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.

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