DOI https://doi.org/10.15407/csc.2023.03.054
UDC 004.912

D.D. DVOICHENKOV, PhD Student, Computer Science, International Research and Training Centre for Information Technologies and Systems of the NAS and MES of Ukraine,
ORCID: https://orcid.org/0009-0007-1935-6743,
Acad. Glushkov ave., 40, Kyiv, 03187, Ukraine,
supersokol777@gmail.com

KNOWLEDGE GRAPHS AND LARGE LANGUAGE MODELS

Large Language Models based on the Transformer architecture is nowadays one of the most widely used tools in the Natural Language Processing field. Nonetheless, this approach has some limitations and flaws. In particular, these problems become crucial for NLP-based expert systems. The LLMs may sometimes hallucinate and provide non-trustworthy responses. We will advocate the use of Knowledge Graphs for solving this problem.

Keywords: *Knowledge Graphs, Large Language Models, Expert Systems, Natural Language Processing.*

Introduction

During last several years,Large Language Models (LLMs) come to all aspects of modern life. We use them every day they are embedded in modern ope-rational systems not only on computers but even on smartphones.However the problem immediately arises. Can we really trust computer's advices, when we are making our decisions? For example, will you unconditionally trust your's computer advices concerning your own health? In this paper we discuss some details of LLMs, their vulnerabilities and discuss, how to use them in a safe way.

Transformer architecture was recently introduced in the original paper [1]. Based on this approach many different so called LLMs have emerged. These state-of-the-art models have revolutionized various Natural Language Processing (NLP) tasks: text generation [2], sentiment analysis [3], machine translation [4-6], coding [7] and solving various mathematical tasks [8]. LLMs tend to show outstanding language processing capabili-ties. However, they have some specific limitations and vulnerabilities [2, 9-11].

In the present paper we consider a relationship between LLMs and Knowledge Graphs (KGs) [15]. Our aim is to advocate KGs usage to overcome the above mentioned problems. This is especially important. when LLMs are employed in NLP-based expert systems [12].

One of the biggest problems is that LLMs may occasionally hallucinate responses, generating outputs, that are not always reliable or trustworthy [9-12].

Such issues can be fatal in domains, where NLP-based systems are employed to make critical decisions or assist human experts in Medical NLP-based systems [12].

KGs offer a well-organized repository of information, enabling models to ground their responses in factual data and logical relationships [15].

By combining the expressive power of LLMs with the knowledge structure of graphs, we can mitigate some shortcomings of LLMs. This approach can provide more reliable and contextually grounded responses [13, 4].

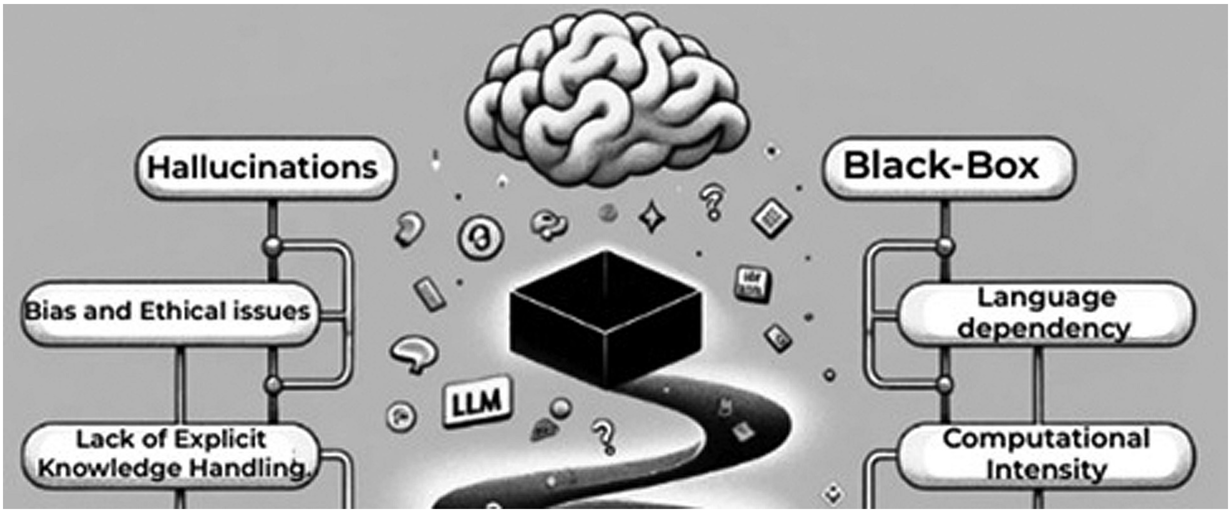

Fig. 1. LLM Flaws

Throughout this paper we explore the basic concepts of both LLMs and KGs. We advocate the usage of KGs to overcome LLMs flaws.

The paper is organized as follows.

Belov I will discuss the problems of LLM development and their vulnerability, and also consider a connection between the KGs and LLM.

Large Language Models and their Vulnerabilities

The Transformer novel architecture revolutionized NLP by the power of self-attention mechanisms enabling the models to capture contextual information effectively. LLMs lead to successful results in various NLP tasks. These models are able to generate human-like responses. They can process and generate text in tasks like text summarization, question-answering, sentiment analysis, etc. These models were pre-trained using massive amounts of human-written texts from the Internet. They include in specific way understanding of grammar, semantics, and world knowledge [1, 10 -11].

Vulnerabilities of LLMs.

While the advantages of LLMs are undeniable, they are not immune to limitations and flaws [11] (see Fig. 1). These weaknesses are crucial in LLM-based real life applications:

1. *Hallucinations*. One of the most significant problems of LLMs is hallucinat responses. Hallucinations mean that model responses may not match original requests [11]. We can define two types of hallucinations (see Fig. 2). The first one is intrinsic hallucinations, i.e., a contradiction between input and output. The second type of hallucinations is extrinsic hallucinations, i.e., an incorrect understanding of the input. These non-trustworthy responses make the model unreliable in some important applications, especially when NLP-based system must make decisions concerning human health or life [9—11, 14]. For example, in [12] the authors demonstrate how novel models behaviour can be compromised by adversarial prompting. Thus LLMs clearly able to produce untrustworthy responses in some situations, and that is clearly undesirable.

2. *Bias and Ethical issues*. LLMs are trained on huge amounts of texts from the Internet. These texts include all types of biases, and LLM learns biases that present in the training data. This raises ethical and fairness issues. Biased responses from the LLMs can reinforce stereotypes and discrimination [10 —12].

3. *Lack of Explicit Knowledge Handling*. LLMs have no mechanisms to handle structured knowledge or verify facts. They often generate responses without grounding them in factual information. This leads to misinformation and inaccuracies [10, 11, 14].

4. *Black-Box*. The LLMs are the so called Black-Box models. It means they represent their knowledge implicitly in their parameters. There are a huge amount of intrinsic parameters (approximately 10^9-10^{11}).

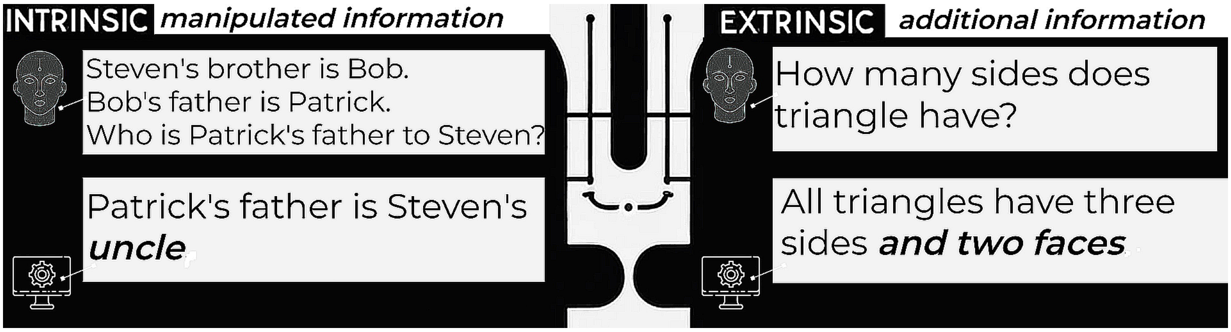

Fig. 2. Two types of LLM hallucinations

Therefore, human being is physically unable to treat these parameters [10 ,11, 14].

5. *Language dependency*. The data in the Internet sometimes have contradictory meaning within the different languages. This evidently leads to mistakes in the output [11] (see Fig. 3).

As we can see on figure responses of LLM are different for English and Ukrainian language requests. Moreover we can see that LLM (here chatGPT 3.5 was used) poorly understands Ukrainian grammar and has made couple of mistakes.

6. *Computational Intensity and Resource Requirements.* The big size and computational demands of LLMs lead to practical challenges. Training and fine-tuning of these models require substantial computational resources. This limits LLMs' applications for small organizations and individual researchers [10, 11].

Implications for NLP-Based Expert Systems.

The vulnerabilities and limitations of LLMs become especially critical when these models are integrated into NLP-based expert systems. Expert systems are designed to provide reliable and informative responses. A presence of hallucinations, biases, and inaccuracies are unacceptable in this case. Hence, addressing these issues is imperative to ensure responsible deployment of these NLP-based expert systems.

In the next section, we explore how KGs can serve as an effective solution to reduce these vulnerabilities in LLMs. By combining the strengths of LLMs with the structured and semantically rich representation of KGs, it is possible to enhance the reliability and trustworthiness of the NLP-based solutions, particularly in the expert systems domain.

KGs and Their Synergy with LLMs

In this section we consider KGs and evaluate their synergy with LLMs. We demonstrate that this rectifies the inherent shortcomings of LLMs when applied to NLP scenarios.

KGs are structured compilations of knowledge that encapsulate facts, entities, and the intricate relationships between them in a graphical format. Each node in this graph denotes a specific entity, while the edges carve out the relationships or connections between these entities. By offering a concrete representation of information, KGs stand in contrast to the unstructured and vast data LLMs typically navigate [15]. One of the distinctive features of KGs is their ability to provide structured and contextually rich information. Unlike unstructured text data, KGs offer a structured framework that models real-world interconnections between distinct entities. This structure is good for precise and reliable knowledge representation, making it an ideal complement to the sometimes ambiguous and ungrounded responses generated by LLMs. Fusion of LLMs with KGs holds significant promise for improving the reliability of NLP-based systems. By incorporating KGs into the decision-making process, LLMs can tap into a curated and validated source of knowledge, reducing the likelihood of generating hallucinated or factually incorrect responses [13, 14]. KGs offer means to contextually ground responses generated by LLMs (see

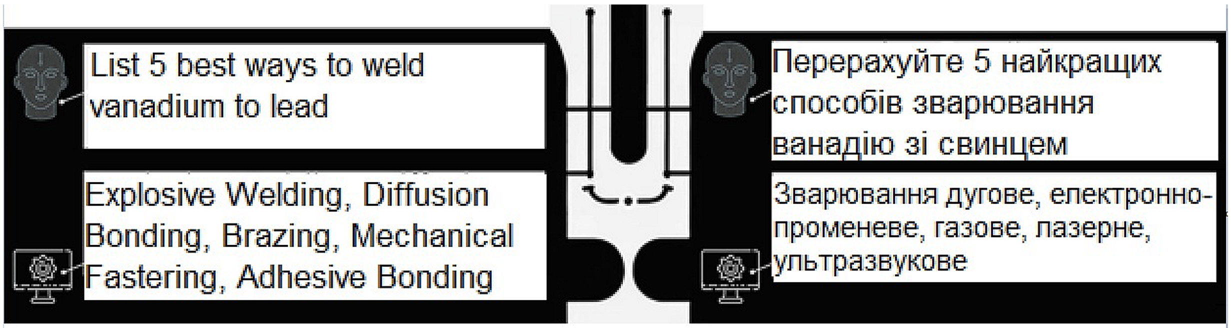

Fig. 3. Language dependency

Fig. 4). When faced with a query or task, LLM can consult KG to cross-check facts and verify relationships, ensuring that their responses align with established knowledge. This fact-checking capability is invaluable in scenarios where accuracy and trustworthiness are paramount, such as medical or legal NLP applications [12]. Furthermore, structured metadata in KGs can highlight the origin, quality, and reliability of the information they contain. This transparency can be leveraged to make LLMs' decisions more explainable and justifiable, addressing the black-box nature of these models to some extent.

Enhancing Knowledge Handling Capabilities of LLMs:

KGs provide an organized and easily accessible source of explicit knowledge. By interfacing LLMs with KGs, these models can access factual information without relying solely on their internal parameters, thus improving their ability to produce informed responses. This also overcomes the limitation of LLMs regarding lack of explicit knowledge handling, as the structured nature of KGs ensures that the provided information is both accurate and contextually relevant [13].

Addressing Language Dependency:

The multilingual nature of some KGs can help address the language dependency issue of LLMs. By referencing KGs, LLMs can cross-verify information across different languages, ensuring that the generated responses are coherent and culturally appropriate. Moreover, KGs can serve as a bridge to understand context and semantics across languages, aiding LLMs in delivering accurate translations or responses in multilingual scenarios.

Mitigating Bias and Promoting Fairness:

KGs can also play a role in addressing bias and promoting fairness in NLP systems. By curating the KGs with diverse and representative data sources, we can reduce the risk of perpetuating biases present in training data. Additionally, KGs can provide guidance to LLMs in generating unbiased and contextually appropriate responses.

Efficient Computation and Resource Utilization:

While LLMs are computationally intensive, KGs, by their structured nature, can simplify certain computational tasks. For example, a direct lookup in a KG can provide quick answers to fact-based queries, reducing the need for LLM to engage in extensive computations. This synergy can lead to more efficient resource utilization, making it feasible for smaller organizations or researchers with limited computational resources to deploy powerful NLP solutions.

Strengthening LLMs in Expert Systems:

In domains such as medical diagnosis or legal advisories, the integration of LLMs with KGs ensures a two-fold verification system. LLM can generate a response based on its vast training data, while KG can serve as a fact-checking layer to validate the response. This ensures that the information provided is both contextually grounded and factually accurate, enhancing the trustworthiness and reliability of the expert system.

Beyond Textual Knowledge:

KGs are not limited to textual information. They can represent a wide range of data types, including images, audio, and structured data. This versatility enables LLMs to leverage KGs for a more compre-

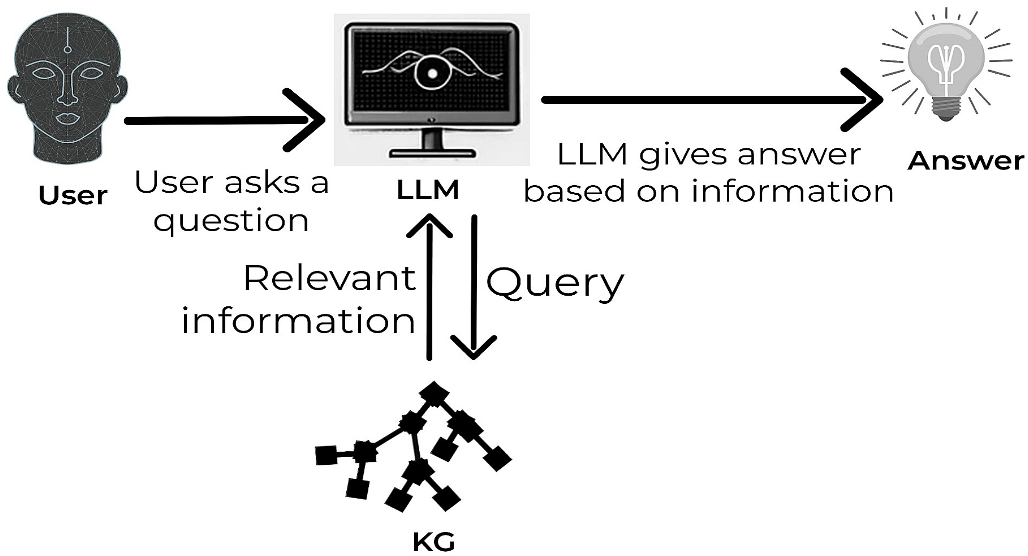

Fig. 4. Grounding LLM with KG

hensive understanding of the world, making them suitable for multimodal NLP tasks

Future Directions and Challenges:
While the integration of LLMs with KGs offers many advantages, it is not without challenges. One key issue is ensuring the seamless interplay between the LLM and KG. Strategies must be developed to efficiently query KG during LLM's decision-making process. Moreover, as KGs evolve and expand, mechanisms to update and synchronize the knowledge with LLM are crucial. Ensuring KGs' quality and comprehensiveness is another challenge, as outdated or incomplete graphs can compromise LLM's effectiveness.

Summary and Conclusions

This paper provides a detailed examination of the synergetic relationship between LLMs and KGs. It is shown that the usage of KGs can overcome the inherent limitations of LLMs and enhance their performance in NLP tasks. We establish an impact of the Transformer architecture on various NLP tasks. LLMs have great capabilities of natural language understanding. However they also have some vulnerabilities such as hallucinations, biases, black-box nature, language dependency, and high resource requirements. These limitations become particularly problematic in NLP-based expert systems, where the accuracy and reliability of information are crucial. We then introduce KGs as a structured form of knowledge representation. This is considered as a potential way for a suppression of the above mentioned vulnerabilities. We try to demonstrate that KGs can aid LLMs in producing more reliable, factual, and contextually grounded responses. With the help of KGs, LLMs can reference a verified knowledge base, reducing the risks of hallucinations and inaccuracies. This is mostly important for enhancing the trustworthiness of outputs in sensitive applications such as medical and legal advisory systems. We further discuss that KGs can address the challenge of the language dependency in LLMs by providing a cross-linguistic reference. A role of KGs in reducing biases and promoting fairness is also highlighted. We suggest that the nature of KGs can lead to better computational resource management. The combination of LLMs and KGs is especially good for the expert system needs. Moreover, KGs' ability to store various data types opens the way for some more advanced multimodal NLP tasks, expanding the horizon for LLMs applications.

In conclusion, while an integration of LLMs with KGs is promising, it is not an easy task to create and maintain such combined systems. We firmly advocate for a combination of LLMs and KGs as a pathway to more robust, accurate, and fair NLP solutions. In my future research I plan to develop novel strategies for the better and more robust KG generation from text.

Acknowledgments. I am thankful to Profs. Olexander Marchenko for the scientific leadership and Mark Gorenstein for helpful advice.

REFERENCES

1. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, L. Polosukhin, I. (2017). Attention is all you need. Advances in neural information processing systems, 30. https://doi.org/10.48550/arXiv.1706.03762.
2. Chung, J.J.Y., Kamar, E., Amershi, S. (2023). Increasing Diversity While Maintaining Accuracy: Text Data Generation with Large Language Models and Human Interventions. In Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics , Vol. 1: Long Papers, pp. 575–593, Toronto, Canada. https://doi.org/10.18653/v1/2023.acl-long.34.
3. Zhang, W., Deng, Y., Liu, B., Pan, S. J., & Bing, L. (2023). Sentiment Analysis in the Era of Large Language Models: A Reality Check. https://doi.org/10.48550/arXiv.2305.15005.
4. Moslem, Y., Haque, R., Way, A. (2023). Adaptive machine translation with large language models. https://doi.org/10.48550/arXiv.2301.13294.
5. Yao, B., Jiang, M., Yang, D., & Hu, J. (2023). Empowering LLM-based Machine Translation with Cultural Awareness. https://doi.org/10.48550/arXiv.2305.14328.
6. Zhu, W., Liu, H., Dong, Q., Xu, J., Huang, S., Kong, L., Chen, J., Li, L. (2023). Multilingual machine translation with large language models: Empirical results and analysis. https://doi.org/10.48550/arXiv.2304.04675.
7. Wu, Y., Jia, F., Zhang, S., Li, H., Zhu, E., Wang, Y., Lee Y.T., Peng R., Wu, Q., Wang, C. (2023). An Empirical Study on Challenging Math Problem Solving with GPT-4. https://doi.org/10.48550/arXiv.2306.01337.
8. Poldrack, R. A., Lu, T., & Begu , G. (2023). AI-assisted coding: Experiments with GPT-4. https://doi.org/10.48550/arXiv.2304.13187.
9. Maus, N., Chao, P., Wong, E., & Gardner, J. R. (2023, August). Black box adversarial prompting for foundation models. In The Second Workshop on New Frontiers in Adversarial Machine Learning. [online]. Available at: <https://openreview.net/forum?id=aI5QPjTRbS > [Accessed: 23 Sept. 2023].
10. Zhao, W. X., Zhou, K., Li, J., Tang, T., Wang, X., Hou, Y., Min, Y., Zhang, B., Zhang, J., Dong, Z., Du, Y., Yang, Ch., Chen, Y., Chen, Zh., Jiang, J., Ren, R., Li, Y., Tang, X., Liu, Z., Liu, P., Nie, J.-Y., Wen, J.R. (2023). A survey of large language models. https://doi.org/10.48550/arXiv.2303.18223.
11. Kaddour, J., Harris, J., Mozes, M., Bradley, H., Raileanu, R., McHardy, R. (2023). Challenges and applications of large language models. arXiv preprint arXiv:2307.10169. https://doi.org/10.48550/arXiv.2307.10169.
12. Singhal, K., Tu, T., Gottweis, J., Sayres, R., Wulczyn, E., Hou, L., Clark, K., Pfohl, S., Cole-Lewis, H., Neal, D., Schaekermann, M., Wang, A., Amin, M., Lachgar, S., Mansfield, Ph., Prakash, S., Green, B., Dominowska, E., Arcas, B.A., Tomasev, N., Liu, Y., Semturs, Ch., Mahdavi, S.S., Barral, J., Webster, D., Corrado, G.S., Matias, Y., Azizi, Sh., Karthikesalingam, A., Natarajan, V. (2023). Towards expert-level medical question answering with large language models. https://doi.org/10.48550/arXiv.2305.09617.
13. Choudhary, N., Reddy, C. K. (2023). Complex Logical Reasoning over Knowledge Graphs using Large Language Models. https://doi.org/10.48550/arXiv.2305.01157.
14. Pan, S., Luo, L., Wang, Y., Chen, C., Wang, J., & Wu, X. (2023). Unifying Large Language Models and Knowledge Graphs: A Roadmap. https://doi.org/10.48550/arXiv.2306.08302.
15. Hogan, A., Blomqvist, E., Cochez, M., d'Amato, C., Melo, G. D., Gutierrez, C., Gayo, J.E.L., Kirrane, S., Neumaier, S., Neumaier, A., Navigli, R., Schmelzeisen, L., Sequeda, J., Staab, S., Zimmermann, A. (2021). Knowledge graphs. ACM Computing Surveys (Csur), 54(4), pp. 1-37. https://doi.org/10.1145/3447772.

Received 30.10.2023

Д.Д. Двойченков, аспірант, Міжнародний науково-навчальний центр
інформаційних технологій і систем НАН та МОН України,
ORCID: https://orcid.org/0009-0007-1935-6743,
03187, м. Київ, просп. Академіка Глушкова, 40, Україна.
supersokol777@gmail.com

ГРАФИ ЗНАНЬ ТА ВЕЛИКІ МОВНІ МОДЕЛІ

Вступ. Великі мовні моделі (*Large Language Models - LLM*), засновані на архітектурі Transformer, на сьогодні є одними з найширше використовуваних інструментів у галузі обробки природної мови (*Natural Language Processing - NLP*). Проте цей підхід має певні обмеження та недоліки. Зокрема, ці проблеми стають критичними для експертних систем, заснованих на *NLP*. *LLM* іноді можуть генерувати помилкові та ненадійні відповіді. У роботі ми обгрунтовуємо використання структурованих графів знань *KG* для розв'язання цієї проблеми.

Мета. Основна мета статті - дослідити взаємозв'язок між *LLM* та структурованими графами знань *KG*, а також показати, як графи знань можуть допомогти розв'язати проблеми, пов'язані з *LLM*, зокрема у експертних системах. Ми аргументуємо, що поєднання експресивної сили *LLM* зі структурою знань графів *KG* може забезпечити надійніші та контекстуально точніші відповіді.

Методи. Розглянуто інструментарій побудови графів знань та великих мовних моделей.

Результати. Детально розглянуто синергетичний зв'язок між великими мовними моделями *LLM* та графами знань *KGs*. Показано, що використання *KG* може подолати властиві обмеження *LLM* та підвищити їхню продуктивність у задачах обробки природної мови. Встановлено вплив архітектури Transformer на різні завдання *NLP*. *LLM* мають великі можливості розуміння природної мови. Однак вони також мають деякі вразливі місця, такі, як галюцинації, упередження, природа чорної скриньки, залежність від мови та високі вимоги до ресурсів. Ці обмеження стають особливо проблематичними в експертних системах на основі *NLP*, де точність і надійність інформації мають вирішальне значення.

Висновки. Внаслідок здійсненого дослідження зроблено висновок, що запропонована інтеграція *LLM* із *KG* може призводити до більш надійніших, точніших і справедливіших рішень *NLP*, але створити та підтримувати такі комбіновані системи досить нелегко. У майбутніх дослідженнях планується розробити нові стратегії для кращого та надійнішого створення *KG*-текстів.

Ключові слова: *графи знань, великі мовні моделі, експертні системи, обробка природної мови.*