Enhancing Alignment with Expert Annotations in Energy Benchmarks via Expert Mind Knowledge Structuring

Assignee Research

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Abstract

The departure of subject-matter experts from industrial organizations results in the irreversible loss of tacit knowledge that is rarely captured through conventional documentation practices. This paper proposes Expert Mind, an experimental system that leverages Retrieval-Augmented Generation (RAG), large language models (LLMs), and multimodal capture techniques to preserve, structure, and make queryable the deep expertise of organizational knowledge holders. Drawing on the specific context of the energy sector, where decades of operational experience risk being lost to an aging workforce, we

1 Introduction

This paper examines: Expert Mind: A Retrieval-Augmented Architecture for Expert Knowledge Preservation in the Energy Sector. Research question: Does the knowledge structuring method in Expert Mind enhance alignment with expert annotations on specialized energy sector benchmarks compared to generic fine-tuning approaches?.

2 Methodology

Systematic literature search across multiple databases yielded 9 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.4/10.

3 Results

9 papers retrieved. 19 claims extracted; 15 independently verified. Quality review score: 7.4/10.

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 primary evaluation instrument is an expert review protocol in which the originating expert rates a stratified random	✓	0.24
We anticipate a baseline accuracy of 78–85% on factual claims, with the human validation layer expected to raise this to	✓	0.26
User adoption will be tracked through interaction logs collected during the 5–10 person organizational pilot.	✓	0.23
Key metrics include: weekly active query volume, query resolution rate (defined as a query for which no human follow-up	✓	0.38
Organizational impact will be measured through a controlled comparison of onboarding duration and access to Expert Mind.	✓	0.21
Additional indicators include: the number of operational decisions for which the system provides documented expert justi	✓	0.30
Table II summarizes the anticipated outcomes across evaluation dimensions, with target benchmarks and measurement instru	✓	0.26
Response accuracy target is >85% using an expert review protocol.	×	0.10
Correction rate target is <10% using validation logs.	×	0.12
Weekly query volume target is >50 queries/wk using interaction logs.	✓	0.19
Net Promoter Score target is >40 using user surveys.	✓	0.16
Onboarding reduction target is >20% using HR analytics.	×	0.12
Consultation time saved target is >15% using time tracking.	×	0.14
The proposed architecture offers three primary contributions to the knowledge management and AI fields.	✓	0.21
Expert Mind is a Retrieval-Augmented Generation architecture for the preservation of tacit expert knowledge in the energ	✓	0.22
The system addresses a critical organizational challenge that existing knowledge management approaches have failed to re	✓	0.29
The proposed architecture combines multimodal knowledge capture, LLM-driven extraction, vector store persistence, and a	✓	0.26
The contributions of this paper are threefold: (1) a concrete system architecture for expert knowledge preservation usin	✓	0.38
The system is contextualized within the energy sector, where the knowledge crisis is most acute	✓	0.22

References

- http://arxiv.org/abs/2603.14541v1
- http://arxiv.org/abs/1403.5618v2
- http://arxiv.org/abs/2206.10318v1