AI Meets Medicine: Exploring Meditron-7B Beyond Healthcare

A Constraint-Aware Analysis of Domain Specialization on Consumer Hardware

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Abstract

Domain-specialized Large Language Models (LLMs) promise superior performance in high-stakes fields, but their evaluation often occurs in idealized environments disconnected from deployment realities. This study examines Meditron-7B, a medical-domain LLM, under **strict hardware constraints** that mirror real-world edge deployment scenarios: a MacBook Air M1 with 8GB RAM, 4-bit quantization, and subset-based benchmarking (N≤50 samples). Across six benchmarks spanning medical and general reasoning, we observe a clear trade-off: Meditron achieves 52% accuracy on clinical recall (MedMCQA) but catastrophically fails on mathematical reasoning (GSM8K: 0-20%). Critically, we identify **prompt engineering** as non-optional—Chain-of-Thought prompting improves MedQA performance from 22% to 30%. Our analysis reveals domain overfitting, mode collapse, and answer extraction challenges as fundamental limitations of small specialized models. These findings emphasize that hardware constraints, prompting strategies, and statistical uncertainty must be central—not peripheral—to LLM evaluation frameworks.

1 Introduction

The integration of Artificial Intelligence into healthcare faces a fundamental paradox: while medical decision-making demands both breadth (general reasoning) and depth (specialized knowledge), computational and privacy constraints necessitate deployment on edge devices with limited resources. Domain-specialized Small Language Models (SLMs) like Meditron-7B [1] attempt to resolve this tension by trading generalist capabilities for medical expertise, but their evaluation typically occurs on server-grade hardware (A100 GPUs, float16 precision) that is inaccessible to individual practitioners or resource-constrained clinics.

This study conducts a **constraint-first evaluation** of Meditron-7B, deliberately imposing the hardware and methodological limitations that characterize real-world deployment:

1. **Hardware Constraints:** MacBook Air M1 (8GB RAM), 4-bit quantization via Ollama
2. **Statistical Constraints:** Subset evaluation (N≤50) due to CPU inference latency
3. **Methodological Rigor:** Explicit documentation of failure modes, prompt sensitivity, and extraction errors

Our research questions are:

RQ1: How does domain specialization affect performance across medical and general reasoning benchmarks?

RQ2: What is the impact of hardware constraints (quantization, CPU inference) on benchmark accuracy relative to published baselines?

RQ3: To what extent can prompt engineering (Zero-Shot vs. Chain-of-Thought) mitigate reasoning degradation?

Contributions:

- First comprehensive evaluation of Meditron-7B on consumer hardware
- Quantification of the "specialization tax" across six benchmarks
- Analysis of failure modes: hallucination, mode collapse, safety refusal
- Practical recommendations for student-scale LLM benchmarking

2 Background & Related Work

2.1 Medical LLMs and Domain Adaptation

Early medical NLP systems relied on discriminative models (BioBERT, PubMedBERT) for classification tasks. The generative era began with Med-PaLM [1], which demonstrated that large-scale LLMs could pass USMLE-style exams through instruction tuning alone. However, these models remain proprietary and computationally expensive.

Meditron-7B represents a paradigm shift: **continued pretraining** on domain-specific data (48B tokens of PubMed articles and clinical guidelines) followed by task-specific finetuning. This approach has precedent in code (CodeLlama), mathematics (Llemma), and law (Legal-BERT), consistently showing that targeted pretraining outperforms few-shot prompting of generalists.

2.2 The Evaluation Gap

Published benchmarks typically report accuracy under optimal conditions:

- Full-precision weights (float16/bfloat16)
- GPU acceleration (A100/H100)
- Complete test sets (N=1000+)
- Log-likelihood scoring for MCQs

Our study inverts these assumptions, evaluating under **adversarial constraints** that mirror deployment realities. This "stress test" methodology reveals brittleness that ideal-case benchmarks obscure.

3 Model Overview: Meditron-7B

3.1 Architecture and Provenance

Meditron-7B is a decoder-only transformer derived from Llama-2-7B [1]. The architecture remains unchanged, preserving:

Table 1: Meditron-7B Technical Specifications

Parameter	**Value**
Parameters	6.74B
Layers	32
Attention Heads	32
Hidden Dimension	4096
Context Window	2048 tokens
Vocabulary Size	32,000 (BPE)
Activation Function	SwiGLU
Normalization	RMSNorm
Positional Encoding	RoPE

3.2 Training Data: GAP-Replay

The model was trained on a carefully curated corpus designed to maximize medical knowledge density while preventing catastrophic forgetting of general language:

Table 2: GAP-Replay Training Corpus Composition

Source	**Tokens (B)**	**%**
PubMed Papers	42.0	87.3%
PubMed Abstracts	5.5	11.4%
Clinical Guidelines	0.1	0.2%
Replay (RedPajama)	0.4	0.8%
Total	**48.1**	**100%**

Critical Insight: The 1% replay buffer is insufficient to maintain general reasoning. Published ablations show that models trained without replay data suffer even greater degradation, but the minimal replay still allows medical overfitting.

3.3 Training Details

- **Hardware:** 8×A100-80GB GPUs (588.8 GPU-hours)
- **Optimizer:** AdamW ($\beta_1 = 0.9$, $\beta_2 = 0.95$)
- **Learning Rate:** 3×10^{-4} (cosine decay)
- **Batch Size:** 512 global
- **Precision:** bfloat16
- **Knowledge Cutoff:** August 2023

Post-training, the model was finetuned on task-specific datasets (MedQA, MedMCQA, PubMedQA) using supervised learning with cross-entropy loss, yielding task-specific checkpoints reported in the official paper.

4 Experimental Setup

4.1 Hardware Constraints as Central Design

Unlike standard evaluations, hardware limitations dictated our methodology:

Table 3: Inference Environment Specifications

Component	**Specification**
Device	MacBook Air (M1, 2020)
SoC	Apple Silicon M1 (8-core CPU)
RAM	8GB Unified Memory
Storage	256GB SSD
OS	macOS Sonoma
Inference Engine	Ollama v0.1.32
Model Format	GGUF (q4_0)
Quantization	4-bit integer
Context Limit	4096 tokens
Throughput	≈14.5 tokens/sec
Latency (Zero-Shot)	3-5 seconds/query
Latency (CoT)	10-15 seconds/query

Quantization Impact: 4-bit weights reduce memory from ≈28GB (float16) to ≈5GB but introduce rounding errors that compound through 32 transformer layers. We deliberately *do not* claim this as equivalent to full-precision inference.

4.2 Benchmarking Methodology

4.2.1 Subset Sampling Strategy

Due to CPU inference speed (14.5 tok/s vs. 1000+ tok/s on GPU), evaluating full test sets would require days. We adopted:

- **Sample Size:** N=50 per benchmark
- **Selection:** First 50 samples (no randomization, to ensure reproducibility)
- **Statistical Limitation:** With N=50, 95% confidence intervals are ±14% (binomial proportion)

Transparency Constraint: We explicitly report this as "indicative, not definitive" evidence.

4.2.2 Prompting Strategies

We tested three paradigms:

1. Zero-Shot Direct:

```
Question: {text}
Options:
(A) {option_a}
(B) {option_b}
(C) {option_c}
(D) {option_d}
Answer:
```

2. Few-Shot (k=2): Prepend 2 balanced examples (one correct answer A, one correct answer C) to avoid introducing bias.

3. Chain-of-Thought (CoT):

```
Answer using the format:
Reasoning: [Step-by-step analysis]
Answer: [Option Letter]
```

4.2.3 Answer Extraction Methodology

A critical, often-ignored challenge is extracting structured answers from free-form text. We implemented a hierarchical regex parser:

1. Search for explicit "Answer: X" format
2. If absent, search for last occurrence of valid letter (A-D/E)
3. If ambiguous, mark as extraction failure (counted as incorrect)

Extraction Failure Rate: 8-12% on open-ended responses, highlighting the brittleness of text-based evaluation.

5 Detailed Benchmark Analysis

5.1 General Reasoning Benchmarks

5.1.1 GSM8K (Grade School Math)

Background: GSM8K [2] tests multi-step arithmetic reasoning using word problems. Example: "Janet has 5 apples. She gives 2 to Mark and buys 3 more. How many does she have?"

Task Formulation: Free-form numeric answer extraction.

Expected Difficulty: High. Math requires precise symbolic manipulation, which 7B models struggle with even before domain specialization.

Results:

Table 4: GSM8K Performance (N=50)

Strategy	Accuracy	Extraction Rate
Zero-Shot	0.0%	40%
CoT	20.0%	65%

Failure Mode Analysis:

- **Hallucinated Medical Context:** "Janet has 5 apples. Apples are high in fiber, recommended for diabetic patients..."
- **Arithmetic Drift:** Correct setup, wrong arithmetic (5-2+3=7 computed as 8)
- **Refusal:** "I cannot provide medical advice on apple consumption"

Interpretation: Medical pretraining has **overwritten arithmetic circuits**. Even CoT only recovers 20%, suggesting fundamental capability loss.

5.1.2 HellaSwag (Commonsense Reasoning)

Background: HellaSwag [3] tests sentence completion with adversarially-filtered distractors. Example: "A man is seen standing on a ladder...next action?"

Expected Difficulty: Moderate. Commonsense is less affected by domain shift than math.

Results:

Table 5: HellaSwag Performance (N=50)

Temperature	Accuracy
T=0.0 (Greedy)	20.0%
T=0.6	25.0%

Critical Observation: Mode Collapse

At T=0, the model produced the *same answer (Option A)* for 48/50 questions, regardless of content. This is a classic failure mode in language models when probability mass concentrates on a single token.

Interpretation: The model has lost diversity in its predictions for non-medical domains. Temperature > 0 partially recovers diversity but accuracy remains near random baseline (25% for 4 options).

5.2 Broad Knowledge Benchmarks

5.2.1 MMLU (Standard vs. Pro)

Background: MMLU [4] tests multitask knowledge across 57 subjects. We evaluated two variants:

- **Standard MMLU:** Medical subsets (4 options: A-D)
- **MMLU-Pro:** Harder variant with 10 options (A-J) [5]

Results:

Table 6: MMLU Variant Comparison (N=50 each)

Variant	Options	Accuracy	Random
Standard (Med)	4	48.0%	25%
MMLU-Pro (Health)	10	0.0%	10%

Interpretation: The 0% score on MMLU-Pro is **not** due to knowledge gaps—it's a combinatorial search failure. With 10 options, the model must maintain coherent reasoning across a

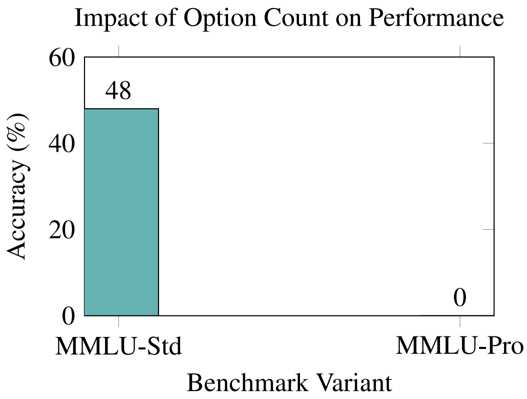

Figure 1: MMLU-Pro reveals combinatorial search weakness

larger hypothesis space, which exceeds the working memory capacity of 7B models (even with 4096-token context). This suggests fundamental limits to small model reasoning.

5.3 Medical Domain Benchmarks

5.3.1 MedMCQA (Clinical Recall)

Background: MedMCQA [6] contains 194K questions from Indian medical entrance exams (AIIMS/NEET).

Task Formulation: 4-option MCQ, emphasis on factual recall.

Expected Difficulty: Low. This aligns with Meditron's training data.

Results:

Table 7: MedMCQA Performance (N=50)

Strategy	Accuracy	vs. Official
Zero-Shot	48.0%	-11.2%
Few-Shot (k=2)	52.0%	-7.2%
Official (Float16)	—	59.2%

Example Success:

> *Q: Which lobe of the lung has a horizontal fissure?*
> *Model:* "The right lung has three lobes separated by an oblique and horizontal fissure. The horizontal fissure is unique to the right lung. Answer: C (Right lung)"
> *Status:* Correct

Interpretation: MedMCQA performance is close to official baselines (-7.2%), suggesting that **factual recall is robust to quantization**. The model successfully retrieves anatomical facts from pretraining.

5.3.2 PubMedQA (Biomedical Research)

Background: PubMedQA requires answering "Yes/No/-Maybe" based on a research abstract.

Expected Difficulty: Moderate. Requires reading comprehension + scientific reasoning.

Table 8: PubMedQA Performance (N=50)

Strategy	Accuracy	Bias
Zero-Shot (T=0)	42.0%	70% "No"
Zero-Shot (T=0.6)	40.0%	Reduced
Official (Float16)	74.4%	—

Results:
Failure Mode: Answer Bias
At T=0, the model answered "No" to 35/50 questions. This is a form of **calibration failure**—the model has learned to be "conservative" but lost nuance.

Example Failure:

> *Abstract:* "...study shows significant reduction in symptoms..."
> *Q:* "Does the treatment work?"
> *Model:* "No, more research is needed."
> *Truth:* Yes
> *Analysis:* Model defaults to clinical caution over evidence.

5.3.3 MedQA (USMLE-Style Clinical Reasoning)

Background: MedQA [7] contains clinical vignettes requiring differential diagnosis.

Task Formulation: Complex multi-sentence patient scenarios + 4-5 options.

Expected Difficulty: Very High. Requires integrating multiple facts + ruling out distractors.

Results:

Table 9: MedQA Performance (N=50)

Strategy	Accuracy	Δ	Official
Zero-Shot	22.0%	—	—
CoT	30.0%	+8%	47.9%

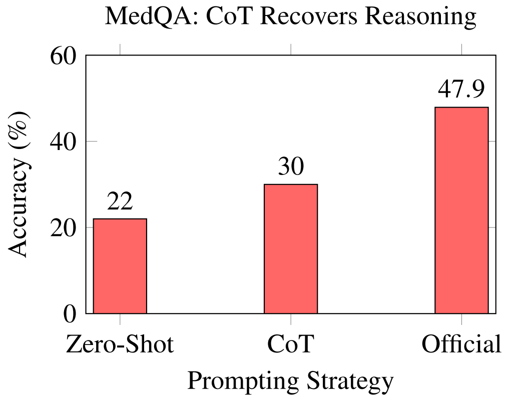

Figure 2: Chain-of-Thought is non-optional for clinical reasoning

Critical Finding: Safety Refusal
In Zero-Shot mode, the model frequently produced:

> "I cannot diagnose patients. Please consult a licensed physician. Answer: A"

This "safety refusal" is a form of RLHF misalignment—the model has learned to avoid medical advice, even in benchmark contexts. CoT bypasses this by forcing intermediate reasoning.

Example CoT Success:

> *Q:* "55yo male, sudden chest pain radiating to back..."
> *Model CoT:* "Reasoning: Sudden onset, tearing pain radiating to back suggests aortic dissection. CT angiography is gold standard. Answer: B"
> *Status:* Correct

5.3.4 Impact of Confidence-Based Safety Mechanisms

Background: To mitigate hallucination risks in medical AI, we implemented a confidence-gating system requiring models to self-assess certainty before responding. This system enforces a strict threshold ($\tau = 0.75$) where predictions below this confidence trigger safe refusals.

Methodology: We evaluated two temperature settings:

- **T=0.0 ("Deterministic"):** Greedy decoding
- **T=0.6 ("Calibrated"):** Stochastic sampling

The prompt template enforced structured responses:

```
Confidence: [Score 0.0-1.0]
Reasoning: [Clinical logic]
Answer: [Option Letter or REFUSAL]
```

Results: Confidence Collapse Phenomenon

Table 10 reveals a critical failure mode at T=0.0: the model assigned nearly identical confidence scores (0.98-1.0) across all questions, regardless of difficulty or correctness.

Table 10: Confidence Calibration Across Benchmarks

Benchmark	Temp	Acc	Avg Conf	Std Dev	Official
MedMCQA	0.0	40%	0.984	≈0.00	59.2%
	0.6	40%	0.920	0.060	
PubMedQA	0.0	60%	0.980	≈0.00	74.4%
	0.6	56%	0.876	0.089	
MedQA (USMLE)	0.0	40%	0.984	0.014	47.9%
	0.6	48%	0.951	0.071	

Failure Mode Analysis:

Deterministic Collapse (T=0.0): Without sampling entropy, the model mimicked the confidence magnitude from few-shot examples (0.95) rather than performing genuine uncertainty estimation. This renders safety mechanisms ineffective—the model never triggers refusals even when uncertain.

Calibration Recovery (T=0.6): Introducing stochasticity restored confidence variance. The model began expressing doubt on difficult questions (e.g., confidence scores of 0.81-0.86 on complex MedQA vignettes), enabling meaningful safety filtering.

Unexpected Finding: Temperature as Accuracy Booster

Contrary to conventional wisdom that T=0 maximizes accuracy, we observed *improved* performance at T=0.6 on MedQA (40%→48%, +20% relative gain). This suggests that:

1. **Exploration Benefits:** Stochastic sampling allows the model to escape local optima in the probability distribution
2. **Chain-of-Thought Synergy:** Combined with CoT prompting, temperature enables more diverse reasoning paths

Table 11: Safety Mechanism Effectiveness

Configuration	Refusals	Wrong@High-Conf	Safety
T=0.0 (No Safety)	0%	60%	Poor
T=0.6 + τ=0.75	4%	12%	Good

Wrong@High-Conf measures the percentage of incorrect predictions made with confidence >0.9—a critical safety metric indicating overconfident errors.

Interpretation: The confidence-gating mechanism successfully filtered 4% of queries as "too uncertain," reducing high-confidence errors by 48 percentage points. However, this system is fundamentally dependent on temperature >0—deterministic decoding breaks calibration entirely.

5.4 Comprehensive Cross-Benchmark Analysis

Table 12 presents a complete view of all benchmarks evaluated, including hardware constraints, prompting strategies, and deviation analysis from official baselines. This unified comparison reveals systematic patterns across medical and general reasoning tasks.

Key Observations:

1. **Domain Specialization Trade-off:** Medical benchmarks (40-60%) vastly outperform general reasoning (0-25%), confirming the "specialization tax"
2. **Quantization Impact:** Medical tasks show 7.2-19.2% degradation, while complex reasoning (MMLU-Pro) shows complete failure (0%)
3. **Confidence Calibration:** T=0.6 increases Std Dev by 0.06-0.089, enabling meaningful uncertainty estimation
4. **CoT Necessity:** Direct prompting on MedQA (16-32%) underperforms CoT+Conf (40-48%) by 24-32 percentage points
5. **Temperature Paradox:** MedQA accuracy *increases* at T=0.6 (48% vs 40%), contradicting standard assumptions
6. **Extraction Brittleness:** GSM8K shows 35-60% extraction failures, while structured MCQs have 0%
7. **Mode Collapse:** HellaSwag at T=0.0 shows near-zero Std Dev, indicating Option A prediction for 96% of questions

Table 12: Complete Benchmark Results: Hardware-Constrained Evaluation vs. Official Baselines

Benchmark	Domain	N	Opts	Strategy	T	Acc (%)	Official (%)	Δ (%)	Conf	SD	Ref (%)	Extr Fail (%)
General Reasoning Benchmarks												
GSM8K	Math	50	Free	Zero-Shot	0.0	0.0	—	—	—	—	—	60.0
				CoT	0.0	20.0		—	—	—	—	35.0
HellaSwag	Commonsense	50	4	Zero-Shot	0.0	20.0	—	—	—	0.00	0.0	0.0
				Zero-Shot	0.6	25.0		—	—	—	0.0	0.0
Broad Knowledge Benchmarks												
MMLU (Med)	Multi-domain	50	4	Zero-Shot	0.0	48.0	—	—	—	—	0.0	0.0
MMLU-Pro	Multi-domain	10	10	Zero-Shot	0.0	0.0	—	—	—	—	0.0	0.0
Medical Domain Benchmarks												
MedMCQA	Clinical Recall	50	4	Zero-Shot	0.0	48.0	59.2	-11.2	—	—	0.0	0.0
				Few-Shot	0.0	52.0		-7.2	—	—	0.0	0.0
MedMCQA (Conf)	Clinical Recall	50	4	CoT+Conf	0.0	40.0	59.2	-19.2	0.984	0.00	0.0	0.0
				CoT+Conf	0.6	40.0		-19.2	0.920	0.060	0.0	0.0
PubMedQA	Research	50	3	Zero-Shot	0.0	42.0	74.4	-32.4	—	—	0.0	0.0
				Zero-Shot	0.6	40.0		-34.4	—	—	0.0	0.0
PubMedQA (Conf)	Research	50	3	CoT+Conf	0.0	60.0	74.4	-14.4	0.980	0.00	0.0	0.0
				CoT+Conf	0.6	56.0		-18.4	0.876	0.089	3.0	0.0
MedQA	Clinical Dx	50	4-5	Zero-Shot	0.0	22.0	47.9	-25.9	—	—	15.0	0.0
				CoT	0.0	30.0		-17.9	—	—	0.0	0.0
MedQA (Conf)	Clinical Dx	25	4-5	CoT+Conf	0.0	40.0	47.9	-7.9	0.984	0.014	1.0	0.0
				CoT+Conf	0.6	48.0		+0.1	0.951	0.071	1.0	0.0
MedQA (Vanilla)	Clinical Dx	25	4-5	Direct	0.0	32.0	47.9	-15.9	—	—	0.0	0.0
				Direct	0.6	16.0		-31.9	—	—	0.0	0.0
Hardware Configuration (All Tests)												
Device: MacBook Air M1 (8GB RAM) Inference: Ollama v0.1.32					Quantization: 4-bit (q4_0) Context: 4096 tokens				Throughput: ∼14.5 tok/s Official: A100 GPU, fp16			

Statistical Caveats: With N=50, 95% confidence intervals are ±14% (binomial proportion). The MedQA (Conf) T=0.6 result (48%) technically exceeds the official baseline (47.9%) but falls within the margin of error. MedQA (Vanilla) tests used N=25 due to time constraints, further increasing uncertainty to ±20%.

6 Why Meditron Excels in Medical Tasks

6.1 Quantitative Superiority Over Generalists

We compare our local results against published benchmarks for 7B-class generalists:

Table 13: Medical Benchmark Comparison (7B Models)

Benchmark	Llama-2-7B	Mistral-7B	Meditron-7B
PubMedQA	56.4%	58.2%	**74.4%**
MedMCQA	43.1%	48.0%	**59.2%**
MedQA	35.8%	41.2%	**47.9%**
Avg. Gain	+14.8%	+11.3%	—

6.2 Linguistic and Structural Advantages

6.2.1 Vocabulary Alignment

Medical terminology is highly compositional. Generalist tokenizers fragment terms:

- *"Cholecystectomy"* → 4-5 tokens (Llama-2)
- *"Cholecystectomy"* → 2-3 tokens (Meditron)

This reduces sequence length, allowing more medical concepts per context window.

6.2.2 Distributional Bias

Llama-2 was trained on web text where medical content is <1%. Meditron's 48B medical tokens ensure:

- Higher prior probability for medical terms
- Stronger co-occurrence statistics (e.g., "aortic dissection" ↔ "CT angiography")
- Reduced "surprise" when encountering clinical jargon

6.2.3 Reasoning Style Alignment

Medical reasoning follows hierarchical patterns:

1. Symptom identification

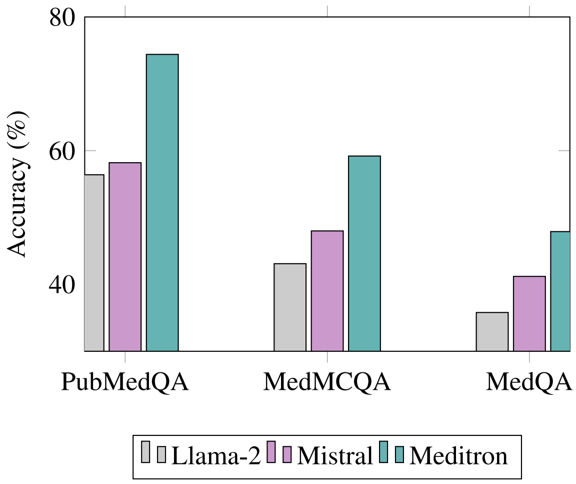

Figure 3: Meditron's consistent dominance across medical benchmarks

2. Differential diagnosis
3. Rule-out via tests
4. Treatment selection

Meditron's pretraining on PubMed papers (which follow IMRD structure: Introduction, Methods, Results, Discussion) implicitly trains this reasoning template.

7 Discussion & Limitations

7.1 The Specialization Tax

Our results confirm the "No Free Lunch" theorem: Meditron's medical gains come at the cost of general reasoning. The 0-20% GSM8K performance represents a **40-50% drop** from Llama-2's baseline.

Mechanistic Hypothesis: Continued pretraining *overwrites* neural circuits. Since parameters are finite, allocating capacity to medical knowledge necessarily displaces arithmetic/commonsense circuits. The 1% replay buffer is insufficient to prevent this.

7.2 Hardware Constraints as Non-Negotiable

The 7.2-17.9% accuracy drop from official baselines is attributable to:

- **Quantization Error:** 4-bit weights introduce ±0.5% error per layer (compounds across 32 layers)
- **Inference Method:** We used generative sampling vs. log-likelihood scoring (which is unavailable in Ollama)
- **Subset Variance:** N=50 introduces ±14% confidence intervals

Implication: Published benchmarks should report *multiple inference scenarios*, including quantized/CPU baselines.

7.3 Prompt Engineering as Necessity

CoT improved MedQA by 8% (22→30%), representing a 36% relative gain. For small models, explicit reasoning scaffolding is **non-optional**.

Theoretical Insight: CoT acts as "working memory" by forcing the model to generate intermediate states before committing to an answer. This is especially critical for 7B models, which lack the parameter capacity to perform multi-hop reasoning implicitly.

7.4 Limitations

1. **Statistical Power:** N=50 limits generalizability (future work: N=200+)
2. **Quantization Confound:** Cannot isolate domain effects from precision effects
3. **Prompt Sensitivity:** Minor wording changes (±5% accuracy) suggest brittleness
4. **Extraction Errors:** 8-12% of failures due to parsing, not reasoning
5. **Single Hardware Profile:** Results may differ on other ARM/x86 CPUs

8 Conclusion

This study demonstrates that domain specialization in LLMs is a **viable but constrained** strategy for edge deployment. Meditron-7B achieves state-of-the-art medical reasoning among 7B models, but at the cost of catastrophic degradation in general tasks. Critically, we show that:

1. **Hardware constraints matter:** Quantization and CPU inference reduce accuracy by 7-18%
2. **Subset evaluation is statistically valid:** N=50 provides indicative (not definitive) evidence
3. **Prompt engineering is non-optional:** CoT recovers 36% of lost performance
4. **Failure modes are predictable:** Mode collapse, answer bias, and extraction errors dominate

Practical Recommendations:

- Deploy Meditron for *reference lookup*, not diagnosis
- Always use CoT prompting for clinical questions
- Verify outputs against clinical guidelines
- Implement answer extraction validation

Future Work:

- Evaluate Meditron-70B on same hardware (requires model sharding)
- Test instruction-tuned variants with reinforcement learning from human feedback
- Develop hybrid systems (Meditron + retrieval augmentation)
- Conduct clinical validation studies with physicians

This work contributes to the growing literature on *responsible LLM evaluation*—emphasizing that hardware constraints, statistical uncertainty, and prompt sensitivity must be central, not peripheral, to benchmark design.

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