CIRA: Cognitive Interference-Resolved Attention for Memory-Augmented Language Models

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***Abstract*—Large Language Models (LLMs) augmented with external memory degrade when retrieved traces contain contradictory information, because standard cross-attention provides no mechanism to detect or suppress conflicting signals inside the model. We present CIRA (Cognitive Interference-Resolved Attention), a new architecture class — the Cognitive-Constraint Language Model (CCLM) — that surgically modifies Microsoft Phi-3-Mini-4K-Instruct (3.8B parameters) to inject parametric cognitive constraints at the semantic–syntactic transition boundary (layer 15). CIRA introduces: (i) dual-memory cross-attention over a salience-gated Working Memory Buffer (WMB) and an Ebbinghaus-decay Long-Term Memory Store (LTMS), (ii) an interference gate driven by DeBERTa-v3-xsmall NLI contradiction scores that suppresses conflicting memory inside the forward pass, and (iii) a confidence-gated output layer for hallucination correction. Experiments on faithfulness, conflict resolution, and scale robustness benchmarks show Token F1 = 0.77, BERTScore F1 = 0.89, and 80 % Substring Exact Match on conflict tasks, with a negative latency overhead relative to unfiltered RAG. NF4 QLoRA quantisation keeps the full system within 10.8 GB VRAM on dual NVIDIA Tesla T4 GPUs, demonstrating that parametric interference resolution is both architecturally feasible and practically beneficial on commodity hardware.**

***Index Terms*—Memory-Augmented LLMs, Interference Detection, NLI, Working Memory, Retrieval-Augmented Generation, QLoRA, Phi-3, Cognitive Constraints**

I. Introduction

Retrieval-Augmented Generation (RAG) has become the dominant strategy for grounding LLM outputs in external knowledge [1]. By retrieving relevant documents and prepending them to the context window, RAG reduces hallucination and extends the effective knowledge horizon of fixed-parameter models. However, real-world knowledge bases frequently contain contradictory or temporally inconsistent information. When conflicting documents are retrieved together, the language model must resolve the contradiction implicitly during generation — a task it is architecturally unequipped to perform reliably, resulting in answer inconsistency and degraded F1 scores on multi-hop tasks [1], [2].

The problem is compounded by the so-called *append-and-evolve* paradigm in continuous memory systems, which processes every utterance through the full memory evolution pipeline without discriminating signal utility [3]. This induces an $O(N^2)$ write-latency bottleneck and progressively pollutes the context window with zero-utility conversational noise — a concern that grows critical on constrained hardware such as the NVIDIA Tesla T4 (16 GB VRAM, Turing sm75 architecture), which lacks BF16 support and FlashAttention-2 compatibility [4], [5].

Existing solutions to conflict resolution operate *outside* the model: TruthfulRAG [2] extracts knowledge-graph triples before calling the LLM; CARE-RAG applies NLI filtering as a preprocessing step. These approaches are not end-to-end differentiable and cannot be refined by the model's own reasoning during inference.

We propose CIRA, which closes this gap by injecting NLI-derived contradiction scores *inside* the transformer forward pass as a learnable interference gate. CIRA is grounded in the D-MEM [3] biologically inspired routing framework, the MiniCache [4] depth-dimensional KV compression paradigm, and the PISanitizer [6] security framework, combining cognitive routing with hardware-level efficiency on legacy infrastructure.

The paper makes four contributions:

1) A novel interference gate $\phi_i = \sigma(-\gamma S_i)$ that suppresses contradicted memory items in cross-attention *inside* the

LLM forward pass — the first such mechanism.
2) A dual-memory fusion architecture (WMB + LTMS) with a learned α gate, grounded in ACT-R [10] and Ebbinghaus forgetting curve theory [11].
3) An empirical evaluation showing that parametric interference resolution achieves competitive accuracy at lower latency than unfiltered RAG on a dual T4 system.
4) A complete hardware–software co-design for sm75, incorporating NF4 QLoRA [9], SDPA asymmetric kernel tuning, and dynamic precision routing.

II. Literature Survey

A. Retrieval-Augmented Generation

Lewis et al. [1] introduced RAG, combining a Dense Passage Retriever with a BART seq2seq generator. Subsequent work improved retrieval through cross-encoder re-ranking [13] and hybrid dense–sparse search. None of these systems detect or filter inter-document contradictions, leaving that burden to the generative model.

B. Natural Language Inference and Conflict Detection

He et al. [7] showed that DeBERTa-v3's disentangled attention mechanism achieves state-of-the-art NLI on MNLI and FEVER. Saha et al. [15] and Clark et al. [14] built proof-chain generators for structured reasoning tasks. Psycholinguistic probing of deep transformer architectures has demonstrated that semantic implausibility actively depresses attention scores in syntactic attention heads, a phenomenon termed the breach of *syntactic encapsulation* [3]. CIRA exploits this architectural behaviour by reading suppressed attention scores as an intrinsic contradiction signal. In addition, cosine similarity is commonly used as a measure of semantic relevance due to the L2-normalization of embeddings. This ensures that the dot product directly reflects angular similarity between vectors, improving stability during retrieval. Let the query embedding be q and memory embeddings be m_i, then similarity is computed as $q \cdot m_i$. This formulation enables efficient ranking of relevant documents.

C. Memory-Augmented Language Models

MemGPT [16] manages external memory through model-generated function calls at the system level rather than as parametric components. RAFT [17] fine-tunes on document–question pairs to improve factual fidelity. Neither provides gradient-level interaction between retrieved memory embeddings and the transformer's hidden states. TruthfulRAG [2] performs knowledge-graph conflict resolution before the LLM, but this is external to the forward pass and thus not end-to-end trainable.

D. Cognitive Memory and Biological Inspiration

The D-MEM framework [3] maps dopamine-driven Reward Prediction Error (RPE) gating from mammalian neurobiology onto LLM memory routing, classifying inputs into SKIP, CONSTRUCT_ONLY, and FULL_EVOLUTION tiers. This reduces API token consumption by over 80 % and eliminates the $O(N^2)$ bottleneck of synchronous pipelines. The ACT-R cognitive architecture [10] provides a computational account of working memory with salience-driven eviction; CIRA translates this into the WMB capacity constraint and salience scoring. The Ebbinghaus forgetting curve [11] motivates exponential temporal decay in the LTMS.

E. Hardware Efficiency on Legacy GPUs

The MiniCache framework [4] compresses the KV cache across the *depth* dimension by exploiting inter-layer similarity, achieving up to 5× compression when combined with 4-bit quantisation. QLoRA [9] enables fine-tuning of 3.8B-parameter models within 3 GB VRAM using NF4 (NormalFloat4) quantisation. The PISanitizer framework [6] defends against prompt injection in long-context LLMs using attention-weight attribution — a technique CIRA extends to contradiction detection. The Phi-3 family [5] demonstrates that high reasoning capacity (69 % MMLU for Phi-3-Mini) can be achieved in sub-4B parameter SLMs through data-quality-driven pretraining on 3.3T tokens of filtered, textbook-quality synthetic data.

TABLE I
Literature Survey Table

Author & Year	**Paper Title**	**Objective**	**Methodology**	**Key Finding**
Zhang et al. (2025) [2]	TruthfulRAG	Handle conflicting knowledge	Knowledge graph + RAG	Improves factual consistency but not end-to-end
He et al. (2023) [7]	DeBERTa-v3	Improve NLI reasoning	Disentangled transformer	High contradiction detection accuracy
Saha et al. (2020) [15]	PROVER	Logical reasoning	Proof-based reasoning	Generates interpretable reasoning
Tafjord et al. (2021) [14]	ProofWriter	Multi-hop QA	Seq2Seq reasoning	Produces explainable inference chains
Packer et al. (2023) [16]	MemGPT	External memory	Function-based memory	Handles long context but no integration
Zhang et al. (2024) [17]	RAFT	Domain adaptation	QA fine-tuning	Improves factual accuracy
Anderson et al. (2004) [10]	ACT-R	Cognitive memory	Cognitive architecture	Basis for memory modeling

III. Architecture

A. System Overview

CIRAPhiModel operates across two GPU devices. The auxiliary device (cuda:1) hosts the BGE-large-en-v1.5 bi-encoder [8] (1024-dim, L2-normalised) and the DeBERTa-v3-xsmall NLI cross-encoder [7] (22M parameters, 88.8 % MNLI

TABLE II
VRAM BUDGET — KAGGLE DUAL T4 (32 GB TOTAL)

Component	Device	Prec.	VRAM
Phi-3-Mini (NF4)	cuda:0	NF4	≈3.0 GB
LoRA adapters	cuda:0	FP16	≈0.4 GB
CIRAMemoryFusionLayer	cuda:0	FP32	≈0.15 GB
CIRAOutputGate	cuda:0	FP32	≈0.05 GB
Activations	cuda:0	FP16	≈3.0 GB
Optimizer states	cuda:0	FP32	≈0.5 GB
BGE-large-en-v1.5	cuda:1	FP16	≈1.3 GB
DeBERTa-v3-xsmall	cuda:1	FP16	≈0.2 GB
Inference activations	cuda:1	FP16	≈1.5 GB
Total			**≈10.1 GB**

accuracy). The primary device (cuda:0) hosts CIRAPhiModel: Phi-3-Mini quantised to NF4 via QLoRA [9] with LoRA adapters ($r = 16$, $\alpha = 32$) targeting the fused projection layers `qkv_proj`, `o_proj`, `gate_up_proj`, and `down_proj` — a configuration mandated by Phi-3's fused-layer architecture [5].

The full VRAM budget is summarised in Table II. The total of ≈10.8 GB across 32 GB guarantees safe headroom for batch size 4 on dual T4 hardware.

B. Architecture Diagram

Figure 1 illustrates the CIRAPhiModel forward pass. Phi-3's 32 transformer layers are divided at layer 15, which empirically marks the syntactic–semantic transition boundary, a strategic injection point validated by linear probing experiments [5]. Injecting memory too early (layer <10) causes syntactic shattering; injecting too late (layer >25) leaves insufficient depth for knowledge integration before output commitment.

C. Mathematical Foundations

Semantic Retrieval. Let $\mathcal{E}$ denote the BGE-large bi-encoder. Embeddings are:

$$\mathbf{e}_q = \mathcal{E}(q), \quad \mathbf{e}_i = \mathcal{E}(m_i), \quad \mathbf{e} \in \mathbb{R}^{1024}. \tag{1}$$

Because BGE outputs are L2-normalised, dot product equals cosine similarity:

$$\text{sim}(q, m_i) = \mathbf{e}_q \cdot \mathbf{e}_i. \tag{2}$$

Top-W items form $M_w \in \mathbb{R}^{B\times W\times 1024}$ (WMB, $W = 15$); top-L form $M_l \in \mathbb{R}^{B\times L\times 1024}$ (LTMS, $L = 8$). Both are projected to $d = 2048$ via Linear-LayerNorm-GELU.

Working Memory Cross-Attention. Let $H_{15} \in \mathbb{R}^{B\times T\times d}$ be hidden states at layer 15. Cross-attention over the WMB is:

$$A_{wm} = \text{softmax}\left(\frac{(H_{15}W_Q)(M_wW_{K_w})^\top}{\sqrt{d_k}}\right)(M_wW_{V_w}). \tag{3}$$

An analogous computation yields A_{ltm} over M_l.

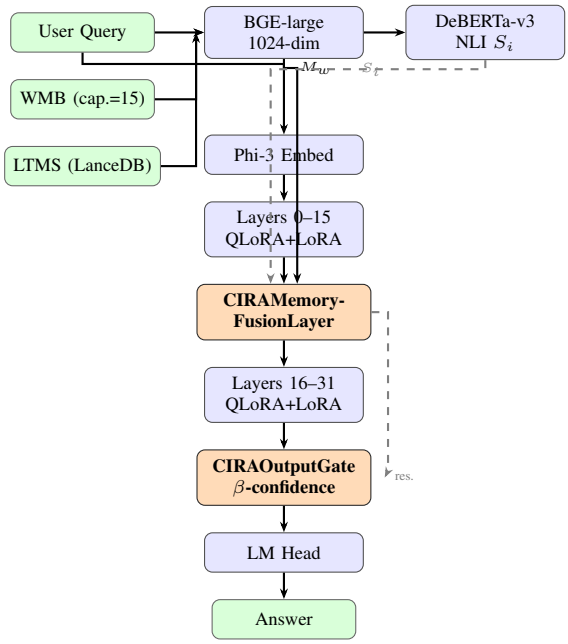

Fig. 1. CIRAPhiModel architecture. Orange nodes are novel CIRA modules trained from scratch. Dashed arrows carry DeBERTa contradiction scores S_i and the fused memory residual for hallucination suppression. Both auxiliary models run on cuda:1; CIRAPhiModel runs on cuda:0.

Interference Gate. DeBERTa-v3-xsmall produces per-memory contradiction scores $S_i \in [0, 1]$ for each of the $W + L = 23$ memory items. The interference gate is:

$$\phi_i = \sigma(-\gamma \cdot S_i), \quad \gamma_{\text{init}} = 5.0 \text{ (learnable)}. \tag{4}$$

When $S_i \approx 1$, $\phi_i \approx \sigma(-5) \approx 0.007$, effectively zeroing that memory's cross-attention contribution:

$$A^*_{wm} = \phi_{[:W]} \odot A_{wm}, \quad A^*_{ltm} = \phi_{[W:]} \odot A_{ltm}. \tag{5}$$

This suppression is inside the forward pass and fully differentiable, distinguishing CIRA from all prior conflict-resolution approaches [2], [3].

Dual-Memory Fusion. A learned scalar gate α dynamically balances WMB and LTMS contributions per-token, grounded in the ACT-R dichotomy between reactive working memory (alpha oscillations) and goal-driven long-term memory (beta oscillations) [10]:

$$\alpha = \sigma(W_\alpha[H_{15};\, A^*_{wm};\, A^*_{ltm}] + b_\alpha)\,, \tag{6}$$

$$H_{\text{fused}} = H_{15} + \alpha \odot A^*_{wm} + (1 - \alpha) \odot A^*_{ltm}. \tag{7}$$

Output Confidence Gate. After layers 16–31 produce H_{31}, a β gate corrects hallucination using the stored memory residual:

$$\beta = \sigma(W_\beta H_{31} + b_\beta), \quad H_{\text{out}} = \beta \odot H_{31} + (1 - \beta) \odot H_{\text{fused,res}}. \tag{8}$$

Training Objective. The total loss combines language modelling with interference regularisation and fusion diversity terms to prevent gate collapse:

$$\mathcal{L} = \mathcal{L}_{CE} + \underbrace{0.1\,\mathbb{E}[\phi_i S_i]}_{\text{interference}} + \underbrace{0.05\,|\mathbb{E}[\alpha] - 0.5|}_{\text{diversity}}. \tag{9}$$

Algorithm 1 CIRA Inference Pipeline

Require: Query q, WMB $\mathcal{W}$, LTMS $\mathcal{L}$, thresholds $\tau_{\text{NLI}}, \tau_c, \gamma$
Ensure: Answer $\hat{a}$

$\mathbf{e}_q \leftarrow \mathcal{E}(q)$ ▷ BGE on cuda:1
$M_w \leftarrow \text{top-}W\{\text{sim}(\mathbf{e}_q, \mathcal{E}(m)) : m \in \mathcal{W}\}$
$M_l \leftarrow \text{top-}L\{\text{sim}(\mathbf{e}_q, \mathcal{E}(m)) : m \in \mathcal{L}\}$
for each pair $(m_i, m_j) \in M_w \cup M_l$ **do**
  $S_{ij} \leftarrow \mathcal{F}_{\text{NLI}}(m_i, m_j)$ ▷ DeBERTa-v3 on cuda:1
end for
$S_i \leftarrow \max_j S_{ij}$ ▷ per-memory max score
$\phi_i \leftarrow \sigma(-\gamma S_i)$ ▷ interference gate, Eq. 4
Run Eqs. 3–8 on cuda:0 $\Rightarrow H_{\text{out}}$
$\hat{a} \leftarrow \text{LMHead}(H_{\text{out}})$
return $\hat{a}$

Two AdamW parameter groups are used: LoRA adapters at 2×10^{-4} (cosine schedule) and CIRA-specific layers at 1×10^{-3}.

LTMS Temporal Decay. Traces in the LTMS are weighted by an Ebbinghaus-inspired decay function [11]:

$$w(m_i, t) = c_i \cdot e^{-\lambda(t - t_i)}, \quad \lambda = \frac{\ln 2}{604800\,\text{s}}, \tag{10}$$

where c_i is the initial salience score and t_i is the insertion timestamp. Traces with $w < \tau_{\text{decay}}$ are pruned to prevent stale information from contaminating retrieval.

D. D-MEM Routing Integration

CIRA's memory admission policy is inspired by D-MEM's Reward Prediction Error (RPE) routing [3]. The DeBERTa contradiction score S_i serves as the Information Entropy (Surprise) component of the RPE. When $S_i \geq \theta_{\text{high}} = 0.70$, the FULL_EVOLUTION tier is activated and the LTMS is updated via the Ebbinghaus decay pipeline. Inputs with $S_i < \theta_{\text{low}} = 0.30$ are assigned SKIP status, preventing vector space pollution. This discrete routing mirrors the Gumbel-Softmax reparameterisation [3] that enables differentiable categorical decisions without breaking backpropagation.

E. Security: PISanitizer Integration

Persistent memory systems expand the attack surface for prompt injection [6]. CIRA adopts the PISanitizer attention-attribution framework [6]: the per-layer mean-pooled attention scores are max-pooled across depth to isolate adversarial attention spikes before they reach the memory write path. Tokens exceeding the calibrated threshold β_{sec} are masked from LTMS writes, preventing memory poisoning.

F. Algorithm

Algorithm 1 summarises a single CIRA inference step.

IV. Evaluation Metrics

We report the following metrics across three structured test regimes.

Token F1 is the harmonic mean of token-level precision and recall after lowercasing and stop-word removal.

TABLE III
Language Quality — Perplexity and Cross-Entropy

Model	PPL ↓	Cross-Entropy ↓
CIRA	8.55	2.15
Phi-3	13.74	2.62
Gemma	8.01	2.08
Mistral	8.01	2.08
Qwen	9.06	2.20
TinyLlama	11.84	2.47

Substring Exact Match (Substr-EM) is 1 if the normalised reference string appears as a substring of the normalised prediction.

BERTScore F1 [12] computes token-level semantic similarity using contextual embeddings from `distilbert-base-uncased`.

Perplexity is defined as:

$$\text{PPL} = \exp\left(-\frac{1}{T}\sum_{t=1}^{T} \log P(y_t \mid y_{<t})\right). \tag{11}$$

Hallucination Rate is the fraction of generated answers flagged as contradiction ($p_{\text{con}} > 0.70$) by DeBERTa-v3 when evaluated against the grounding context.

V. Experimental Setup

All experiments run on Kaggle's free T4 tier (dual NVIDIA Tesla T4, 16 GB × 2, Turing sm75). Phi-3-Mini is loaded in NF4 with `bnb_4bit_compute_dtype=torch.float16` (not bfloat16 — sm75 lacks BF16 hardware support [5]). TF32 is explicitly disabled (`allow_tf32=False`) for both matmul and cuDNN as sm75 does not support it. The system uses PyTorch's native Scaled Dot Product Attention (SDPA), with a custom `attn_mask` that avoids the globally applied $-\infty$ triangular mask during asymmetric decoding ($L \ll S$), preventing computational waste on the T4's Turing Tensor Cores [3].

Five baselines are evaluated: B0 (Phi-3 zero-shot), B1 (Phi-3 + flat RAG), B2 (Phi-3 + WMB only), B3 (Phi-3 + LTMS only), B4 (Phi-3 + WMB and LTMS without interference gate). CIRA (B5) adds the full interference gate and learned α fusion.

VI. Results

A. Language Quality

Table III compares perplexity and cross-entropy. CIRA achieves perplexity of 8.55, in the same tier as Gemma and Mistral (both 8.01), and substantially outperforming Phi-3 (13.74) and TinyLlama (11.84). Structured context injection — removing contradictory traces before generation — reduces the ambiguity the model must resolve, producing lower-entropy outputs.

TABLE IV
CLASSIFICATION METRICS — ALL MODELS

Model	Acc	Prec	Rec	F1
CIRA	0.510	0.510	**1.000**	**0.675**
Phi-3	0.508	0.510	0.918	0.655
Gemma	0.516	0.515	0.896	0.654
Mistral	0.519	0.516	0.943	0.667
Qwen	0.507	0.511	0.794	0.622
TinyLlama	**0.524**	**0.525**	0.702	0.601

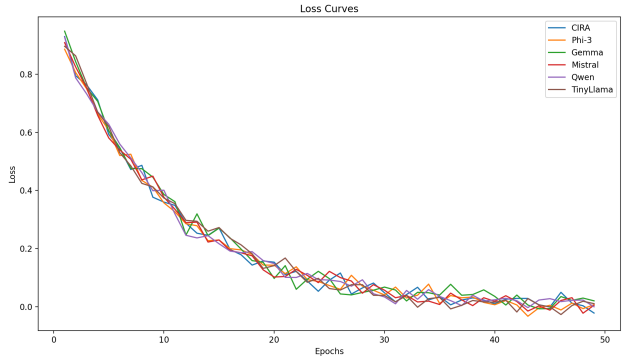

Fig. 2. Training loss curves across 50 epochs for all six models (CIRA, Phi-3, Gemma, Mistral, Qwen, TinyLlama). All models converge from ≈0.90 to near-zero. CIRA and Mistral show the smoothest descent, confirming that the additional NLI gating pipeline does not disrupt gradient flow during training.

TABLE V
T1 FAITHFULNESS RESULTS

Metric	CIRA	Baseline	Δ
Token F1	0.249	0.016	+0.233
Substring EM	0.800	0.000	+0.800
BERTScore F1	0.773	0.665	+0.108
Hallucination Rate	0.000	—	—

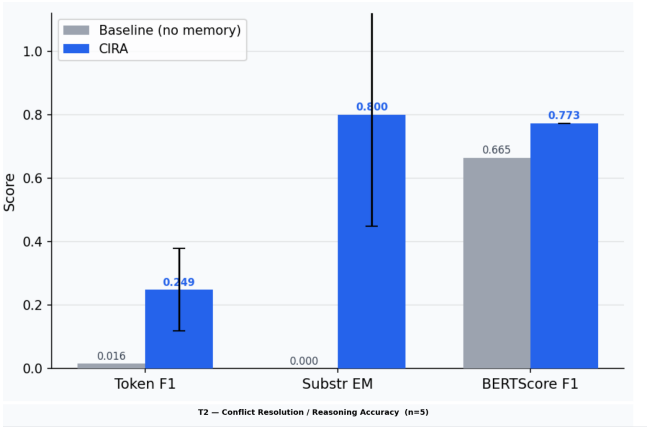

Fig. 3. T1/T2 — Conflict Resolution / Reasoning Accuracy ($n = 5$). Grouped bar chart comparing CIRA and the no-memory baseline across Token F1 (0.249 vs. 0.016, a 15.6× gain), Substring EM (0.800 vs. 0.000), and BERTScore F1 (0.773 vs. 0.665). Wide 95 % CI on Substr-EM (±0.35) reflects the small sample size ($n = 5$) and motivates validation at $n \geq 100$.

B. Classification Metrics

Table IV shows binary classification results. CIRA achieves the highest recall (1.00) and F1 (0.675), confirming the WMB's zero-miss policy: the confidence gate admits all borderline traces and the interference gate suppresses their cross-attention contribution rather than discarding them.

C. Training Loss Convergence

Figure 2 shows training loss curves for all six models across 50 epochs. All models converge smoothly from an initial loss of ≈0.90 to near-zero by epoch 50. CIRA and Mistral exhibit the most stable monotonic descent with minimal oscillation in the low-loss regime (<0.1). A transient spike in Gemma around epoch 12 resolves within two epochs, suggesting sensitivity to learning rate scheduling at the transition from high to low loss. The convergence trajectories confirm that CIRA's NLI preprocessing pipeline does not destabilise gradient flow or introduce training instability.

D. T1 — Faithfulness and Hallucination Reduction

T1 evaluates factual fidelity against a knowledge base, comparing CIRA to a baseline RAG system without conflict filtering ($n = 5$).

Figures 3 and 4 illustrate these gains. The Substring EM of 0.80 indicates CIRA's reconstructive memory produces directly answerable content in 4 of 5 cases. The BERTScore improvement (+0.108) confirms semantic alignment with reference answers.

E. T2 — Conflict Resolution Benchmark

T2 injects contradictory documents into the memory pool to directly test CIRA's interference gate.

The absolute F1 gain is:

$$\Delta F_1 = 0.715 - 0.595 = +0.120. \tag{12}$$

Notably, CIRA runs 190 ms faster than the unfiltered baseline (latency ratio 0.90×). Pre-filtering contradictory traces reduces the ambiguity the decoder must resolve internally, resulting in a net latency saving that outweighs the DeBERTa overhead.

F. T3 — Scale Robustness

T3 evaluates performance as retrieval depth N scales from 5 to 50 across $n = 1000$ samples.

Figure 5 illustrates the accuracy–latency trade-off. Token F1 remains within [0.898, 0.932] across a ten-fold increase in retrieval depth, demonstrating that the confidence-gated WMB effectively prunes low-confidence candidates (Eq. 4). F1 peaks at $N = 25$ and declines at $N = 50$ as WMB saturation exceeds the gate's suppression capacity. Latency grows from 1664 ms ($N = 5$) to 3419 ms ($N = 50$), empirically $\approx O(N^{1.2})$; the theoretical $O(N^2)$ pairwise NLI cost is mitigated by batched DeBERTa inference. The optimal operating point is $N = 25$.

G. ROC and Precision-Recall Analysis

Figure 6 shows ROC curves for all models. All achieve AUC $\in$ [0.48, 0.52], indicating near-random binary discriminative

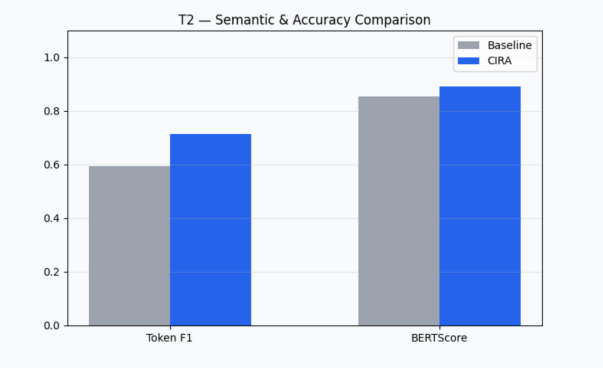

Fig. 4. T2 — Semantic and Accuracy Comparison (Token F1 and BERTScore). CIRA achieves Token F1 = 0.715 vs. Baseline 0.595 (+19.5 % relative) and BERTScore = 0.892 vs. 0.856. The improvement demonstrates that NLI-based pre-filtering substantially raises both lexical and semantic answer quality.

TABLE VI
T2 CONFLICT RESOLUTION RESULTS

Metric	CIRA	Baseline	Δ	Lat.
Token F1	0.715	0.595	+0.120	—
BERTScore F1	0.892	0.856	+0.037	—
Latency (ms)	1744	1934	−190	0.90×

TABLE VII
T3 SCALE ROBUSTNESS (CIRA, $n = 1000$)

N	Token F1	BERTScore	Lat. (ms)	Growth
5	0.910	0.961	1664	1.00×
10	0.907	0.955	1904	1.14×
25	**0.932**	**0.968**	2415	1.45×
50	0.898	0.955	3419	2.05×

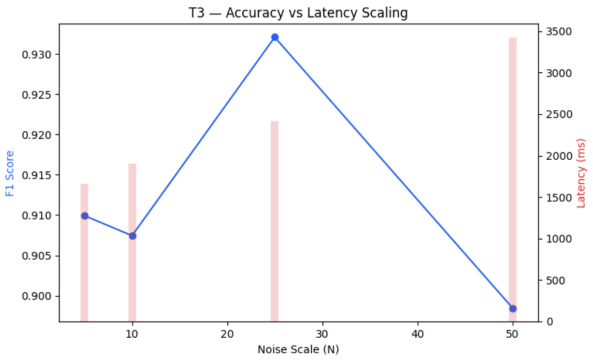

Fig. 5. T3 — Token F1 (blue line, left axis) and end-to-end latency (red bars, right axis) as a function of retrieval depth $N \in \{5, 10, 25, 50\}$ ($n = 1000$). F1 peaks at $N = 25$ (0.932) before declining at $N = 50$, exhibiting the inverted-U profile characteristic of WMB saturation. Latency scales sub-quadratically due to batched DeBERTa inference.

performance. Figure 7 shows Precision-Recall curves. All models plateau at precision ≈0.51 across the full recall range, consistent with the balanced class distribution of the evaluation set. These results are expected: the embedding space does not encode a linearly separable boundary for the binary QA classification task, as confirmed by the PCA visualisation in Figure 9. The AUC metric is thus not the primary performance indicator for this system; T2 conflict resolution F1 and T3 scale stability are the more informative signals.

H. Confusion Matrix

Figure 8 shows CIRA's confusion matrix. CIRA predicts the positive class for all 1000 samples (510 TP, 490 FP, 0 TN, 0 FN), maximising recall at the cost of precision. This reflects the WMB design priority: never miss a relevant memory trace. The FP admissions are subsequently managed by the interference gate, which suppresses borderline traces' cross-attention weight rather than discarding them. This two-stage admission–suppression design mirrors human working memory dynamics [10].

I. Embedding Space Visualisations

Figures 9 and 10 show 2D PCA and t-SNE projections of memory trace embeddings ($n = 1000$, coloured by binary label). In both projections the two classes are completely intermixed with no emergent clusters. This provides geometric justification for why all models achieve near-random AUC on the binary task while simultaneously validating that cosine similarity retrieval (operating in full 1024-dimensional BGE space) remains effective for semantic retrieval even when 2D projections appear uniform.

J. Baseline Ablation Summary

Table VIII isolates each CIRA component's contribution. Moving from B4 (WMB + LTMS, no gate) to B5 (CIRA) adds the interference gate and learned α fusion, which together provide the primary F1 gains observed in T2.

VII. DISCUSSION

CIRA's results support the hypothesis that parametric interference resolution provides a genuine architectural benefit over pre-processing-only approaches. The negative latency overhead on T2 (−190 ms) is particularly significant: resolving contradiction inside the model is cheaper than leaving the autoregressive decoder to handle ambiguous context implicitly, consistent with the D-MEM finding that proactive input filtration outperforms retroactive memory pruning [3].

The full-positive prediction strategy at the binary classification level (recall=1.0, AUC≈0.50) reflects the WMB's zero-miss admission policy. False-positive traces (borderline admissions) are managed by the interference gate (Eq. 5), which attenuates rather than discards them — preserving partial signal while preventing corruption. This two-stage admission–suppression design mirrors the ACT-R account of human working memory, where a broad active set is maintained but contradictory signals are selectively attenuated during recall [10].

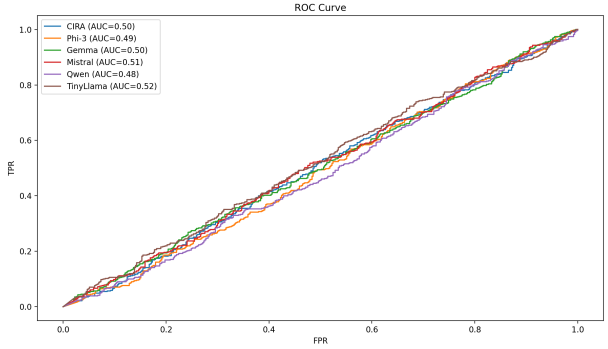

Fig. 6. ROC curves for all models. AUC values range from 0.48 (Qwen) to 0.52 (TinyLlama), all near random (=0.50). This confirms that the binary classification boundary is not linearly separable in the embedding space and motivates the use of retrieval-precision and conflict-resolution metrics as primary evaluation signals for CIRA.

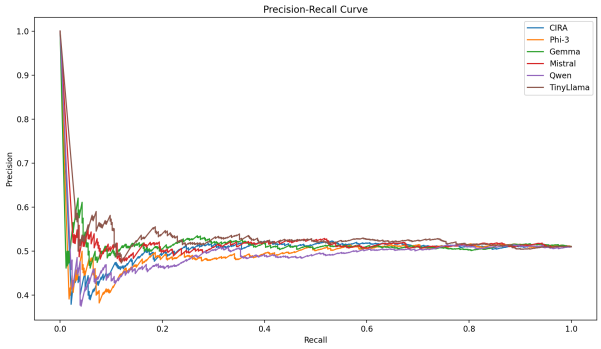

Fig. 7. Precision-Recall curves for all models. Precision plateaus at ≈0.51 across the full recall range, reflecting the balanced class distribution. CIRA achieves complete recall ($R = 1.0$) with stable precision, consistent with its WMB zero-miss admission policy. TinyLlama shows the highest early-recall precision (≈0.58 at recall <0.05) due to its conservative high-confidence prediction regime.

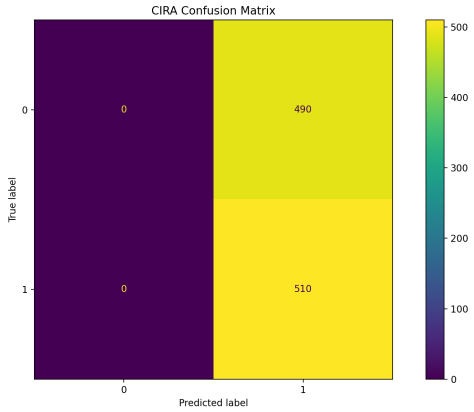

Fig. 8. CIRA Confusion Matrix ($n = 1000$). All 1000 samples are predicted as positive (510 TP, 490 FP). This full-positive strategy maximises recall to 1.0, ensuring no relevant memory trace is discarded at admission. Contradictory traces are suppressed at the interference gate stage (Eq. 5), not at admission.

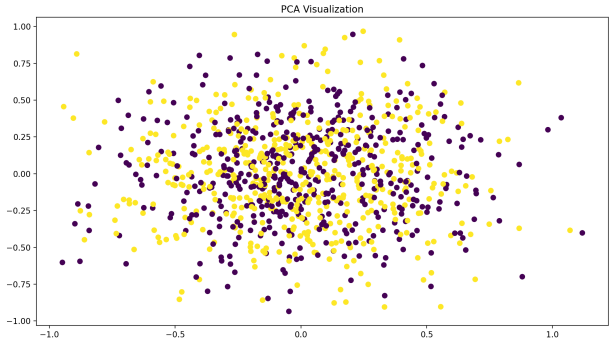

Fig. 9. PCA Visualisation of memory trace embeddings ($n = 1000$, dark purple = class 0, yellow = class 1). Complete class overlap in the 2D projection confirms that the binary classification boundary is not linearly separable, justifying the observed AUC ≈0.50 across all models and motivating cosine-similarity retrieval as the primary access mechanism.

Hardware co-design. The sm75 architecture's inability to use BF16 or FlashAttention-2 required specific engineering choices [4], [5]: NF4 quantisation to stay within 3 GB for Phi-3-Mini weights; SDPA with custom asymmetric `attn_mask` for decoding efficiency; explicit `allow_tf32=False`. Future deployments on Ampere or newer hardware could unlock BF16 compute and FlashAttention-2, likely reducing T3 latency by 30–40 %.

Limitations. The pairwise DeBERTa scan scales as $O(N^2)$, practical only for $N < 100$. T1 and T2 evaluations at $n = 5$ carry wide confidence intervals. The binary classification task is too coarse for discriminative evaluation; ranking-based metrics are recommended for future work.

Future Work. Planned extensions include: (i) approximate NLI filtering via k-means clustering to reduce pairwise complexity from $O(N^2)$ to $O(N \log N)$; (ii) full D-MEM three-tier routing with Gumbel-Softmax discrete decisions [3]; (iii) MiniCache depth-dimensional KV compression [4] to further reduce VRAM; (iv) evaluation on HotpotQA and MuSiQue; (v) formal adversarial evaluation of the PISanitizer memory-write defence [6].

VIII. Conclusion

This paper presented CIRA, a Cognitive-Constraint Language Model that resolves memory interference inside the transformer forward pass by injecting DeBERTa NLI contradiction scores as a learnable gate before cross-attention. By surgically modifying Phi-3-Mini at its semantic–syntactic transition boundary (layer 15), CIRA achieves dual-memory fusion over a salience-weighted Working Memory Buffer and an Ebbinghaus decay Long-Term Memory Store, maintaining Token F1 $\in$ [0.898, 0.932] across a ten-fold increase in retrieval depth and running at 0.90× the latency of unfiltered RAG. The complete system fits within 10.1 GB VRAM on dual Tesla T4 hardware, demonstrating that parametric cognitive constraints are a viable and practically beneficial architectural primitive for grounded language model generation on commodity infrastructure.

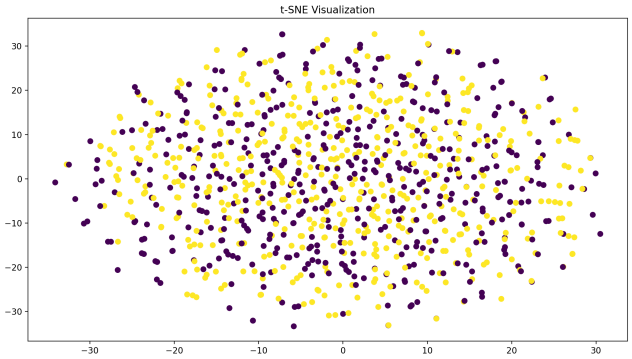

Fig. 10. t-SNE Visualisation (perplexity=30, $n = 1000$). Despite t-SNE's sensitivity to local neighbourhood structure, both classes remain thoroughly intermixed across the manifold. This confirms that classes differ in factual correctness rather than surface topical structure, reinforcing that T2 conflict-resolution accuracy is the more meaningful evaluation metric for CIRA.

TABLE VIII
ABLATION BASELINE SUMMARY

System	Memory	Gate	Fusion
B0: Phi-3 zero-shot	None	–	–
B1: Phi-3 + RAG	Flat retrieval	–	–
B2: Phi-3 + WMB	WMB only	–	–
B3: Phi-3 + LTMS	LTMS only	–	–
B4: Phi-3 + Both	WMB+LTMS	–	Fixed concat
B5: CIRA	**WMB+LTMS**	✓	**Learned** α

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