Large Language Models and the Elicitation of Tacit Knowledge

A Literature Review to Explore the AI Techniques in Uncovering Tacit Knowledge

Yanzhi Chen

Supervisor(s): Ujwal Gadiraju, Shreyan Biswas

EEMCS, Delft University of Technology, The Netherlands

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Name of the student: Yanzhi Chen
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Thesis committee: Ujwal Gadiraju, Shreyan Biswas, Ricardo Marroquim

Abstract

This study explores the application of Large Language Models (LLMs) for eliciting tacit knowledge, a challenging area crucial for enhancing decision-making and innovation in organizations. Using a systematic literature review based on PRISMA workflow, the research assesses the potential of LLMs to bridge the gap between tacit knowledge and its articulation. Findings reveal that LLMs, with their advanced natural language processing capabilities, are suitable for capturing tacit knowledge that is typically inaccessible through traditional methods. This paper concludes that while LLMs hold potential for revolutionizing knowledge elicitation practices, careful consideration of their limitations and ethical use is essential. This research contributes to broader discussions on integrating AI in knowledge management and future directions to optimize LLMs' utility in practical settings.

1 Introduction

Tacit knowledge, deeply embedded within individual experiences and expertise, plays a crucial role for decision-making and innovation. However, it is something "we can know more than we can tell"[18], its elusive nature makes it typically difficult to capture and articulate. Consider a master chef's ability to instinctively blend spices, a skill honed through years of experience. This tacit knowledge, characterized by nuanced decisions made subconsciously and adjusted based on contextual factors, presents significant challenges in articulation and transfer.

The advancement of **Large Language Models (LLMs)** in the field of **Natural Language Processing (NLP)** has demonstrated their capabilities to process complex language constructs, making them exceptionally suited for elicitation of knowledge. These models, through their advanced language understanding capabilities, offer a promising solution to the inherent difficulties in capturing tacit knowledge.

This research aims to explore how LLMs can be integrated to enhance the elicitation of tacit knowledge, which is vital for organizational learning and competitive advantage.

The main research question for this paper is: **How can LLMs be leveraged for tacit knowledge elicitation?** This study further explores several sub-questions to refine the scope of investigation:

1. What characteristics of LLMs make them suitable for eliciting tacit knowledge?
2. How do methodologies utilizing LLMs for tacit knowledge elicitation compare with traditional methods?
3. What are the ethical considerations of using LLMs for tacit knowledge elicitation?

This research evaluates the potential of Large Language Models (LLMs) to elicit tacit knowledge, employing a literature survey of existing literature guided by the PRISMA workflow. It aims to identify and evaluate specific features and configurations of LLMs that can enhance the elicitation of tacit knowledge, and finally assess the limitations and ethical considerations associated with using LLMs for this purpose.

[1]The rest of the paper is organized as follows: Section 2, Background, provides background information and explores of prior studies and frameworks relevant to LLMs and tacit knowledge elicitation, establishing the theoretical foundations for this research. Section 3, Methodology, details the approaches and criteria used in this research to explore the capabilities of LLMs in eliciting tacit knowledge. Section 4, Findings and Discussion, presents the primary results derived from our analyses, highlighting the effectiveness of LLMs in this context, followed by a discussion of their implications. Section 5, Limitations, acknowledges the constraints and potential biases of this study, and lastly Section 6, Conclusion, summarizes the research contributions and implications.

2 Background

This section lays the foundational context for our exploration of integrating Large Language Models (LLMs) in tacit knowledge elicitation. It provides a comprehensive overview of the current state of these technologies and their applications across various fields, drawing on relevant literature to highlight their potential and limitations.

2.1 Terminology

- **Tacit knowledge** is often referred as implicit or non-verbalized knowledge, it is typically personal and deeply rooted in individual experience[18]. However, it is inherently challenging to communicate and formalize, as it involves "technical skills – the kind of informal, hard-to-pin-down skills, ... A master craftsman after years of experience develops a wealth of expertise 'at his fingertips.' But he is often unable to articulate the scientific or technical principles behind what he knows" [15]. This type of knowledge is crucial for decision-making and innovation within organizations but is often not fully leveraged due to the difficulties in its articulation and dissemination[4].
- **Knowledge elicitation** is the process of collecting information from a human source of knowledge, that is thought to be relevant to that knowledge. "It is part of the larger process of knowledge acquisition, which itself constitutes the "front-end" of knowledge engineering, the process of building an expert system or a knowledge based system in general"[3].
- **Knowledge Graph (KG)** "is a structured representation of facts, consisting of entities, relationships, and semantic descriptions." [9] It may contains entities representing both real-world objects and abstract concepts, with relationships and textual explanations for each entities.
- **Scalability** refers to the ability to handle increasing amounts of work or to be readily expanded. In the context of knowledge elicitation, scalability issues arise

[1]ChatGPT was used in this section for inspiration.

when the method cannot be efficiently expanded or applied to large numbers of people or across multiple organizational settings without a significant increase in resources or time.

- **Depth** refers to the degree to which intricate, detailed, and comprehensive knowledge is extracted from a source. Traditional methods often struggle to reach the deeper layers of tacit knowledge that are embedded in personal experiences and complex expert insights.
- **Efficacy** refers to the ability to produce a desired or intended result. In the context of tacit knowledge elicitation using LLMs, efficacy measures how effectively these models can elicit and articulate tacit knowledge, ensuring that the knowledge extracted is accurate and comprehensive.
- **Efficiency** concerns the optimal use of resources to achieve desired results with minimal waste. In this context, efficiency refers to the ability of LLMs to elicit tacit knowledge using fewer resources, such as time and human effort.

2.2 Capabilities of LLMs

Large Language Models (LLMs) such as GPT and BERT have emerged as pivotal technologies in the field of NLP, offering advanced capabilities for handling complex language tasks. LLMs are extremely useful in enhancing the processing of contextual information and providing dynamic responses in real-time applications. For instance, an experiment was done on a dialogue based framework and demonstrated that it could achieve around 99% evaluation accuracy while reducing the human effort required by about 50% compared to traditional methods[28]. LLMs excel in a variety of tasks from natural language understanding to generation and reasoning tasks[19]. Through their extensive pre-training on diverse data sets, can acquire a deep contextual awareness that is crucial for tasks requiring nuanced language generation and comprehension[27]. This capability makes them suited for tacit knowledge elicitation, where the depth of expert knowledge must be captured and articulated effectively.

2.3 The Elicitation Challenge of Tacit Knowledge

Tacit knowledge is still a largely untapped resource in many organizational and technological contexts, valuable for innovation and decision-making. Its elicitation poses significant challenges because it is deeply personal, context-sensitive, and often subconscious. Traditional methods like interviews and expert consultations are foundational but limited in scalability and depth [25]. "Experts possess tacit knowledge that is subjective and personal, making it difficult to extract" [24], emphasizing the need for innovative elicitation methods that can overcome these barriers.

2.4 Integrating LLMs

Large Language Models have the ability to improve the efficacy and boost efficiency of tacit knowledge elicitation by capturing more precise and relevant information through NLP techniques[13]. They process and analyze data at a scale unmanageable for human experts alone, facilitating quicker decision-making and reducing the overall resource expenditure. This is especially advantageous in sectors such as healthcare and engineering, where the depth and accuracy of elicited knowledge are important. For example, LLMs can effectively apply expert medical knowledge and reasoning skills to answer complex medical questions, which rely heavily on tacit knowledge [14].

2.5 Approaches with LLMs and Knowledge Graphs (KGs)

The convergence of Large Language Models (LLMs) and Knowledge Graphs offers promising pathways for enhancing tacit knowledge elicitation. For instance, a roadmap was proposed for integrating these technologies to leverage the contextual understanding capabilities of LLMs with the structured, factual precision of KGs[16]. This integration is particularly useful to tacit knowledge, as it could significantly enhance the accuracy and depth of knowledge elicitation by combining intuitive, generative abilities of LLMs with the precise, structured information from KGs.

2.6 Technological and Ethical Considerations

Techniques such as few-shot learning, transfer learning, and reinforcement learning from human feedback have significantly enhanced the responsiveness and adaptability of LLMs[10]. These methods help models better understand and adapt to specific domains or tasks without extensive additional data. As LLMs become more widespread, issues such as bias in model outputs, misuse of generative capabilities, and the implications of replacing human decision-making with automated processes have come to the forefront[12; 26]. Addressing these concerns is crucial for the responsible deployment of LLMs in sensitive areas like tacit knowledge elicitation.

- **Bias in Model Outputs:** Biases in LLMs, stemming from skewed training data or pre-existing prejudices, can lead to erroneous interpretations and applications of tacit knowledge, potentially reinforcing stereotypes or omitting vital minority perspectives.
- **Misuse of Generative Capabilities:** The powerful generative abilities of LLMs raise risks related to the creation of misleading or inaccurate content. In tacit knowledge applications, it is crucial to ensure the authenticity and accuracy of the information to maintain organizational trust and decision-making integrity.
- **Automated Decision-Making:** Relying on automated processes for decisions that traditionally require human nuance may result in oversimplified outcomes that fail to capture complex human insights, especially in nuanced scenarios typical of tacit knowledge contexts.

3 Methodology

This section outlines the methodology employed to answer the research questions posed in this study. The methodology was designed to ensure a comprehensive and systematic review of the literature concerning the application of Large Language Models (LLMs) for tacit knowledge elicitation.

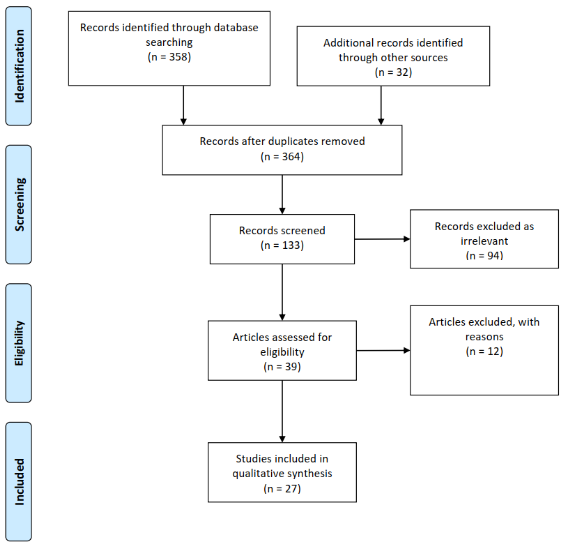

Figure 1: PRISMA diagram

3.1 Research Methodology

The primary methodological approach for this study involves a systematic literature review, inspired and guided by the PRISMA workflow. PRISMA is chosen for its rigorous, transparent framework which is designed to enhance the replicability and validity of the research findings. This workflow is particularly suitable for this study as it provides a systematic approach to identifying, evaluating, and synthesizing the research findings across different fields such as artificial intelligence and knowledge management. The PRISMA framework helps ensure a comprehensive understanding of the capabilities and challenges of using Large Language Models for tacit knowledge elicitation. Google Scholar is used as the primary search engine, facilitated access to a broad range of interdisciplinary sources, enhancing the diversity and comprehensiveness of the literature review.

3.2 Keywords Used

The search strategy involved specific keywords and phrases to capture relevant studies. Some examples of keywords included “Large Language Models”, “tacit knowledge”, “knowledge elicitation”, “natural language processing”, “artificial intelligence” and “knowledge management”. These terms were used in various combinations to maximize the findings of relevant articles.

3.3 Arrival at the Set of Papers

The initial search yielded a preliminary pool of articles. The selection process began with a screening based on titles and abstracts to assess their direct relevance to the research questions. This stage was followed by a full-text review to ensure that the articles met the inclusion criteria thoroughly.

As we delved deeper into the initial set of articles, additional papers were identified and added to the review pool. This often occurred through references within the read articles or by discovering relevant works cited by these papers. This iterative process helped broaden the scope of our review and ensured a more comprehensive coverage of the subject matter. This dynamic addition of sources aimed to capture a wide spectrum of perspectives, ranging from technical descriptions of LLM mechanisms to their practical applications in various domains. The inclusion of papers was influenced by the need to cover these diverse perspectives, enhancing the richness and depth of our systematic review.

3.4 Selection Criteria

- **Foundational Understanding:** For a general understanding of LLMs and tacit knowledge elicitation, articles were initially selected based on their citation counts, which reflects their impact and authority in the field, then followed by their relevance to the research questions. (Around 35 records were initially screened and 27 of them were excluded)
- **In-depth Research:** For more detailed investigations, articles were chosen on their direct relevance to the research questions, focusing specifically on those that discussed the application of LLMs to knowledge elicitation or provided insights into the capabilities of LLMs in NLP contexts relevant to knowledge management, prioritizing more recent publications(last 5 years), to ensure the up-to-date understanding of the field. (Around 98 of them were initially screened and 79 of them were excluded)

3.5 Use of AI in Research

In the process of this study, tools like ChatGPT were employed to assist with initial drafting for the purpose of inspiration of ideas, as well as re-phrasing and grammar correction of sentences. Some examples of usage can be found in the Appendix section.

4 Findings and Discussion

This section presents a synthesis of the results obtained from the systematic review, focusing on the application of Large Language Models (LLMs) for tacit knowledge elicitation and comparing these approaches to traditional methods, followed by a discussion of those findings.

4.1 Enhancing Tacit Knowledge Elicitation

The capability of LLMs to engage in nuanced, context-aware dialogues ability makes them particularly useful for tacit knowledge elicitation. “LLMs can facilitate interactive and dynamic text-based conversations, enabling a deeper exploration of stakeholder needs and expectations”[1]. Studies have also shown that LLMs can significantly enhance the extraction of medical expertise by engaging healthcare professionals in complex, scenario-based dialogues, facilitating a deeper understanding of implicit knowledge [23]. This capability is critical for capturing the depth of tacit knowledge embedded in personal experiences and expert insights.

4.2 Traditional Methods of Knowledge Elicitation

Traditional techniques for eliciting tacit knowledge typically involve interviews, observation, reports, process tracing, formal modelling and other conceptual techniques[3;

6]. These methods may rely heavily on personal interaction and the ability to observe and interpret non-verbal cues and contextual information. While they can provide deep insights, they are often labor-intensive, time-consuming, and subject to interviewer bias, making them less scalable and consistent. However, traditional methods have also emphasised the iterative nature of modeling, where elicitation is not just about gathering data but also about refining mental models and improving understanding through interaction and feedback.

4.3 Methodologies of Integrating LLMs

In contrast, LLMs can automate much of the process by dynamically generating inquiries and processing the textual data from expert interactions without requiring the manual construction of models by human experts. However, LLMs may lack the depth of engagement in the initial stages that traditional methods provide.

- LLMs can be used for automating the extraction and structuring of complex medical data from Electronic Medical Records[24], which are reflective of physicians' tacit knowledge. NLP capabilities were utilized to analyze and interpret data, extracting meaningful patterns, relationships, and insights that constitute tacit knowledge. This process involved recognizing medical terminology, understanding the context of their use, and discerning the underlying medical concepts that are crucial for diagnostic and treatment decisions. Once the tacit knowledge was captured and structured, they will be transformed into concept maps using algorithms that identify and link related concepts based on their occurrences and contextual relationships in the data, to visualize complex relationships between symptoms, diagnoses, and treatments, illustrating the clinical reasoning of experienced physicians[24]. This automation of knowledge extraction and representation by LLMs reduces the time and effort significantly comparing to traditional methods.
- Researches demonstrated that LLMs can be used to build intelligent assistants which have superiority over traditional intent-based systems in terms of user experience and efficiency[7]. LLMs can enhance tacit knowledge elicitation by leveraging advanced NLP capabilities to maintain dialogue context and adapt responses[11], which is crucial in dynamic settings where precision and adaptability in communication are essential. Through conversational AI systems, can offer more efficient and less resource-intensive methods for eliciting tacit knowledge[12]. These systems are potentially more adaptable to changing environments and can handle the informal and often uncodified exchanges that characterize tacit knowledge sharing among people[11]. Unlike traditional methods that may require extensive human intervention and are often limited in scalability, LLMs can interact with numerous individuals simultaneously, offering a scalable solution to knowledge elicitation in large organizations.[7].
- LLMs can be integrated with methods like **Knowledge Graphs (KGs)**, they can significantly enhance the elicitation of tacit knowledge. "**KGs** use a graph-based data model to capture knowledge in application scenarios that involve integrating, managing and extracting value from diverse sources of data at large scale."[8] KGs can aid LLMs by structuring data and providing a framework that supports the extraction and organization of knowledge. The synergy between LLMs' linguistic capabilities and KGs' structured knowledge can potentially transform the elicitation process, making it more robust and comprehensive[16]. For instance[4], KGs begin with the collection and processing of textual data from diverse sources like manuals, reports, and operation documents. Using NLP techniques[22], important entities and their relationships are extracted to form the initial structure of the KG. Named entity recognition and relation extraction methods identify and link key concepts, forming a structured representation of the data that encapsulates both entities and their interrelations. Further more, KGs are continuously updated to ensure a more accurate and comprehensive representation of tacit knowledge[4]. Unlike traditional methods, KGs provide a structured and queryable repository of knowledge that can be easily navigated and expanded, the visualization of graphs can also help users to understand complex information effectively.
- Moreover, games can be integrated for tacit knowledge elicitation[2; 4]. For instance, by requiring players to articulate questions about implicit characteristics of concepts, the game facilitates the externalization of tacit knowledge[2]. From the interaction of questions asked and answers given can generates data tuples that capture the knowledge exchanged. These tuples are structured as positive or negative assertions about the relationships between concepts, helping in building a nuanced knowledge base. The competitive and game-like aspects keep players engaged and motivated to participate, participants are likely to provide more accurate and comprehensive information.
- LLMs can be conceptualized as digital tools that simulates traditional elicitation methodologies, for example through tool-based interviews, which differs from traditional discourse-based interviews. For instance with the experiments involving different writers, by altering the digital interface or functionalities, researchers could provoke reflections on writing processes that would not typically be vocalized[20]. By engaging experts in dialogues that deviate from standard questioning, LLMs can retrieve deeper reflections, uncovering layers of tacit knowledge that are typically inaccessible through traditional methods[12].

4.4 Challenges and Limitations Faced by LLMs

Despite their advantages, LLMs are not without challenges. They require vast amounts of data to train effectively, are susceptible to biases in the training data, such as statistical bias and historical bias[17; 21], which data can be inaccurate and outdated. Therefore LLMs can sometimes generate misleading or incorrect information if not properly supervised. Furthermore, the complexity of setting up and maintaining LLMs and knowledge systems can be a significant barrier.

- Studies have shown LLMs can indeed generate output that are generally understandable. However, issues with completeness and correctness are significant, particularly when the input are ambiguous or inconsistent[5], such as having terms like “it” without explicitly mentioning what “it” refers to. This aligns with the challenges for tacit knowledge elicitation, where the nuances and depth of knowledge may not be fully captured and can have poor input quality due to its elusive nature.
- Studies also point out the difficulty in eliciting detailed, operational-level knowledge[6], a challenge that remains relevant for LLMs, especially when dealing with specialized or highly contextual knowledge. The precision and contextual sensitivity required in formal modeling are areas where LLMs need to be enhanced through better training and input.

4.5 Technological Advancements and Future Directions

The ongoing advancements in machine learning, such as the development of more sophisticated models for few-shot learning and transfer learning, are likely to further enhance the capabilities of LLMs in tacit knowledge elicitation[10]. These technologies promise to improve the adaptability and accuracy of LLMs, potentially overcoming some of the current limitations. Further research should continue to explore hybrid models that combine human expertise with AI capabilities, and expanding these studies into diverse cultural and industrial contexts will provide a broader understanding of the effectiveness and adaptability of these technologies.

4.6 Ethical Considerations

While all these technologies can enhance knowledge capture and organizational learning, they must be implemented with strict adherence to ethical standards to protect worker privacy and the integrity of the knowledge captured. Issues such as data privacy, consent for participation, concerns about job displacement and the potential manipulative capabilities of LLMs are important ethical implications to ensure that the elicitation process remains respectful and non-invasive[12]. These ethical implications for knowledge elicitation, especially in sensitive or heavily regulated industries, remain a significant concern that future research must address.

5 Limitations

This section explores some of the limitations of this research, particularly focusing on the potential biases and the reproducibility of the methodologies employed.

5.1 Responsible Research and Ethical Implications

As we harness the capabilities of LLMs for tacit knowledge elicitation, it is important to conduct this research responsibly. This study not only seeks to advance knowledge in the field but also aims to do so by upholding rigorous ethical standards.

- **Methodological Transparency:** The systematic approach to the literature review was detailed in the Methodology section and all data sources are cited to enhance reproducibility. However, the interpretation of findings involved subjective judgments about the relevance and implications of each study, which may vary among researchers.
- **Data Integrity:** We adhere to the principles of data integrity, ensuring that no data manipulation or misrepresentation occurs. As we aggregate findings from various studies, we ensure that all interpretations are based on accurately reported results from the original literature.
- **Addressing of Limitations and Ethical Concerns:** With the significant role of biases in affecting research outcomes, the potential limitations and ethical implications in integrating LLMs for tacit knowledge elicitation were also discussed.

5.2 Bias and Representation[2]

- **Source Diversity:** Although we included a broad range of studies on integrating LLMs for tacit knowledge elicitation, the majority of literature originates from technologically advanced regions. The generalizability of the findings to global contexts may be limited, particularly in developing regions where AI adoption may lack.
- **Potential Biases:** The selection of literature primarily focused on recent studies published in English, where a language bias might appear that ignores research published in other languages or older seminal works. To mitigate this, key foundational texts were included and sought to balance newer technologies with established theories.
- **Availability of Sources:** Another limitation is the accessibility and availability of the methodologies in some of the reviewed papers. Not all studies explains full methodological frameworks, which can hinder the ability to replicate or validate the findings comprehensively.

6 Conclusions

This research explored the utilization of Large Language Models for the elicitation of tacit knowledge, addressing the central research question: How can LLMs be leveraged for tacit knowledge elicitation?

6.1 Overview

Our study concluded that LLMs can be integrated with various methods, and can significantly enhance the process of eliciting tacit knowledge. The integration leverages the generative capabilities of LLMs and the methods such as Knowledge Graphs to not only simplify the elicitation process but also to ensure the accuracy and relevance of the knowledge extracted. This approach presents a valuable improvement over traditional methods, which are often labor-intensive and subjective to personal biases.

[2]ChatGPT was used in this section for inspiration.

6.2 Contributions[3]

The primary contributions of this research include:

- Demonstrating the feasibility of using advanced computational models to capture and utilize tacit knowledge, and compare with traditional methods that has been challenging to articulate and formalize.
- Discussing capabilities of integrating LLMs with Knowledge Graphs, which can also serve as insights for future implementations in various industrial and organizational contexts.
- Highlighting the ethical considerations and the limitations of AI technologies in knowledge management practices.

6.3 Practical and Theoretical Implications

The findings from this study offer both practical and theoretical implications:

- **Practical**: Organizations can adopt LLM and Knowledge Graphs integrations to enhance their knowledge management systems, leading to improved decision-making processes and innovation capabilities. This model provides a scalable and efficient approach to managing the vast amounts of tacit knowledge that exist within companies and industries.
- **Theoretical**: This research contributes to the theoretical understanding of knowledge management by illustrating how modern AI technologies can be applied to tacit knowledge elicitation. It helps to extending the boundaries of current theories by incorporating elements of artificial intelligence and Knowledge Graph technologies.

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A Utilization of Large Language Models

Tools like ChatGPT were used were used to assist the process of this study. Mainly for the purpose of ideas generation, rephrasing of words and grammar/spelling checking.

A.1 Prompts

Some examples of prompts used include:

- "What are the possible limitations when doing literature reviews?"
- "Can you rephrase this sentence for me?: Knowledge Graph is a useful tool to be integrated with LLMs for tacit knowledge elicitation, as it has the capability of retrieving implicit knowledge."
- "What are the possible synonyms for the words "important" and "utilization" when used in sentence?"
- "Can you check if anything is wrong with the grammar or if there are any other mistakes in my writing of this paragraph?: "Terminology Tacit knowledge....".