across four separate datasets and a combined dataset. Specifically, the Mean Reciprocal Rank (MRR) values for individual datasets were 0.7087 for BAB 1, 0.7255 for BAB 2, 0.8592 for BAB 3, and 0.8250 for BAB 4, with HITS@10 values of 0.9398, 0.9274, 0.9982, and 1.0 respectively. The combined dataset achieved an MRR of 0.7695 and HITS@10 of 0.9570, indicating strong performance in prioritizing and retrieving relevant information. These results highlight the potential of ChatGPT LLMs to transform unstructured text into dynamic, interactive knowledge representations, significantly enhancing the accessibility and utility of educational content. Future work should focus on optimizing the extraction process and expanding the dataset scope to further validate and improve this approach, thereby enriching educational resources and supporting data-driven decision-making in various domains.

ACKNOWLEDGMENT

We would like to express our gratitude to all the researchers and practitioners in the fields of natural language processing, knowledge graph construction, and machine learning for their contributions and shared knowledge, which have been essential foundations for this study. Our thanks also go to the pioneers in the use of ChatGPT and other large language models, whose innovations have paved the way for progress in this field. Additionally, we extend our appreciation to Neo4j and all the contributors to the tools and datasets that have provided crucial resources that have significantly advanced our research. We also deeply appreciate the moral support from our colleagues, who have provided encouragement, motivation, and understanding throughout the research process. Your presence and support have been a driving force in overcoming the challenges we encountered.

REFERENCES

- [1] Y. Zhu, X. Wang, J. Chen, S. Qiao, Y. Ou, Y. Yao, and N. Zhang, "Llms for knowledge graph construction and reasoning: Recent capabilities and future opportunities," *arXiv preprint arXiv:2305.13168*, 2023.
- [2] Z. Bi, J. Chen, Y. Jiang, F. Xiong, W. Guo, H. Chen, and N. Zhang, "Codekge: Code language model for generative knowledge graph construction," ACM Transactions on Asian and Low-Resource Language Information Processing, vol. 23, no. 3, pp. 1–16, 2024.
- [3] X. Ma, "Knowledge graph construction and application in geosciences: A review," *Computers & Geosciences*, vol. 161, p. 105082, 2022.
- [4] S. Alaswad, T. Kalganova, and W. S. Awad, "Using chatgpt and other llms in professional environments," 2023.
- [5] H. Shatnawi and J. Saquer, "Encoding feature models in neo4j graph database," in *Proceedings of the 2024 ACM Southeast Conference*, 2024, pp. 157–166.
- [6] M. Rizun, "Knowledge graph application in education: A literature review," *Acta Universitatis Lodziensis. Folia Oeconomica*, vol. 3, no. 342, pp. 7–19, 2019.
- [7] P. Chen, Y. Lu, V. W. Zheng, X. Chen, and B. Yang, "Knowedu: A system to construct knowledge graph for education," *IEEE Access*, vol. 6, pp. 31 553–31 563, 2018.
- [8] R. Omar, O. Mangukiya, P. Kalnis, and E. Mansour, "Chatgpt versus traditional question answering for knowledge graphs: Current status and future directions towards knowledge graph chatbots," arXiv preprint arXiv:2302.06466, 2023.
- [9] X. Q. Dao, N. B. Le, B. B. Ngo, and X. D. Phan, "Llms' capabilities at the high school level in chemistry: Cases of chatgpt and microsoft bing ai chat," 2023.
- [10] J. Zhang, "Graph-toolformer: To empower llms with graph reasoning ability via prompt augmented by chatgpt," arXiv preprint arXiv:2304.11116, 2023

- [11] H. Paulheim, "Knowledge graph refinement: A survey of approaches and evaluation methods," *Semantic Web*, vol. 8, no. 3, pp. 489–508, 2017.
- [12] X. Zou, "A survey on application of knowledge graph," in *Journal of Physics: Conference Series*, vol. 1487, no. 1. IOP Publishing, 2020, p. 012016.
- [13] M. Kejriwal, "Knowledge graphs: A practical review of the research landscape," *Information*, vol. 13, no. 4, p. 161, 2022.
- [14] K. R. S. Wiharja, D. T. Murdiansyah, M. Z. Romdlony, T. Ramdhani, and M. R. Gandidi, "A questions answering system on hadith knowledge graph," *Journal of ICT Research & Applications*, vol. 16, no. 2, 2022.
- [15] C. T. Hoyt, M. Berrendorf, M. Galkin, V. Tresp, and B. M. Gyori, "A unified framework for rank-based evaluation metrics for link prediction in knowledge graphs," arXiv preprint arXiv:2203.07544, 2022.
- [16] Y. Wang, C. Zhang, and K. Li, "A review on method entities in the academic literature: Extraction, evaluation, and application," *Scientometrics*, vol. 127, no. 5, pp. 2479–2520, 2022.
- [17] Y. Lu, Q. Liu, D. Dai, X. Xiao, H. Lin, X. Han, and H. Wu, "Unified structure generation for universal information extraction," arXiv preprint arXiv:2203.12277, 2022.
- [18] P. Fergus and C. Chalmers, "Performance evaluation metrics," in Applied Deep Learning. Computational Intelligence Methods and Applications. Springer, Cham, 2022.
- [19] X. Lu, J. Wu, and J. Yuan, "Optimizing reciprocal rank with bayesian average for improved next item recommendation," in *Proceedings of the* 46th International ACM SIGIR Conference on Research and Development in Information Retrieval, July 2023, pp. 2236–2240.
- [20] W. Cai, W. Ma, L. Wei, and Y. Jiang, "Semi-supervised entity alignment via relation-based adaptive neighborhood matching," *IEEE Transactions* on Knowledge and Data Engineering, 2022.
- [21] M. Saad, Y. Zhang, J. Tian, and J. Jia, "A graph database for life cycle inventory using neo4j," *Journal of Cleaner Production*, vol. 393, p. 136344, 2023.