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COMPARISON OF THE CONCEPTUAL FRAMEWORK NODE OF KNOWLEDGE (NOK) WITH LARGE LANGUAGE MODELS (LLM)

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ABSTRACT

A system based on the conceptual framework Node of Knowledge (NOK) enables the recording of natural language sentences and questions in the NOK relational database, as well as the retrieval of answers to those questions. Large Language Models (LLMs) are designed for the same purpose: to provide answers to questions. Therefore, comparing large language models with a system built using the Node of Knowledge conceptual framework is an important research question. This paper addresses this by comparing these two systems. Among large language models, GPT was selected for comparison as it is one of the most widely used models. The comparison was conducted in two parts. First, the process models of the two systems were compared. Second, an analysis was performed on the answers produced by the NOK-based system and by ChatGPT, representing large language models, for a selected natural language sentence and set of questions. All comparison elements revealed similarities and differences between the systems, which are presented in this paper.

Keywords: *Node of Knowledge (NOK), Knowledge Representation, Question Answering (QA), Large Language Model (LLM), GPT*

1. INTRODUCTION

The challenge of representing and retrieving knowledge from natural language has driven decades of research in artificial intelligence, knowledge engineering, and natural language processing. Two fundamentally different paradigms have emerged: explicit, structured knowledge representation systems and implicit, neural-based language models.

Natural language processing (NLP) is the automation of human language processing and can also be described as semi-automatic processing (Elallaoui *et al.*, 2018). NLP is closely related to linguistics, as natural language processing tools enable automated linguistic analysis (Lash *et al.*, 2012; Suman, 2021). Linguistic analysis refers to the use of language and how specific words and phrases reflect human thought (Amirhosseini *et al.*, 2018). In natural language applications, semantic inference is particularly important and presents a challenge in their development. Semantic inferences are essential for natural language understanding and are an integral part of many natural language applications, such as question-answering systems (Bhagat *et al.*, 2007).

There are various methods for knowledge representation, one of which is the conceptual framework Node of Knowledge (NOK) (Pavlic *et al.*, 2013). It consists of the Node of Knowledge (NOK) method and three associated formalisms: the graphical representation formalism (Diagram Node of Knowledge, DNOK), the textual knowledge representation formalism (Formalised Node of Knowledge, FNOK), and the question formalisation formalism (Question Formalised Node of Knowledge, QFNOK). The application of the NOK method, together with the DNOK and FNOK formalisms, to complex sentences in fables is presented in (Rauker Koch *et al.*, 2014; Rauker Koch *et al.*, 2017). Previous research on the NOK conceptual framework has shown that it is possible to store natural language sentences and questions in a relational database using the FNOK formalism (Candrlic *et al.*, 2019) and the QFNOK formalism (Asenbrener Katic *et al.*, 2024), and to obtain answers to posed questions through a question-answering (QA) system.

To make NLP more accessible to people outside linguistics and computer science, tools are being developed to broaden NLP literacy (Baglini, Hjorth, 2021; Libbrecht *et al.*, 2020).

The article outlines the basic properties of the NOK method and presents preliminary results. The initial comparison between NOK and LLM aims to identify possibilities for their integration, with NOK serving as a method for knowledge formalisation and LLM as a user interface that utilises this formalised knowledge. The structure is as follows: after the introduction and the presentation of related works in Section 1 and Section 2, the motivation for the research is presented in Section 3. Section 4 describes the research methodology. Section 5 presents the research results. Finally, Section 6 provides the conclusion.

2. RELATED WORK

Question Answering (QA) systems aim to answer questions posed in natural language, providing an automated method for retrieving answers to such questions (Caballero, 2021).

All QA systems share three basic phases in finding the answer (Hovy *et al.*, 2020; Iftene, 2009; Ojokoh, Adebisi, 2019; Prager *et al.*, 2000):

- question analysis,
- answer candidate retrieval,
- answer selection.

These phases are also evident in the QA system framework, which is divided into four modules (Pundge *et al.*, 2016): the question processing module, the document processing module, the passage extraction module, and the answer extraction module.

Large Language Models (LLMs) have recently come to dominate the field of natural language processing and question answering systems, leading to significant advancements and its use in business systems has expanded (Vukelic *et al.*, 2024). Unlike knowledge bases, which contain large amounts of data, LLMs demonstrate strong generalisation capabilities across a wide range of textual, tabular, general, and mathematical question answering tasks, often requiring only a few in-context examples (Li *et al.*, 2023).

Min *et al.* (2023) define three paradigms, used individually or in combination, by large pretrained language models (PLMs):

- pre-training followed by fine-tuning – general pre-training on large amounts of non-specific data, followed by task-specific fine-tuning,
- instruction learning – solving tasks by leveraging similarities to tasks encountered during pre-training,
- text generation – generating text based on knowledge encoded in a generative language model (e.g. GPT).

Studies involving models (Liu, 2024) of various sizes and across different formal languages show that LLMs' understanding of logical forms has approached human-level comprehension. However, there remains substantial room for improvement in generating correct logical forms. This suggests that LLMs may be more effective when used to generate additional natural language data as input for smaller models, rather than being used directly to answer questions. Furthermore, evaluation results indicate that LLMs exhibit varying sensitivity to different formal languages, favouring those with lower levels of formalisation (Liu, 2024).

More recently, Retrieval-Augmented Generation (RAG) has combined the generative capabilities of LLMs with external knowledge retrieval mechanisms. By grounding responses in retrieved documents or structured knowledge bases, RAG systems address key limitations of pure LLMs, such as hallucinations, outdated information, and the lack of verifiable sources (Klesel, Wittmann, 2025; Lewis *et al.*, 2020). This paradigm shift has prompted renewed interest in how structured knowledge representation methods like NOK compare with, and might complement, neural approaches. RAG emerged as a solution to the limitations of pure LLMs by integrating external knowledge retrieval with neural generation.

The Node of Knowledge (NOK) conceptual framework represents the former tradition, providing a formal method for transforming natural language sentences into graphical and textual representations stored in relational databases (Pavlic *et al.*, 2013). In contrast, Large Language Models (LLMs), such as ChatGPT, have revolutionised natural language understanding through large-scale neural networks trained on diverse text corpora, learning implicit representations of knowledge (Zhao *et al.*, 2023).

The NOK method represents a formal, structured approach to knowledge representation that transforms natural language into graphical and formalised records stored in relational databases implemented in Oracle. In contrast, LLMs and RAG systems use neural architectures and external knowledge retrieval to generate contextually relevant responses. NOK uses explicit, rule-based formalisation with semantic enrichment, while LLMs rely on implicit, distributed representations learned from large text corpora. RAG systems combine these approaches by augmenting LLMs with external knowledge retrieval.

3. RESEARCH MOTIVATION

Currently, the most well-known LLMs include GPT, developed by OpenAI, and Copilot, developed by Microsoft, which is based on GPT technology. As they can be considered QA systems, and the conceptual framework Node of Knowledge (NOK) can also be treated as a QA system, the aim of this paper is to compare these QA systems, specifically, two approaches to working with natural language and their respective methods, and to answer the research question posed. The research presented forms part of a broader study investigating whether the use of LLM models can improve the accuracy, reliability, and interpretability of the NOK system.

For this purpose, the free version of ChatGPT was used, as the NOK system is also free to use, and no additional settings were applied. This version is the most widely used among the student population at our institutions, for whom the NOK system is intended.

4. METHODOLOGY

The research question was formulated as follows: How does the Node of Knowledge (NOK) conceptual framework differ from Large Language Models (LLMs) in terms of knowledge representation?

The operation of both systems is described and compared in terms of the models and processes they use to execute queries, the data they rely on to answer questions, and the resulting outputs. The comparison focuses on the mode of operation, process models in the context of knowledge representation, and the identification of differences to demonstrate the usefulness of these systems in various application contexts.

Testing of the NOK method has so far been conducted on 100 simple sentences (Asenbrener Katic, 2017) and 100 complex sentences containing conjunctions (Rauker Koch, 2024). In this paper, a sentence from Rauker Koch (2024) is used as an illustrative example, and the answers generated by ChatGPT are analysed and compared with those obtained from the NOK system, as well as with the expected answers a human would provide. In addition to the answers themselves, their structure is also compared to identify similarities and differences between these systems based on the results.

5. RESULTS AND DISCUSSION

The following section presents the conceptual framework Node of Knowledge (NOK), large language models, and the results of the comparison.

5. 1 The conceptual framework Node of Knowledge (NOK)

The conceptual framework Node of Knowledge (NOK) was developed to prepare natural language sentences for storage in a relational database. Its aim is to represent textual knowledge as a knowledge network (Pavlic *et al.*, 2013). The formalisation of the NOK method is presented in (Jakupovic *et al.*, 2014; Pavlic *et al.*, 2015). This method analyses natural human language, sentences, words, and their meanings, as well as related word sequences that form more complex phrases (Asenbrener Katic *et al.*, 2015). The NOK method first transforms knowledge into a model and then searches for the knowledge contained in that model. It can then answer questions related to the stored knowledge (Tomljanovic *et al.*, 2014). The characteristics of the NOK method are (Jakupovic *et al.*, 2013):

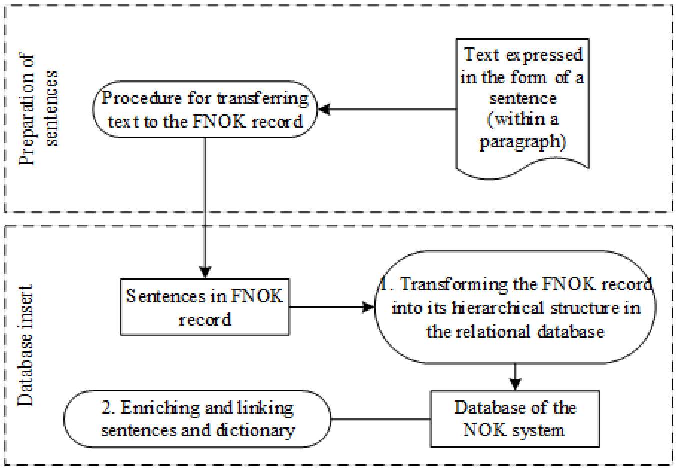
- simplicity,
- richness in representing various types of human knowledge,
- ability to automatically discover new knowledge from existing knowledge,
- ability to guide the entry of new knowledge, and
- possibility of easily creating user queries over the knowledge base.

Asenbrener Katic (2017) analysed approaches for writing textual knowledge into a relational database and presented data and process models describing the transformation system. Transformation rules for converting natural language sentences into FNOK notation have been defined for verbs (Asenbrener Katic *et al.*, 2018), nouns (Asenbrener Katic *et al.*, 2021), adjectives (Pavlic *et al.*, 2017), adverbs and prepositions (Asenbrener Katic *et al.*, 2022), most pronouns, numbers, as well as rules for transforming natural language questions into QFNOK notation for Croatian and English (Asenbrener Katic *et al.*, 2024). Algorithms for transforming FNOK notation into a relational database, QFNOK notation into a relational database, and for generating answers are also described (Asenbrener Katic, 2017).

For the automatic conversion of English sentences into the formalised NOK notation (FNOK), a Python application called PSA–FNOK has been developed, as described by Dovedan Han (2021), Jakupovic *et al.* (2014) and Pavlic *et al.* (2015), with its testing presented by Rauker Koch *et al.* (2022).

Figure 1 shows the process model of the system that enables the storage of natural language sentences in the database.

Figure 1. Process model of the transformation of text to database



Source: Candrlic (2019)

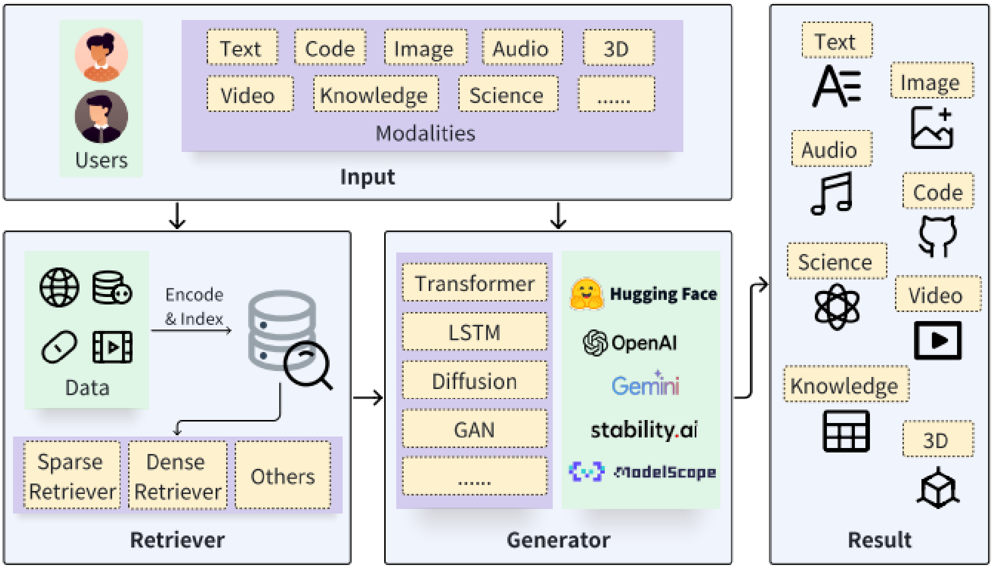
5. 2 Large language models (LLM)

Large language models used to answer queries search through huge amounts of knowledge, raising concerns about the accuracy of their generated answers. This limitation is often referred to as hallucination (Athaluri *et al.*, 2023; Lewis *et al.*, 2020; Romano *et al.*, 2024). A method for improving LLMs by incorporating information from external knowledge sources and increasing their factual accuracy is generally known as Retrieval-Augmented Generation (RAG) (Lewis *et al.*, 2020). RAG has been proposed as a solution to this and similar challenges, such as maintaining up-to-date knowledge and preventing the leakage of private data, through its adaptable data repository (Zhao *et al.*, 2026).

A typical RAG process (Figure 2) begins with an input query, after which the retriever locates and searches relevant data sources. The retrieved results then interact with the generator to improve the overall generation process (Zhao *et al.*, 2026).

Open-Domain Question Answering (ODQA) methods typically use a two-stage architecture, in which the retriever and the generator are trained separately, whereas RAG integrates these two components into a single architecture (Siriwardhana *et al.*, 2023). The use of RAG, which combines parametric and non-parametric memory, generally results in reduced hallucination and greater interpretability in tasks such as question answering and summarisation (Komeili *et al.*, 2022; Siriwardhana *et al.*, 2023).

Figure 2. Generic RAG architecture



Source: Zhao (2026)

The process model of GPT (Generative Pre-trained Transformer) features a complex architecture based on transformer networks. The key stages in this process are (Yenduri *et al.*, 2024):

1. Pre-training involves unsupervised learning on large volumes of text from diverse sources, without predefined task-specific objectives. Tokenisation divides text into tokens that may represent whole words or subword units. Token embedding transforms tokens into numerical vectors, allowing the model to process text as sequences of numerical values. Transformer blocks consist of multiple layers that use attention mechanisms to understand the context of each token in relation to all other tokens in the input.

2. Fine-tuning trains the model on smaller, task-specific datasets, such as those for question answering, translation, or text generation, which are directly related to the intended tasks.

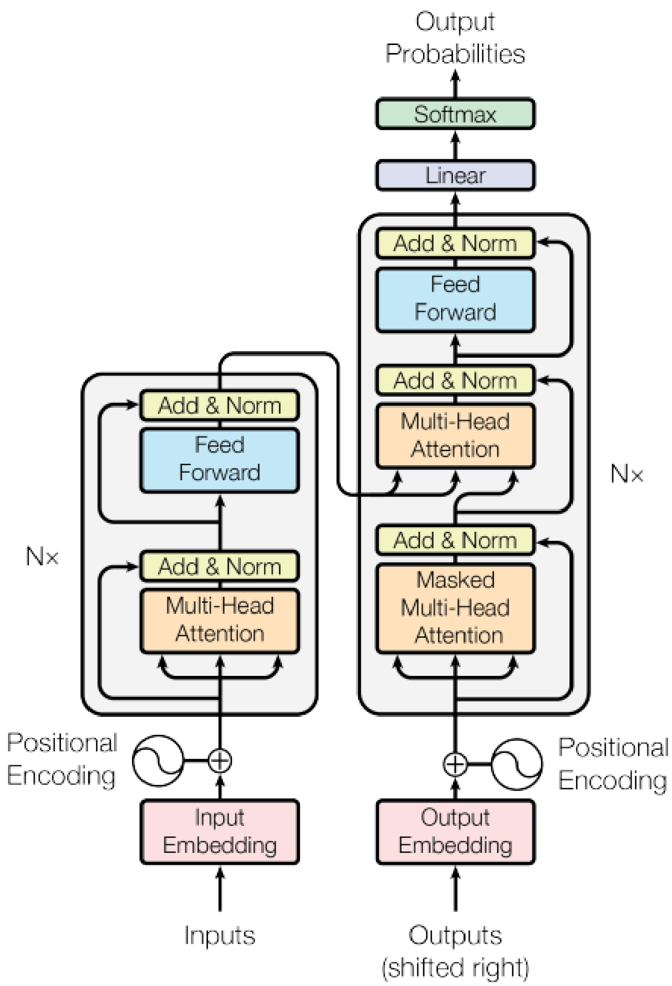
3. Text generation selects tokens based on probabilities learned during pre-training and fine-tuning. The model considers all preceding tokens in the sequence to predict the most probable next token.

4. Output presents the generated text to the user as the final product, whether as an answer to a question, part of a story, or any other form of text.

The GPT model uses deep learning and advanced algorithms to handle complex language generation tasks, making it one of the leading tools in artificial intelligence for natural language processing.

The transformer is the fundamental element underlying GPT's operation. Its architecture is shown in Figure 3 and consists of two components: an Encoder (left) and a Decoder (right) (Vaswani *et al.*, 2017).

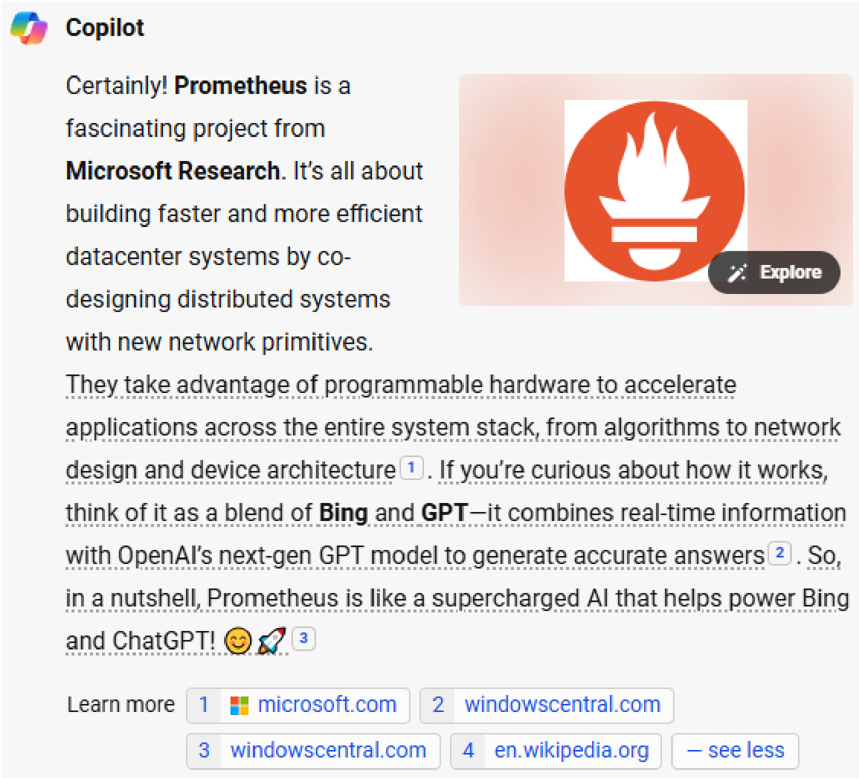
Figure 3. Model architecture of Transformer



Source: Vaswani (2017)

Microsoft's Copilot, a generative AI tool and large language model, is integrated into the Bing search engine and is available as a Microsoft 365 application. Copilot is built on OpenAI's language models, which are also used by ChatGPT, but is enhanced with Microsoft's proprietary Prometheus model (Reddy, Pratt, 2025; Santoso *et al.*, 2011). This enables it to search and reference online sources while generating responses to queries. Copilot can extract and summarise information it classifies as relevant, enriching its responses with contextually significant content sourced directly from the web (Romano *et al.*, 2024) (Figure 4).

Figure 4. Copilot's response to the query "What is Prometheus?" with references to sources included



Source: Authors

5. 3 Results of the comparison

A key innovation of the NOK framework is its integration with relational database technology. The FNOK formalism enables natural language sentences to be stored as structured records in relational databases, allowing SQL-based querying and reasoning (Candrlic *et al.*, 2019). This approach provides several advantages: persistent storage of knowledge and efficient retrieval using database query languages. The framework has been implemented in systems like QANOK (Question Answering NOK), which accepts natural language questions and retrieves answers from formalized knowledge bases.

Large Language Models (LLMs) represent a paradigm shift in natural language processing, utilising transformer architectures (Vaswani *et al.*, 2017) and training on large-scale text corpora to learn implicit representations of language and knowledge (Yenduri *et al.*, 2024). Models such as GPT-3 (Brown *et al.*, 2020), GPT-4, and their conversational variant ChatGPT have shown remarkable abilities in understanding context, generating coherent text, and performing a range of language tasks without task-specific training (Bahrini *et al.*, 2023). Unlike explicit knowledge representation systems, LLMs encode knowledge in distributed neural network parameters through self-supervised learning on billions of tokens (Brown *et al.*, 2020). ChatGPT and similar conversational LLMs have been widely adopted for question answering, content generation, and decision support across various domains (Bahrini *et al.*, 2023).

GPT, Copilot, and Node of Knowledge (NOK) are tools used for language processing and information understanding, but they differ significantly in their approaches and applications. This paper compares these tools based on their characteristics and operational principles, as described in previous sections. To evaluate the performance of GPT, and indirectly Copilot, which relies on it, their results were compared using a concrete example.

The difference between GPT and NOK is evident at the process model level. The GPT process model uses a complex architecture based on transformer networks and relies on deep learning and advanced algorithms to support sophisticated language generation tasks. During its processing and pre-training phases, GPT uses large amounts of text from diverse sources to generate responses. In contrast, the conceptual framework of the Node of Knowledge and the system built upon it are based on a relational database and the transformation of natural language into a formalised structure that can be stored within it. Question answering is performed using texts previously stored in the DBNOK relational database. The use of predefined, formalised text for query answering allows the NOK method to achieve higher accuracy in locating relevant information, whereas for large language models, reliance on vast heterogeneous datasets raises concerns about the accuracy of generated responses, particularly the occurrence of "hallucinations".

For the example, an illustrative sentence was randomly selected from the dataset described by Rauker Koch (2024) and tested. The selected sentence met the requirement of containing basic parts of speech (noun, verb, adjective, conjunction, etc.) used to form a complex sentence, over which NOK successfully enables querying. The aim was to demonstrate the equivalence or similarity of the answers produced by the two systems compared to those a human would provide. The presentation included questions that can be asked about the selected sentence and the corresponding answers generated by the NOK system. All answers were compared with those expected from a human.

The example used for illustration was the sentence: "*Marko is happy because he loves his job*." Table 1 presents the questions, the expected (human) answers, the answers produced by the NOK system, and the answers generated by ChatGPT. The results show that both systems return answers consistent with expectations. The answer to the third question provided by the NOK system is grammatically incorrect, but it is semantically understandable and acceptable to humans, given their ability to interpret meaning from context and the property of redundancy, which enables them to fill gaps during information transmission (Marcan, 2019; Zrinjanin, 2018). Future research on defining the syntactic components of sentences will enable more precise formulation of answers and word order in generated responses.

The main difference in the answers obtained is that the NOK system returns a single word or phrase, while GPT provides a complete sentence. This difference in answer format is expected, given the intended purposes of the QA systems being considered.

Table 1. Comparison of expected and obtained answers for the sentence "Marko is happy because he loves his job."

Question	Expected answer	NOK	ChatGPT
Who loves his job?	Marko	Marko	Marko loves his job.
What is Marko?	happy	happy	Marko is happy.
Why is Marko happy?	because he loves his job	because loves he his job	Because he loves his job.
Who is happy?	Marko	Marko	Marko is happy.

Source: Authors

As an additional element of comparison, the authors posed the following query to ChatGPT: "What are the similarities and differences between ChatGPT and the Node of Knowledge conceptual framework?" to examine the similarities and differences between the two systems (Figure 5). The answer generated by ChatGPT is consistent with the comparison results reached by the authors: these are two fundamentally different QA systems in terms of their construction, operating principles, and, most importantly, intended purpose.

Large language models, such as GPT and Copilot, rely on vast amounts of unstructured knowledge when answering questions, whereas the NOK conceptual framework is characterised by its structured nature. This makes the NOK method suitable for solving problems that require structured knowledge and a precisely selected set of information within which answers are to be found. When answers are searched within a finite, predefined knowledge set, the probability of generating an incorrect answer is minimised, whereas with LLMs there is always a possibility of inaccurate responses or "hallucinations".

Figure 5. Comparison between ChatGPT and the Node of Knowledge (NOK) method, generated by ChatGPT

Similarities

- **Knowledge organization:** Both ChatGPT and the *Node of Knowledge* (NoK) framework aim to structure information in a way that supports understanding.
- **Connections between concepts:** Each system highlights relationships—ChatGPT through patterns learned from data, NoK through explicit conceptual links.
- **Support for reasoning and insight:** Both help users navigate complex topics by revealing how ideas relate to one another.

Differences

- **Type of system:** ChatGPT is an AI language model; NoK is a human-designed conceptual framework for mapping knowledge.
- **How they work:** ChatGPT uses probabilistic neural-network processing, while NoK uses explicit nodes and edges defined by humans.
- **Adaptability:** ChatGPT dynamically adapts to user input and generates new associations in real time; NoK is static unless manually updated.
- **Purpose:** ChatGPT focuses on conversation, explanation, and content generation. NoK focuses on organizing and visualizing knowledge for analysis or learning.

Conclusion

ChatGPT and the Node of Knowledge both deal with how information is structured and connected, but they operate in fundamentally different ways. ChatGPT is a flexible, generative AI system that responds dynamically, whereas NoK is a stable conceptual framework designed to clarify and map knowledge. Together, they represent two complementary perspe[illegible]es on understanding and using information: one data-driven and adaptive, the other structured and conceptual.

Source: Authors using ChatGPT

6. CONCLUSIONS

Today, artificial intelligence, particularly question answering systems, is widely used in everyday applications. Most of these systems are large language models (LLMs) designed for broad, general-purpose use. The system based on the Node of Knowledge (NOK) conceptual framework is also a question answering system, but it is tailored to a specific purpose. While large language models rely on vast amounts of unstructured knowledge to search for answers, the NOK system uses concrete, selected knowledge (predefined text) stored in the relational DBNOK database and queried directly. This makes the NOK system suitable for educational applications, where questions are posed and answers are sought within a finite and clearly defined body of knowledge, such as in testing scenarios.

In this paper, ChatGPT and, indirectly, Copilot, which is based on it, were compared with the conceptual framework NOK. Their process models were examined and found to share no similarities: GPT is based on a transformer architecture and processes large quantities of unstructured knowledge, while the NOK system relies on a relational database containing structured, formalised knowledge. The example-based presentation also showed that an LLM generates textual answers in full sentences, while the NOK system provides short, precise answers.

Since both the Node of Knowledge (NOK) conceptual framework and ChatGPT can be treated as QA systems, the aim was to examine and compare them in more detail, regardless of their different underlying technologies, primarily to demonstrate their differences. The most important characteristic of the NOK conceptual framework is that, as it is based on a finite, controlled, and well-defined dataset, it has minimal possibility of hallucinations. From this, we may conclude that the comparison confirms the appropriateness of using these models within the domains for which they are designed.

This review identifies complementary strengths: NOK's transparent, verifiable knowledge representation versus RAG-LLM's flexibility and broad coverage, indicating the potential for hybrid architectures that combine structured knowledge graphs with neural generation capabilities.

In the future, we plan to enhance the NOK system by integrating LLM models to improve its accuracy, reliability, and interpretability.

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USPOREDBA KONCEPTUALNOG OKVIRA *NODE OF KNOWLEDGE* (NOK) S VELIKIM JEZIČNIM MODELIMA

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SAŽETAK

Sustav temeljen na konceptualnom okviru Node of Knowledge *(NOK) omogućuje zapisivanje rečenica i pitanja prirodnog jezika u relacijsku bazu podataka NOK-a i u njoj traženje odgovora na pitanja. Veliki jezični modeli (engl.* Large Language Models *(LLM)) izrađeni su s istom namjenom, odnosno s ciljem davanja odgovora na pitanja. Postaje neizbježno pitanje usporedbe velikih jezičnih modela sa sustavom izrađenim korištenjem konceptualnog okvira* Node of Knowledge*. U ovom radu traži se odgovor na to pitanje kroz usporedbu ovih dvaju sustava. Od velikih jezičnih modela za usporedbu je odabran GPT, kao jedan od najčešće korištenih modela. Usporedba je provedena u dva dijela. U prvom dijelu, uspoređivani su modeli procesa ovih sustava. U drugom dijelu, napravljena je analiza dobivenih odgovora za odabranu rečenicu i pitanja prirodnog jezika koje su dali sustav temeljen na konceptualnom okviru NOK i ChatGPT kao predstavnik velikih jezičnih modela. Svi elementi usporedbe rezultirali su sličnostima i razlikama između ovih sustava što je pokazano u ovom radu.*

Ključne riječi: Node of Knowledge *(NOK), predstavljanje znanja,* Question Answering *(QA), veliki jezični modeli (LLM), GPT*