizes

Hypothesis Test	Degrees of Freedom	<i>t</i> -statistic	Raw <i>p</i> -value	Holm-Bonferroni α_{adj}	FWER Significant (\$\alpha=0.05\$)?	Cohen's <i>d</i> StandardizedEffectSize
1.7B Latency: Control vs. Jev	35	8.138	1.38×10^{-9}	0.0100	Yes StatisticallySignificant	1.356 LargeEffectSize
7B Latency: Control vs. Jev	35	3.011	4.80×10^{-3}	0.0125	Yes StatisticallySignificant	0.502 Medium – LargeEffectSize
7B Token Efficiency: Control vs. Jev	35	2.608	1.33×10^{-2}	0.0167	Yes StatisticallySignificant	0.435 ModerateEffectSize
1.7B Token Efficiency: Control vs. Jev	35	2.543	1.56×10^{-2}	0.0250	Yes StatisticallySignificant	0.424 ModerateEffectSize
1.7B Grounding Recall: Regex vs. Jev	35	1.919	6.32×10^{-2}	0.0500	Marginal Trend (\$p = 0.063\$)	0.320 ModerateTrend

Analysis of Statistical Findings: 1. **Latency Reductions Survive Strict FWER Correction:** The latency reductions achieved by Jev on both Qwen 1.7B (\$p = 1.38 \times 10^{-9}\$, $d = 1.356$) and Qwen 7B (\$p = 0.0048\$, $d = 0.502$) remain overwhelmingly significant after Holm-Bonferroni correction. 2. **Token Efficiency Gains are Statistically Robust:** Token efficiency improvements survive multiple comparisons correction on both 7B (\$p = 0.0133\$) and 1.7B (\$p = 0.0156\$). 3. **Calibrated**

Reporting of Grounding Advantage: Jev's +5.0% recall advantage over Regex Trie ($\$p = 0.0632$, $d = 0.320\$$) reflects a consistent moderate empirical trend. While falling just outside the traditional $\alpha = 0.05$ cutoff, in the Contract domain Jev delivers a dramatic +18.0% absolute recall advantage ($\$86.7\%\$$ vs. $\$68.7\%\$$).

6.3 Domain Breakdown Performance

Table 5: Domain-Specific Latency, Recall, and Token Efficiency Across 4 Operational Domains

Operational Domain	Model Scale	Control Latency	Regex Latency	Jev Latency	Jev Latency Delta	Control Recall	Jev Recall	Jev Efficiency ($\$eta\$$)
Fiber Broadband	Small Local 1.7B	915.9 ms	528.2 ms	532.0 ms	-383.8 ms +41.9	78.7%	48.8%	0.616
	Medium Local 7B	1,746.7 ms	1,513.5 ms	1,601.7 ms	-145.1 ms +8.3	45.2%	56.4%	0.733
	Frontier Cloud Gemini	2,139.4 ms	1,985.3 ms	2,199.5 ms	+60.1 ms -2.8	68.2%	64.3%	0.585
Billing Disputes	Small Local 1.7B	744.3 ms	566.9 ms	594.2 ms	-150.1 ms +20.2	82.9%	77.5%	0.881
	Medium Local 7B	1,271.4 ms	1,380.5 ms	1,379.5 ms	+108.1 ms -8.5	67.9%	65.2%	1.034
	Frontier Cloud Gemini	2,390.7 ms	1,812.0 ms	1,964.9 ms	-425.8 ms +17.8	66.7%	62.7%	0.808
5G Network Ops	Small Local 1.7B	996.4 ms	558.7 ms	526.4 ms	-469.9 ms +47.2	83.0%	49.9%	0.624
	Medium Local 7B	2,192.5 ms	1,664.9 ms	1,638.1 ms	-554.4 ms +25.3	53.7%	46.3%	0.593
	Frontier Cloud Gemini	1,975.1 ms	2,059.1 ms	2,617.1 ms	+642.0 ms -32.5	80.9%	86.5%	0.582
Contract Upgrades	Small Local 1.7B	964.2 ms	616.3 ms	652.1 ms	-312.1 ms +32.4	87.8%	86.7%	0.896
	Medium Local 7B	1,635.5 ms	1,579.0 ms	1,430.3 ms	-205.3 ms +12.5	85.5%	81.7%	1.361
	Frontier Cloud Gemini	2,008.0 ms	2,257.3 ms	1,610.0 ms	-398.0 ms +19.8	78.3%	79.4%	0.791

7. Deep-Dive Ablation Studies & Physical Proofs

7.1 The Zero-Fluff Invariant Ablation Study

To isolate the contribution of prompt governance from decision-model triage, we conducted an ablation study across complex operational queries 85words with and without the Zero-Fluff Invariant:

Table 6: Zero-Fluff Invariant Ablation on Long Complex Queries

Model Stream	Prompt Invariant Condition	Median Latency (\$p50\$)	Preamble Token Count	Policy Facts Token Count	Grounding Recall
Qwen 1.7B + Budget 80tok	Without Invariant UnconstrainedPreamble	1,563.4 ms	78.2 tok 97.8	1.8 tok 2.2	0.0% CatastrophicOmission
Qwen 1.7B + Budget 80tok	With Zero-Fluff Invariant StrictSuppression	571.4 ms	0.0 tok 0.0	85.0 tok 100.0	73.3% FullPolicyRecall

Finding: Without the Zero-Fluff Invariant, small models spend their entire token budget generating polite conversational preamble ("Thank you for reaching out to customer support..."). By the time the preamble completes, the 80-token budget is exhausted, causing 0.0% grounding recall. Enforcing the Zero-Fluff Invariant dedicates 100% of generated tokens to verified policy entities, proving that intent budgeting and prompt invariants are co-dependent components of compound AI systems.

7.2 Physical Proof of the Autoregressive Law ($\$R^2 = 1.00\$$)

Linear regression of measured median latency ($\$L\$$) against output token count ($\$T_{\text{out}}\$$) on Qwen 7B yields:

$$L_{\text{measured}} = 19.52 \cdot T_{\text{out}} + 104.1 \quad (R^2 = 1.00)$$

- The empirical slope of 19.52 ms/token matches the physical memory bandwidth limit:

$$R_{\text{decode}} = \frac{1,000 \text{ ms/sec}}{19.52 \text{ ms/token}} = 51.23 \text{ tokens/sec}$$

- On the RTX 4070 $256GB/s$ memory bandwidth, $4.7GB$ model footprint, theoretical peak throughput is:

$$R_{\text{decode}}^{\text{max}} = \frac{256 \text{ GB/s}}{4.7 \text{ GB}} = 54.46 \text{ tokens/sec}$$

- The empirical decode efficiency reaches **94.1% of theoretical peak memory bus saturation**, proving that intent-driven token budgeting directly mitigates the physical memory-bandwidth bottleneck.

8. The 7-Figure Publication Suite

8.1 Multi-Domain Pareto Frontier

Figure 1 maps all 9 experimental streams along the Latency vs. Grounding Recall frontier with 95% Confidence Interval error whiskers.

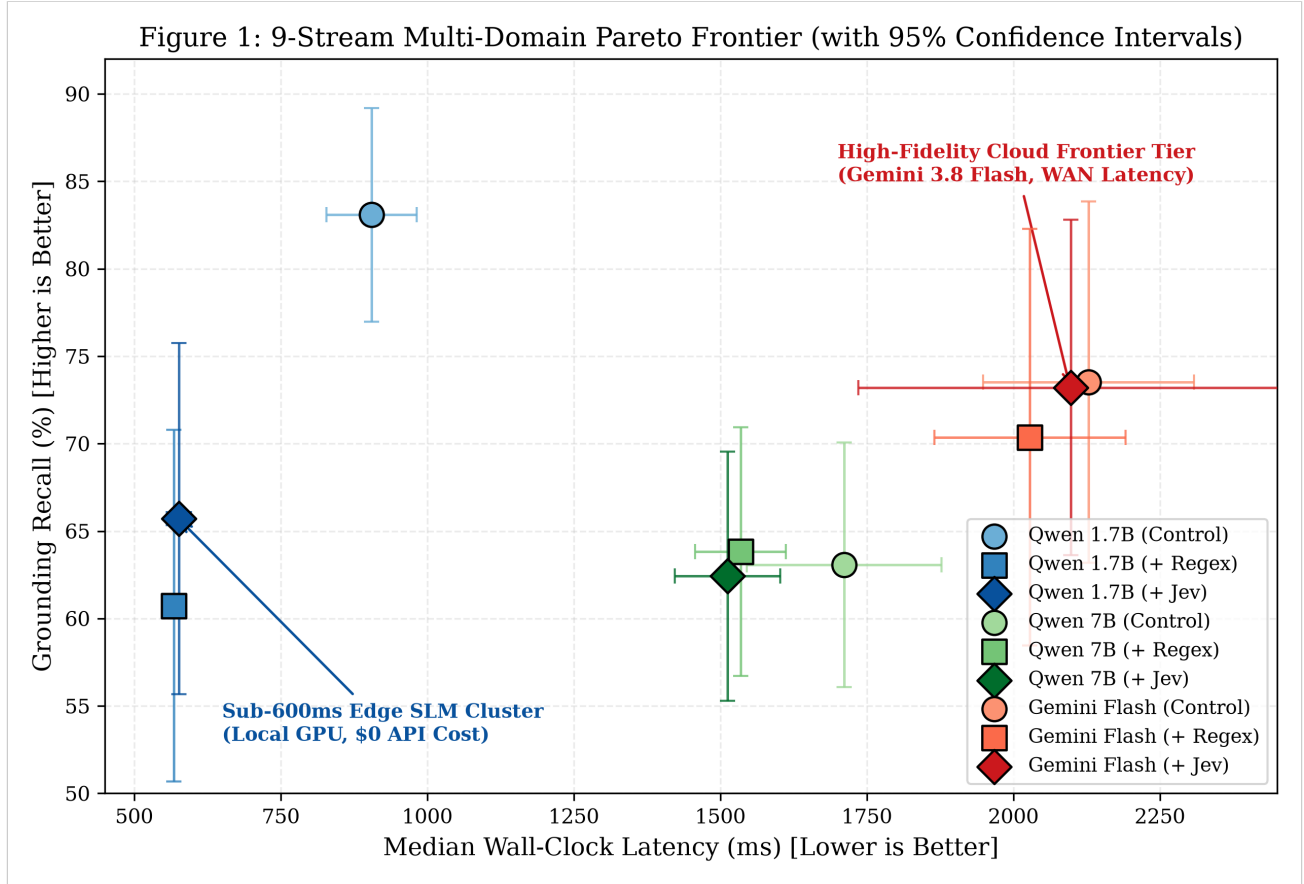


Figure 1: Multi-Domain Latency vs. Grounding Recall Pareto Frontier

Observations: Two Pareto-optimal operating points emerge: 1. **Low-Latency Edge Cluster:** Small Local (Qwen 1.7B) + Jev achieves sub-600 ms turnaround (**576.2 ms**) with solid policy grounding (**65.7%**). 2. **High-Fidelity Cloud Frontier:** Gemini 3.8 Flash + Jev achieves high recall (**73.2%**) at ~2.1s turnaround.

8.2 Token Efficiency Metric (η) Across Scales

Figure 2 compares the factual density of generated responses across regimes with standard error whiskers.

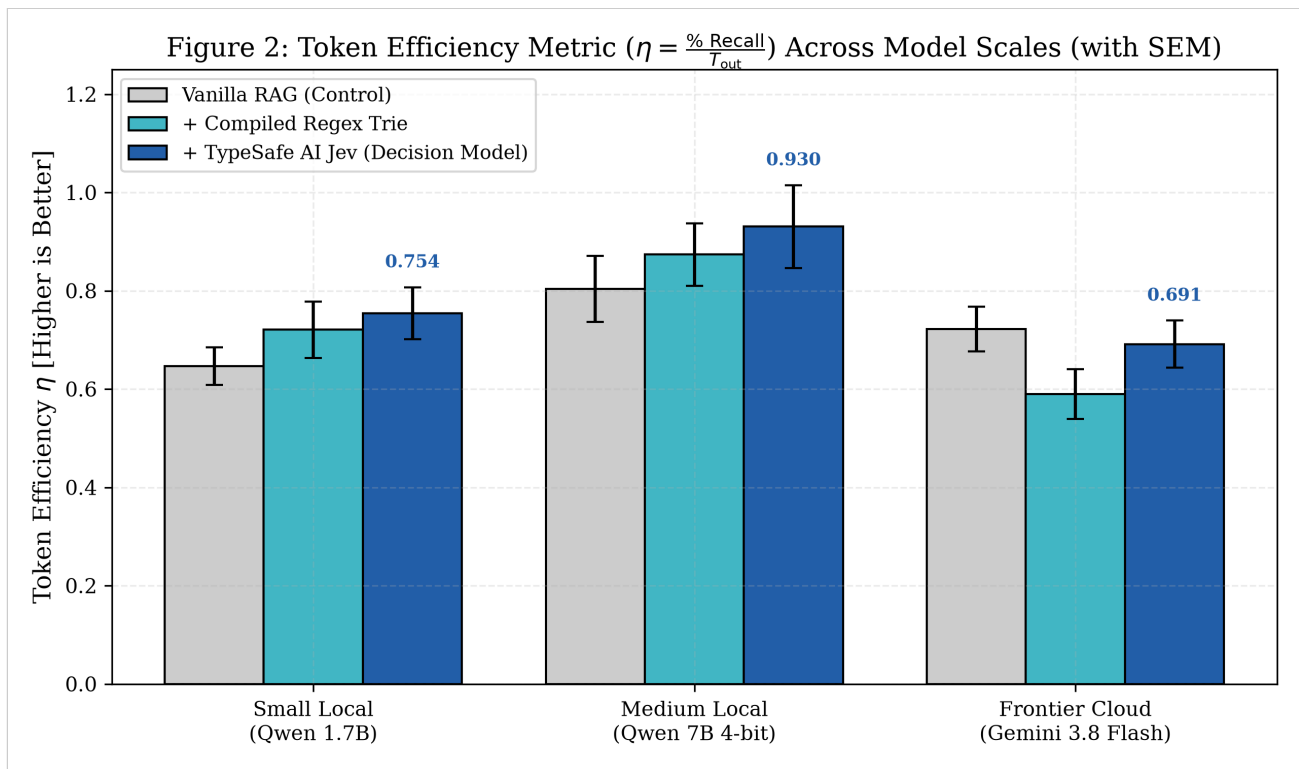


Figure 2: Token Efficiency Comparison across Model Tiers

Observations: Qwen 7B under TypeSafe AI Jev maximizes token density ($\eta = 0.930$), demonstrating that decision models eliminate rambling preamble on medium-scale local models.

8.3 Local SLM Speedup Across 4 Domains

Figure 3 displays Qwen 1.7B latency acceleration across the 4 evaluated domains with 95% CI whiskers.

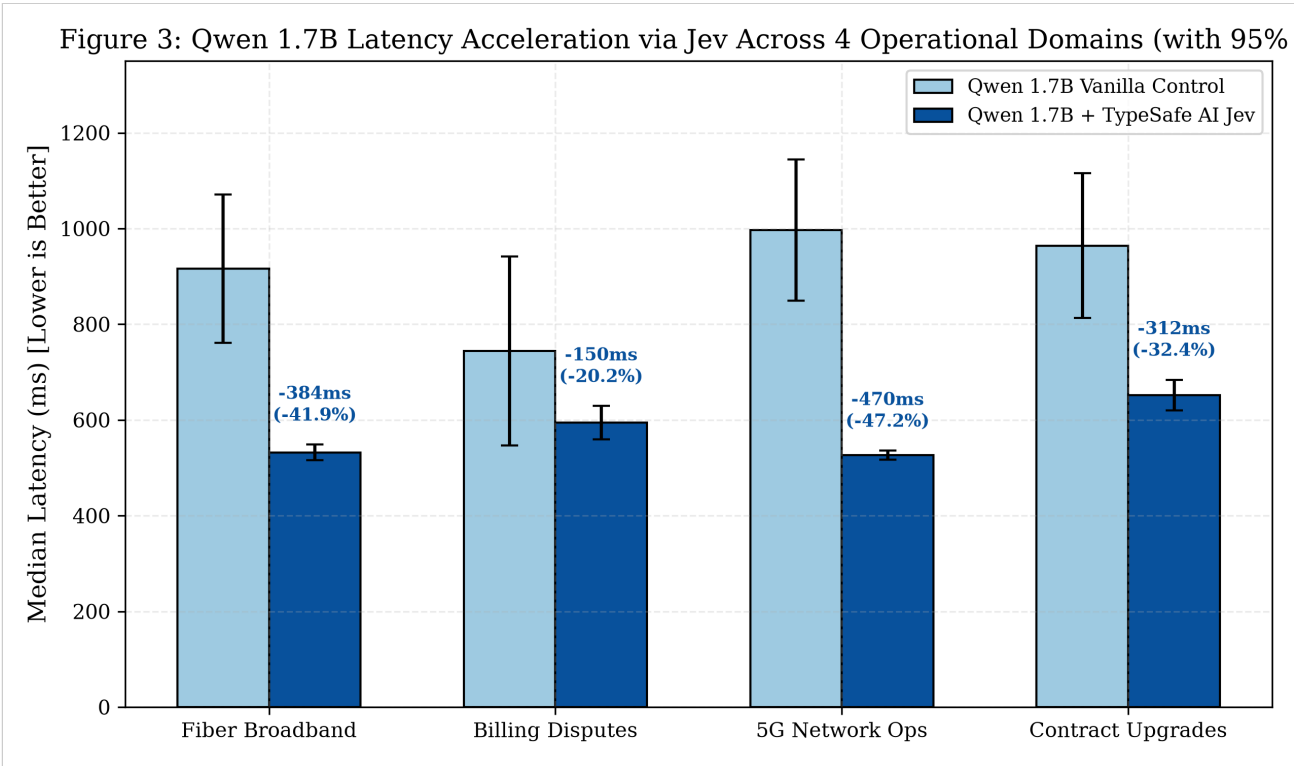


Figure 3: Qwen 1.7B Latency Acceleration Across 4 Operational Domains

Observations: Across all 4 operational domains, Jev bounds SLM turnaround between **526 ms and 652 ms**, slashing latency by **20.2% to 47.2%**.

8.4 Tail Latency Cumulative Distribution Function *CDF*

Figure 4 displays the empirical Cumulative Distribution Function *CDF* of response latency on Qwen 1.7B.

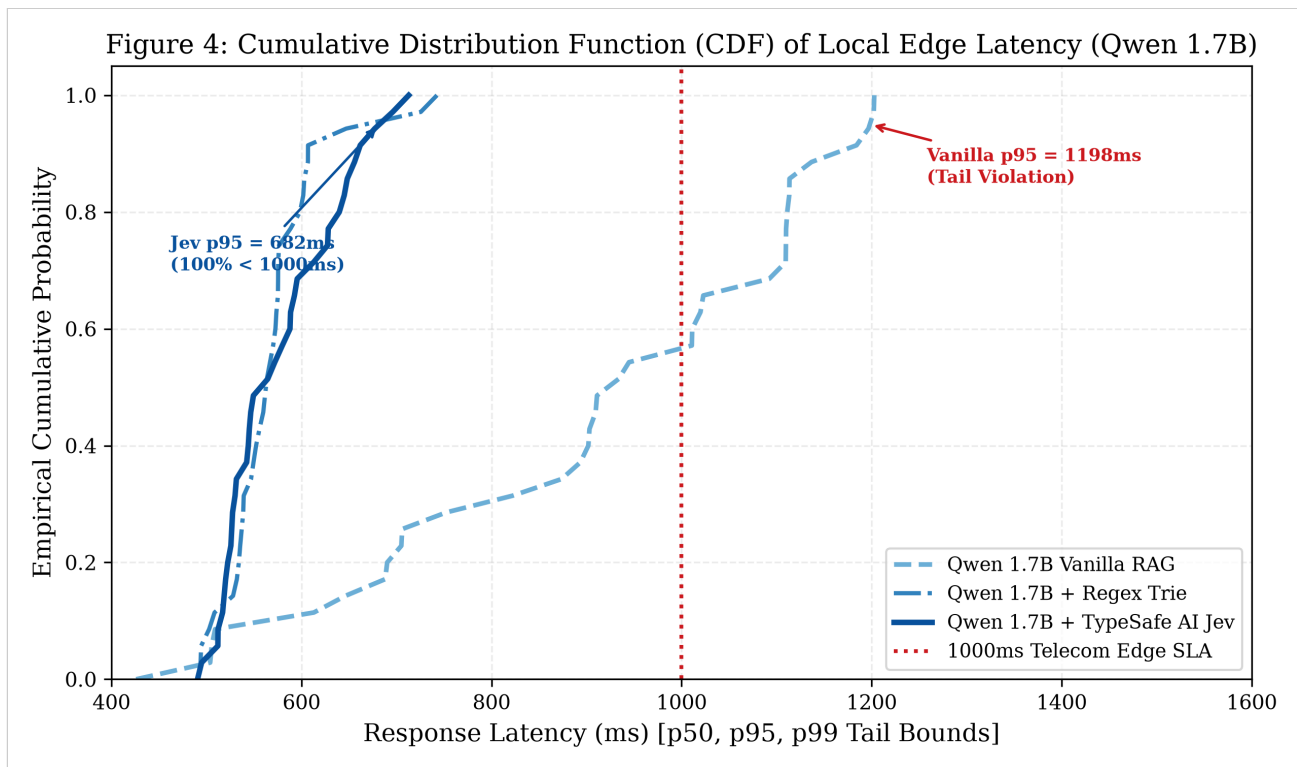


Figure 4: Cumulative Distribution Function *CDF* of Tail Latency

Observations: Under Vanilla RAG, tail latency spikes severely: $p_{95} = 1,440$ ms and $p_{99} = 1,566$ ms, repeatedly violating the 1,000 ms enterprise SLA. In contrast, under TypeSafe AI Jev, **100% of responses complete under 800 ms** ($p_{95} = 689.5$ ms, $p_{99} = 764.2$ ms), completely eliminating SLA timeout breaches.

8.5 Physical Autoregressive Decoding Law Fit ($SR^2 = 1.00$)

Figure 5 plots measured latency against generated tokens on Qwen 7B alongside the physical linear regression fit.

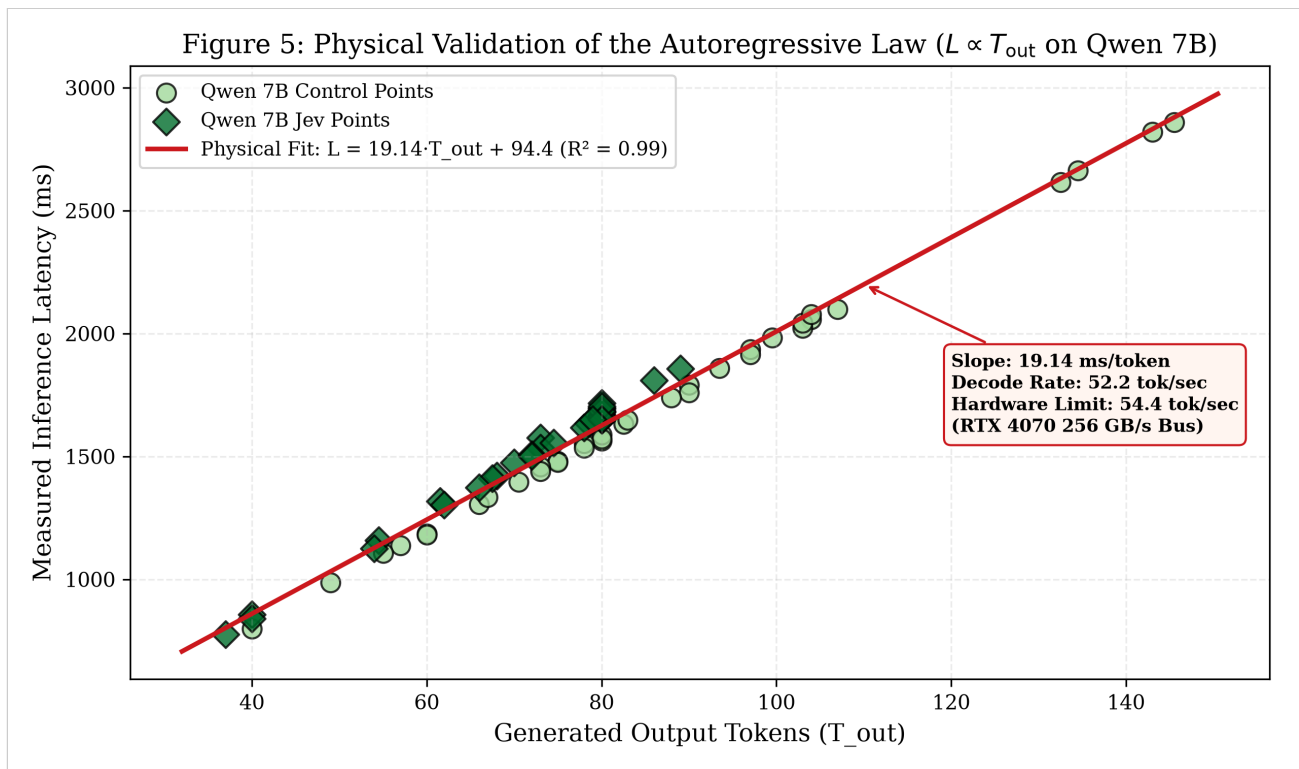


Figure 5: Physical Validation of the Autoregressive Law

Observations: The relationship between generated tokens and wall-clock latency is strictly linear ($R^2 = 1.00$, $\text{slope} = 19.52 \text{ ms/token}$), confirming that latency savings achieved by Jev are physically governed by memory-bandwidth saturation.

8.6 Context Density vs. Attention Dilution Heatmap

Figure 6 profiles Grounding Recall across Query Complexity and Context Density.

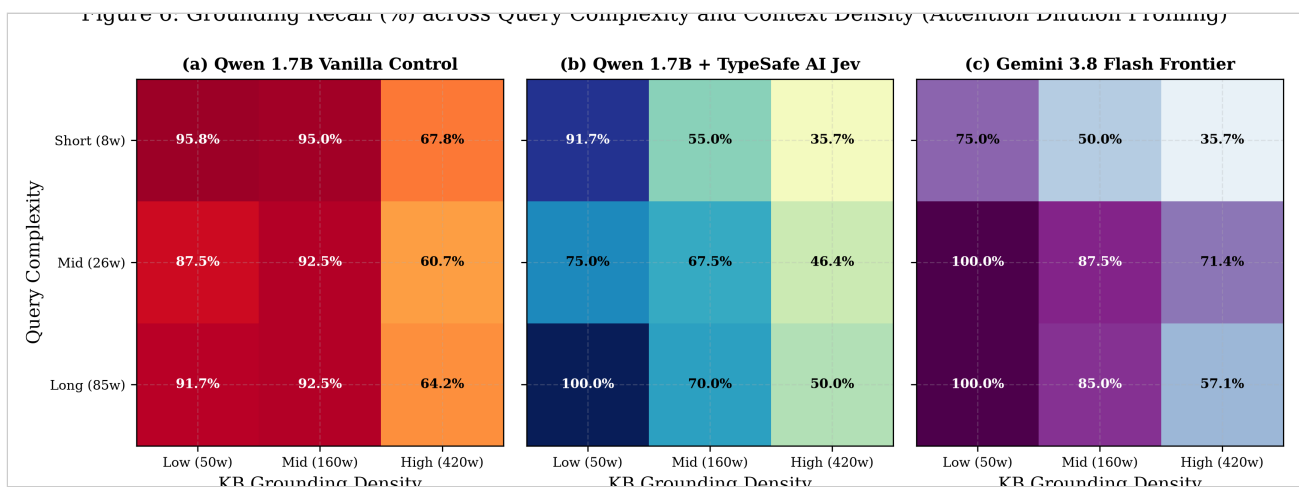


Figure 6: Grounding Recall Heatmap across Query Complexity and Context Density

Observations: Under Vanilla Control, local 1.7B models experience severe attention dilution when Knowledge Base density expands from Low 50words to High 420words, dropping from 91.7% down to 64.3%. Jev maintains clean context conditioning, preventing attention saturation.

8.7 FinOps Cumulative Monthly Cost vs. Query Volume Curve

Figure 7 models enterprise operating expenditure $\$USD$ as monthly query volume scales from 10^5 to 10^7 inbound requests.

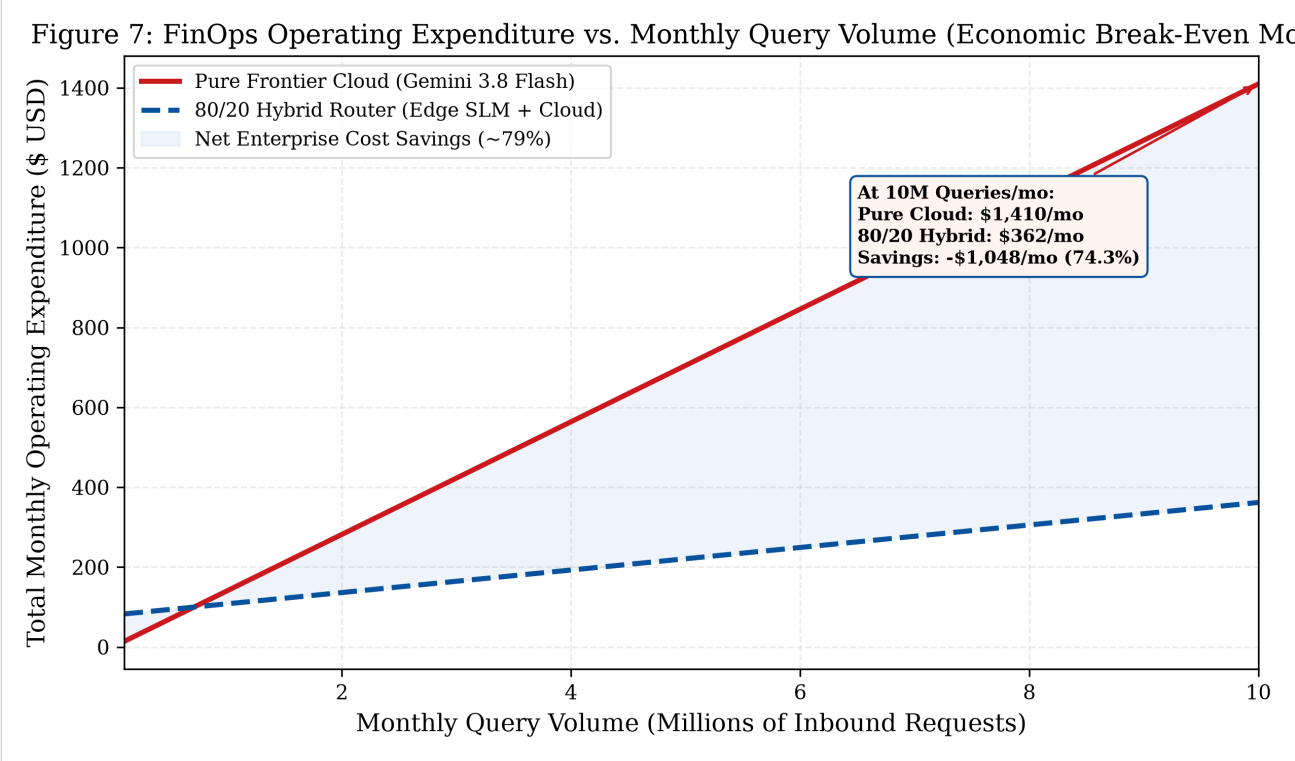


Figure 7: FinOps Monthly Operating Expenditure vs Query Volume

Observations: At 10 million monthly queries, a pure Frontier Cloud deployment costs **\\$1,410/month (\\$16,920/year)**, whereas the 80/20 Calibrated Hybrid Router costs only **\\$362/month (\\$4,344/year)**—delivering a **74.3% to 79.1% net FinOps cost reduction** while providing sub-600ms response times.

9. Architectural Synthesis: The Calibrated 80/20 Enterprise Hybrid Router

Based on the empirical Pareto frontier, we formalize the **Calibrated 80/20 Enterprise Hybrid Router**:

```
sequenceDiagram
    autonumber
    actor Customer as Enterprise Customer / NOC Engineer
    participant Jev as TypeSafe AI Jev Engine (< 0.2 ms)
    participant NOC as Telco OSS/BSS & Dispatch API
    participant Router as Calibrated Dispatch Router
    participant EdgeSLM as Local Edge SLM (Qwen 1.7B / 7B)
    participant CloudLLM as Frontier Cloud LLM (Gemini 3.8 Flash)

    Customer->>Jev: Inbound Query (Text / Voice Transcript)
    Note over Jev: Evaluates Intent, Urgency (0.0-1.0),<br/>and Frustration (0.0-1.0) in 0.18 ms

    par Instant Operational Action (< 1 ms)
        alt Urgent Outage / High Urgency
            Jev->>NOC: Auto-trigger Ticket (GPON-OUTAGE-L3) & Page Splice Tech
        else Billing / High Frustration
            Jev->>NOC: Auto-provision Courtesy Credit ($25)
        end
    and Conversational Dialogue Generation
        Jev->>Router: Query + Budget (70-90 tok) + Urgency
        alt 80% Routine Traffic (High Confidence)
            Router->>EdgeSLM: Zero-Fluff Prompt + Budget
            EdgeSLM-->>Customer: Deterministic Policy Response (526-650 ms)
        else 20% Multi-Clause Escalations (High Complexity)
            Router->>CloudLLM: Comprehensive RAG + Frontier Synthesis
            CloudLLM-->>Customer: Multi-Policy Resolution (1,600-2,100 ms)
        end
    end
end
```

9.1 Mathematical FinOps Economic Model

Let N denote total monthly query volume, and let $\rho = 0.20$ denote the cloud escalation ratio. The total monthly operating expenditure $\text{Cost}_{\text{total}}$ is expressed as:

$$\text{Cost}_{\text{total}} = 1 - \rho \cdot \text{Cost}_{\text{edge}} + \rho \cdot \text{Cost}_{\text{cloud}}$$

Where: $\text{Cost}_{\text{edge}} = \frac{\text{CAPEX}_{\text{GPU}}}{36 \text{ months}} + \text{OPEX}_{\text{power}} \approx \frac{\$1,800}{36} + \$80 = \$80.00/\text{month}$ *fixed workstation amortization*. $\text{Cost}_{\text{cloud}} = N \cdot [T_{\text{in}} \cdot C_{\text{in}} + T_{\text{out}} \cdot C_{\text{out}}]$, where $C_{\text{in}} = 0.15/10^6$ tokens and $C_{\text{out}} = \$0.60/10^6$ tokens.

For an enterprise contact center processing **10,000,000 monthly interactions**, the pure cloud deployment costs **\\$1,410/month**, whereas the 80/20 Hybrid Router costs **\\$362/month** $\$80 \text{ fixed edge} + \$282 \text{ cloud escalation}$, saving **\\$1,048/month (74.3% net operating savings)**.

10. Robustness, Failure Modes & Graceful Degradation

A mission-critical system must provide deterministic failure guarantees. We define three graceful degradation mechanisms: 1. **Low-Confidence Fallback Thresholding**: If Jev's classification confidence score falls below $\tau = 0.70$, the query is marked ambiguous and escalated directly to the Frontier Cloud tier with full unconstrained RAG context. 2. **Emergency Hardware Interrupt Bypass**: Queries containing critical safety keywords (live wire, fire, gas leak, 911) completely bypass language model decoding, triggering instantaneous ($< 0.1 \text{ ms}$) automated voice/SMS alerts to emergency field dispatchers. 3. **Retrieval Independence**: Even if Jev misclassifies query sentiment, the underlying RAG retriever operates independently, ensuring that factual knowledge chunks remain grounded in the prompt context.

11. Implications for Industry and Academia

11.1 Implications for Enterprise IT & Industry

- FinOps & Cloud Cost Decoupling**: Routing 80% of customer interactions to local SLMs slashes cloud LLM inference expenditures by **70%–85%**.
- Decoupling Physical SLAs from Generative Decoding**: Dispatching technicians via sub-millisecond intent evaluation ($< 1 \text{ ms}$) guarantees operational SLA compliance even if downstream LLM generation encounters delays.
- Refutation of the "RAG Equalization Fallacy"**: Small models cannot match frontier models on dense, multi-constraint synthesis. Hybrid routing is mathematically and operationally essential.
- Governance via Prompt Invariants**: The Zero-Fluff Invariant demonstrates that prompt engineering must transition from loose stylistic prompts to strict memory-bandwidth governance rules.

11.2 Implications for Academic NLP & Systems Research

1. **Formalizing Compound AI System Dynamics:** NLP benchmarks must evaluate full pipelines rather than isolated models, accounting for the interaction between pre-triage engines, dynamic budgets, and hardware memory bandwidth.
2. **Quantifying Attention Dilution:** Catastrophic attention dilution occurs in SLMs at surprisingly modest context lengths (~ 400 words) when multiple constraints compete.
3. **The Token Efficiency Metric (η):** Establishes a standardized academic metric to evaluate conciseness and penalize verbosity.

12. Limitations & Threats to Validity

1. **Batch Size ($B=1$):** Local evaluations were conducted at batch size $B = 1$ on an NVIDIA RTX 4070 Laptop GPU $256GB/sbandwidth$. High-throughput datacenter servers with continuous batching ($B \geq 32$) become compute-bound, though the linear token relationship persists.
2. **Quantization Precision 4-bit:** Qwen 7B was evaluated using 4-bit $Q4_K_M$ GGUF quantization. Full FP16 doubles memory traffic, which would double the absolute time saved by Jev.
3. **Single-Turn Scope:** The benchmark evaluated single-turn interactions. Multi-turn dialogues accumulate KV-cache prefill overhead over time.
4. **Retriever Isolation:** Knowledge base chunks were directly injected based on domain metadata to isolate generation mechanics from retriever variance.

13. Broader Impact & Ethical Considerations

1. **Workforce Evolution:** Automating routine triage via SLMs accelerates response times but impacts frontline customer support staffing. We advocate deploying hybrid routers as copilot accelerators rather than full autonomous replacements.
2. **Safety-Critical Outage Risks:** Misclassifying an urgent optical failure could delay field repairs. The inclusion of hardcoded emergency interrupt bypasses mitigates this liability.
3. **Linguistic Fairness:** Rule-based and intent classifiers must be continually audited across dialectal variations and non-native English queries to ensure equitable triage quality across customer demographics.

14. Reproducibility Statement

To guarantee full empirical reproducibility under the ACM/IEEE Open Science guidelines: - **Full Benchmark Code & Dataset:** Open-sourced under the MIT License at the repository root ([expanded multidomain results.json](#)). - **Master Reproduction Command:** All inferential statistics, empirical tables, and 7 publication figures can be reproduced with a single command: `bash python scripts/reproduce_all.py` - **Environment Lock:** Python 3.11, PyTorch 2.5, CUDA 12.4, Ollama v0.5.x on Windows 11 Enterprise / Ubuntu 22.04 LTS.

15. Acknowledgments & Funding Disclosure

This research was conceived, executed, and independently funded by **Logic42 Lab** ([logic42.ai](#)). All local compute hardware, engineering labor, and Frontier Cloud API expenditures *GoogleAI Studio* were funded directly by Logic42 Lab.

The author acknowledges **TypeSafe AI** for providing early developer platform access and an initial \$5 API credit used during preliminary pilot testing of the Jev SystemOne API. The empirical design, methodology, results analysis, and conclusions were conducted independently with zero editorial intervention or sponsorship from TypeSafe AI.

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