

# Language Models in Multi-Hop Scientific Reasoning: A Systematic Evaluation

Assignee Research

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## Abstract

This report synthesises findings from 12 peer-reviewed papers addressing the following research question: How do language models handle multi-hop reasoning chains in scientific question answering v18. 13 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 1.8/10. This report is a machine-generated literature synthesis and does not constitute original research.

## 1 Introduction

This paper examines: Dynamic Reasoning Chains through Depth-Specialized Mixture-of-Experts in Transformer Architectures. Research question: How do language models handle multi-hop reasoning chains in scientific question answering v18.

## 2 Methodology

Systematic literature search across multiple databases yielded 12 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 1.8/10.

## 3 Results

12 papers retrieved. 13 claims extracted; 0 independently verified. Quality review score: 1.8/10.

## 4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce

errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

## 5 Extracted Claims

Claim	Verified	Confidence
The MMDA architecture employs a modular mixture-of-experts design where shallow pattern experts are assigned to high-thr	×	0.11
Input sequences from The Pile dataset were dynamically routed through expert chains of varying depth guided by a dedicat	×	0.11
The DS-MoE algorithm categorizes experts into five types: Shallow Pattern Experts (SPE), Compositional Reasoning Experts	×	0.15
Shallow Pattern Experts (SPE) are specialized for low-depth tasks such as fact lookup and keyword-based answers like 'Wh	×	0.06
Compositional Reasoning Experts (CRE) are specialized for medium-depth tasks including multi-step inference and solving	×	0.12
Logical Inference Experts (LIE) were pre-trained on legal and abstract reasoning texts to improve formal logic and proof	×	0.08
Memory Integration Experts (MIE) were pre-trained on long-context stories for narrative comprehension and context tracki	×	0.04
The DS-MoE architecture achieves a computational complexity of $O(k \log n)$ , representing a $\sim 70\text{--}80\%$ reduction compared to	×	0.08
On the Wikipedia (Shallow) dataset, the DS-MoE model achieved 92.5% accuracy, $0.32 \times 10^{12}$ FLOPs, 45ms inference time, 5	×	0.05
On the GitHub (Compositional) dataset, the DS-MoE model achieved 88.9% accuracy, outperforming the UDT (24L) baseline wh	×	0.05
On the Legal (Deep) dataset, the DS-MoE model used 5.8 GB of memory, whereas the UDT (24L) baseline used 9.6 GB.	×	0.05
The DS-MoE routing network utilizes real-time utilisation monitoring to avoid under- or over-activation and applies dyna	×	0.07
Cross-module coherence in the DS-MoE architecture is enforced through consistency constraints during chain composition.	×	0.03

## References

- <http://arxiv.org/abs/2509.20577v1>
- <http://arxiv.org/abs/2511.07364v1>
- <http://arxiv.org/abs/2103.07492v4>