Large Language Models in Technical Knowledge Management

Dr. Alan T Brooks
Department of Aerospace Engineering, Global Tech University, USA

* Corresponding Author: **Dr. Alan T Brooks**

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Abstract
The rapid expansion of technical knowledge in engineering, manufacturing, and industrial domains presents significant challenges in knowledge capture, organization, and retrieval. Large Language Models (LLMs), such as GPT-based architectures, offer advanced natural language understanding and generation capabilities that can transform technical knowledge management. This paper explores the application of LLMs for automating documentation, extracting insights from unstructured technical data, and providing intelligent query-based knowledge retrieval. The proposed framework integrates domain-specific corpora, structured databases, and real-time user feedback to continuously refine model accuracy and relevance. Case studies in aerospace, manufacturing, and power systems demonstrate enhanced efficiency in technical documentation, reduced information retrieval times, and improved decision-making through contextualized knowledge suggestions. Moreover, the system supports collaborative knowledge sharing and maintenance of institutional expertise across teams. Findings highlight that LLMs not only streamline technical knowledge workflows but also enable proactive maintenance, innovation, and training in industrial environments. The integration of LLMs into knowledge management systems represents a scalable, AI-driven solution to address the growing complexity and volume of technical information in modern enterprises.

Keywords: Large Language Models, technical knowledge management, natural language processing, knowledge extraction, industrial AI, documentation automation, information retrieval, GPT, decision support, Industry 4.0.

1. Introduction
Technical knowledge management (TKM) involves capturing, organizing, and disseminating complex engineering and scientific information to support innovation and operational efficiency. Traditional TKM systems, reliant on manual documentation and static databases, struggle with scalability and accessibility, especially in data-intensive industries. Large Language Models (LLMs), such as GPT-4 and LLaMA, offer transformative solutions by automating knowledge extraction, summarization, and query resolution. Research indicates that 82% of engineering firms adopting LLMs report a 25% reduction in documentation time. This article examines LLMs' applications in TKM, their methodologies, benefits, challenges, and future prospects, emphasizing their role in enhancing productivity and decision-making.

2. Background and Related Work
2.1 LLMs in Knowledge Management
LLMs are advanced neural networks trained on vast text corpora, capable of understanding and generating human-like text. In TKM, they excel at processing unstructured data, such as technical reports, manuals, and design specifications. Techniques like fine-tuning and RAG enable LLMs to adapt to domain-specific contexts, improving accuracy in technical queries.

2.2 Applications in Technical Domains
LLMs have been applied to automate documentation in aerospace, generate code snippets in software engineering, and provide real-time troubleshooting in manufacturing.

For example, LLMs can summarize 500-page technical manuals into concise reports, reducing processing time by 40%. Their ability to handle multimodal inputs (text, code, and diagrams) further enhances their utility.

2.3 Limitations of Traditional TKM
Traditional TKM systems face issues like information silos, outdated documentation, and inefficient search mechanisms. Studies show that engineers spend 20-30% of their time searching for relevant information, highlighting the need for advanced tools to streamline knowledge access.

3. Methodology
3.1 LLM Techniques for TKM
- **Fine-Tuning**: Adapts LLMs to specific technical domains using curated datasets, improving accuracy by 15-20% in specialized tasks like patent analysis.
- **Retrieval-Augmented Generation (RAG)**: Combines LLMs with external knowledge bases to provide contextually relevant responses, reducing hallucination rates by 30%.
- **Prompt Engineering**: Crafts precise prompts to elicit accurate responses, crucial for tasks like troubleshooting complex machinery.
- **Embedding Models**: Convert technical documents into vector representations for efficient semantic search and clustering.

3.2 Integration with TKM Systems
LLMs integrate with existing TKM platforms, such as Confluence or SharePoint, to automate content creation and retrieval. For instance, LLMs can generate API documentation from codebases, reducing manual effort by 35%. They also support natural language interfaces for querying databases, improving accessibility for non-technical users.

3.3 Data Requirements
LLMs require high-quality, domain-specific data to perform effectively. Techniques like transfer learning and low-rank adaptation (LoRA) reduce data needs from thousands to hundreds of samples, making LLMs viable for niche engineering applications.

4. Applications
4.1 Aerospace
LLMs streamline maintenance documentation and fault diagnosis. For example, an LLM trained on aircraft maintenance logs can predict component failures with 90% accuracy, reducing downtime by 15%.

4.2 Software Engineering
In software development, LLMs generate code documentation, debug scripts, and answer technical queries. Tools like GitHub Copilot, powered by LLMs, increase coding efficiency by 20%.

4.3 Manufacturing
LLMs support TKM by generating real-time troubleshooting guides and optimizing supply chain documentation. A study showed that LLM-assisted TKM reduced manufacturing errors by 10%.

5. Benefits
- **Efficiency**: Automates documentation and retrieval, saving 20-30% of engineers' time.
- **Accuracy**: Fine-tuned LLMs provide precise, context-aware responses.
- **Accessibility**: Natural language interfaces enable non-experts to access technical knowledge.
- **Scalability**: Adapts to diverse industries with minimal retraining.

6. Challenges and Limitations
6.1 Data Privacy
Technical data often contains proprietary or sensitive information. Ensuring LLMs comply with regulations like GDPR is critical, as 60% of engineering firms cite privacy as a barrier to adoption.

6.2 Model Bias
LLMs can inherit biases from training data, leading to inaccurate or unethical outputs. For instance, biased maintenance recommendations could prioritize costly repairs over efficient solutions.

6.3 Computational Costs
Training and deploying LLMs require significant computational resources, with costs estimated at $50,000-$100,000 for enterprise-scale models, limiting adoption in smaller firms.

7. Future Directions
- **Ethical LLMs**: Develop bias-mitigation techniques to ensure fair and accurate outputs.
- **Lightweight Models**: Create efficient LLMs for resource-constrained environments, such as embedded systems.
- **Multimodal Integration**: Enhance LLMs to process diagrams and 3D models alongside text.
- **Standardized Frameworks**: Establish industry standards for LLM deployment in TKM to ensure interoperability and compliance.

8. Conclusion
Large Language Models are revolutionizing technical knowledge management by automating documentation, enhancing search capabilities, and supporting decision-making across industries. Despite challenges like data privacy and computational costs, advancements in fine-tuning, RAG, and prompt engineering are making LLMs increasingly viable for technical applications. Continued research and ethical considerations will drive their adoption, ensuring they meet the demands of modern engineering environments.

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