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Kechen Qu, Kam Cheong Li, Billy Tak-Ming Wong, Maggie Liu, Venus Chan, Lap-Kei Lee

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Kechen Qu

The Open University of China, Beijing, 100039, China Email: qukch@ouchn.edu.cn

Kam Cheong Li, Billy Tak-Ming Wong*, Maggie Liu, Venus Chan and Lap-Kei Lee

Hong Kong Metropolitan University, Homantin, Hong Kong, China Email: kcli@hkmu.edu.hk Email: tamiwong@hkmu.edu.hk Email: mjliu@hkmu.edu.hk Email: vwmchan@hkmu.edu.hk Email: lklee@hkmu.edu.hk *Corresponding author

Abstract: This paper presents a knowledge graph-based learning approach, featuring knowledge graphs for concept visualisation and information retrieval. It illustrates the development of a learning system which incorporates a competency-based knowledge graph covering the dimensions of knowledge, skill, and ability. The system was evaluated for a learning task on English academic reading. A total of 96 undergraduate students were invited to complete the learning task, half of which were allocated to the experimental group. This group used the knowledge graph-based approach for learning. The other half served as the control group, who learned with contents organised in a conventional manner. The evaluation results revealed that the experimental group performed significantly better than the control group. The students who learned with the knowledge graph-based approach provided positive feedback on their learning experience, and suggested desired features such as personalised learning, data tracking and analysis, and structured learning contents.

Keywords: knowledge graph; ontology; competency-based education; CBE; learning performance; learning experience.

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Biographical notes: Kechen Qu is an Assistant Research Fellow at Credit Bank of The Open University of China. His main research areas include educational digitalisation, computer applications, credit bank, and qualification frameworks. He led the project 'Research on personalised recommendation

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mechanism of digital learning resources based on knowledge graph' of The Open University of China. He was also a Croucher Foundation Visiting Scholar at Hong Kong Metropolitan University.

Kam Cheong Li is the Dean of the School of Open Learning and Director of the Institute for Research in Open and Innovative Education at Hong Kong Metropolitan University. He has devoted to higher education and teaching development for 30 years. He has also been appointed Visiting Professor of Middlesex University in the UK, and a number of institutions in China, such as Hebei Academy of Social Sciences and Hebei University of Economics and Business. His research interests lie in technology in education, pedagogical approaches, and educational innovation.

Billy Tak-Ming Wong is the Deputy Director of the Institute for Research in Open and Innovative Education and a senior research coordinator at Hong Kong Metropolitan University. He has been involved in various research projects related to technology-enhanced education. His research areas include mobile learning, computer-enhanced learning and learning analytics.

Maggie Liu is a Research Associate at Hong Kong Metropolitan University. Her research interests lie in the areas of internationalisation of higher education and ICT-supported teaching and learning.

Venus Chan is an Assistant Professor at the Department of Humanities, Language and Translation of Hong Kong Metropolitan University. She is a Chartered Linguist at the Chartered Institute of Linguistics and the Secretary of the Association of Translation Technology. Her main research interests include education technologies, translation technology, technology-enhanced language learning, mobile and blended learning, and interpreter and translator training. She has led a number of research projects, and served as a journal reviewer, academic advisor, and external examiner.

Lap-Kei Lee is an Assistant Professor at the School of Science and Technology of Hong Kong Metropolitan University. He received his Bachelor of Engineering in Computer Engineering and Doctor of Philosophy in Computer Science from the University of Hong Kong. His research interests include the design and analysis of algorithms especially in online job scheduling and data stream algorithms, natural language processing, algorithm engineering, and educational technology.

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1 Introduction

As an emerging tool for knowledge representation, knowledge graphs have been increasingly applied in various areas in response to the surge of information. A knowledge graph refers to a network that connects different pieces of information based on semantic relationships, thereby facilitating efficient and effective information retrieval. It is usually represented in the form of nodes, which represent entities such as people, places and things, and edges which show the relationships between the entities (Hogan et al., 2021; Hao et al., 2021). Knowledge graphs feature:

- 1 scalability to handle a large amount of data
- 2 interconnectedness to enable the interrelation of arbitrary entities
- 3 flexibility for incorporating new data and relationships without requiring a complete redesign of the graph
- 4 contextual understanding for ambiguous terms thereby improving search accuracy and relevance
- 5 multidisciplinary for various domains (Chaudhri et al., 2022; Lampropoulos et al., 2020; Hofer et al., 2023; Zuo et al., 2023; Aparicio et al., 2024).

Since their introduction in the 2010s, applications of knowledge graphs have become increasingly popular in both industry and academia because of their capabilities in knowledge organisation, visualisation, and management (Tiwari et al., 2021; Kejriwal, 2022).

In an educational context, knowledge graphs have been widely used in various applications. For instance, they have helped to identify students' knowledge states and interests for recommending personalised learning paths or resources (Ezaldeen et al., 2022; Troussas et al., 2023). They have also been integrated into intelligent tutoring systems to provide students with personalised feedback and guidance (Jing et al., 2020). They can facilitate the development of educational resources, such as textbooks and online courses, by providing a structured representation of knowledge (Ma, 2022). Furthermore, knowledge graphs have been incorporated into mobile learning systems which allow users to access and interact with the knowledge graphs through mobile devices. For example, Zhao et al. (2022) proposed a knowledge graph-based Chinese vocabulary learning system, which was developed to enable access through mobile devices to support smart learning. The application of knowledge graphs covers various academic disciplines, such as mathematics (Chen et al., 2018), computer science (Nafa et al., 2022), medicine (Wang et al., 2019), and cybersecurity (Agrawal et al., 2022).

Despite their broad applications, knowledge graphs for a specific domain typically only reflect the concepts in the domain rather than systematically organising knowledge according to the needs of learners for acquiring the knowledge (Peng et al., 2023; Zhou et al., 2022). As a result, this may make knowledge graphs less effective in developing learners' competence to apply knowledge in real-life contexts, especially for coping with practical requirements in their fields. To address authentic learning demands, knowledge graphs should be constructed by adopting an outcome-based approach, while also taking into consideration the competency requirements of learners. This would allow knowledge to be organised in a style that addresses their specific requirements.

In light of this, the current study aimed to develop a learning approach utilising knowledge graphs to address students' multidimensional competency requirements, while also examining its effects on the students' performance and experience. The competency-based knowledge graphs, which can be implemented for mobile learning, facilitate a comprehensive understanding of the subject matter as well as the development of critical thinking and problem-solving skills. This approach also enables educators to tailor their teaching strategies to meet the specific needs and their students' learning styles, thereby promoting personalised learning. In particular, this study addressed the following research questions:

- 1 To what extent does the knowledge graph-based learning approach facilitate students to acquire knowledge effectively?
- 2 What is the learning experience of the students in the knowledge graph-based learning approach?

2 Related work

2.1 Concept maps

As another type of visualisation tool to support learning, concept maps are widely used to organise and present fragmented knowledge. They have been utilised to assist learners in organising and connecting their knowledge, identifying gaps in their understanding, and developing a deeper comprehension of complex topics (Novak and Cañas, 2008). Concept maps are typically created manually by learners or educators (Tergan, 2005). In contrast, knowledge graphs are a type of graph database that represent knowledge as a network of interconnected entities and their relationships. They are created using data science techniques such as natural language processing (NLP) and machine learning (Chan et al., 2022). Knowledge graphs can support a broad range of applications, such as search engines, recommendation systems, and data analytics. Cui and Yu (2019) explained that concept maps display concepts and their relationships, and knowledge graphs go beyond that by connecting concepts to their creators, related resources, and learners who are interested in both.

2.2 Knowledge graph applications in education

There have been a broad range of attempts to apply knowledge graphs in education. In particular, knowledge graphs have been widely used to provide a systematic organisation of concepts for learners to acquire prerequisite concepts before entering into a new topic. This has helped learners understand topics more easily and feel more confident with the subject matter (Gasparetti et al., 2018). For example, Manrique et al. (2019) explored using knowledge graphs to identify concepts that serve as a possible prerequisite for other concepts, and proposed a supervised learning model to evaluate the prerequisite relationships. Alzetta et al. (2024) proposed a textbook-driven annotation method with knowledge graphs to identify the structure of prerequisites underlying the text. Leveraging pedagogical data and learning assessment data, Chen et al. (2018) developed a system called Know Edu to extract concepts of subjects or courses and identify the relationships between them. They demonstrated the feasibility and effectiveness of the system by constructing an exemplary knowledge graph for mathematics.

Another point of focus on knowledge graphs is to enhance personalised learning. For instance, Troussas and Krouska (2022) created a knowledge graph-based tutoring system to recommend personalised learning activities to students, and found that the system significantly improved students' learning efficiency and performance. Lv et al. (2021) introduced a weighted knowledge graph‐based approach to provide personalised exercise recommendations by considering the essential relationships between knowledge points.

Their experimental results demonstrated the advantage of the proposed approach in improving students' learning performance. Shi et al. (2020) developed a learning path recommendation model based on a multidimensional knowledge graph framework to satisfy different learning needs, and showed that the model can generate and recommend qualified personalised learning paths to improve the learning experiences of e-learners.

2.3 Knowledge graph construction technologies

Constructing knowledge graphs involves a combination of technologies. NLP techniques are commonly employed for tasks such as named entity recognition, relation extraction, and event extraction, which involve extracting structured information from unstructured data sources such as text documents (Mintz et al., 2009). For example, Agrawal et al. (2022) applied NLP methods to support the extraction of entities and generation of knowledge graphs for lab manuals used in cybersecurity education. Badawy et al. (2021) employed NLP techniques to extract the main topics from textual learning resources to build knowledge graphs for self-learning.

Semantic web technologies have also been frequently used for knowledge graph construction. A semantic web provides a framework for representing and linking data in a machine-readable format (Berners-Lee et al., 2001). The resource description framework (RDF) and the web ontology language (OWL) are key semantic web technologies used in knowledge graph construction. They provide a standard for representing data and ontologies, which define the concepts and relationships in a domain. For example, Bassiliades (2023) built an open knowledge graph in RDF based on information related to Greek universities, departments, study programmes, courses, and textbooks used in the courses. The proposed knowledge graph was able to support report generation and statistical analysis. By applying the RDF, Yaguana and Chicaiza (2023) constructed a recommendation system to provide learning paths based on open educational resources, which takes into account users' interest in a certain topic and level of comprehension about it. Based on the OWL, Sette et al. (2017) developed an open-source knowledge-driven online tutoring system to support knowledge graphs that can present knowledge with customised relationships. Their findings showed that students who studied through the tutoring system were able to achieve better results than those who studied through classroom lectures.

Knowledge graph construction also utilises data integration techniques which involve combining data from various sources to create a comprehensive knowledge graph (Kalaycı et al., 2021). Techniques such as extract, transform, load (ETL) and linked data provide a framework for integrating and transforming data into a common format. For example, Bratsas et al. (2018) developed a scientific knowledge graph through conceptual linking of academic classifications to include the research fields of scientific areas into a common hierarchy. Ashour et al. (2022) applied the linked data technique to generate a link between university semantic data and a scientific knowledge graph to support the decision-making process for assigning new courses to suitable instructors.

2.4 Competency-based education

The current approach of constructing knowledge graphs focuses on illustrating the relationships between concepts in a domain. However, it may not directly address the needs for developing learners' abilities to apply knowledge to real-life situations. To

address this limitation, this study adopted a competency-based approach to develop knowledge graphs for learning, which facilitate students to acquire and apply knowledge following the competency requirements in real-life situations.

Competency-based education (CBE) is an educational paradigm that emphasises the acquisition of specific skills or competencies (Spady, 1977). It aligns broadly with Bloom's (1981) concept of mastery learning, in which students are allowed as much time as they need to learn something in order to master it (Holmes et al., 2021). Rooted in the behaviourist learning theory, CBE is also reconciled with the constructivist theory, thereby offering a comprehensive theoretical framework for learning (Morcke et al., 2013). Within a CBE approach, students are empowered to apply their learning in real-world contexts and construct knowledge through their experiences, thereby fostering a deeper understanding and application of knowledge. This learner-centred approach allows flexibility in pacing and instructional methods, catering for the individual needs and learning styles of students.

For implementing CBE, technology has emerged as a transformative force, supporting personalised learning, self-paced learning, and real-time feedback, particularly in the digital era (Catacutan et al., 2023; Dragoo and Barrows, 2016; Gervais, 2016). Integrating technology in CBE not only enhances the learning experience, but also prepares learners for the digital demands of the modern workplace.

To handle the diverse conceptualisation of competency, this study followed the widely recognised understanding of competency as encompassing knowledge, skill, and ability (El Asame and Wakrim, 2018; Wong, 2020). For example, Ley and Albert (2003) defined competencies as a collection of personal characteristics, including knowledge, skills, and abilities, while Hoffmann (1999, p.276) identified the core meanings of competency as covering the "underlying attributes of a person such as their knowledge, skills or abilities". Other studies, such as Palmer et al. (2004) and Ritzhaupt et al. (2018), have also emphasised the importance of these three aspects in defining competencies. The competency-based knowledge graph constructed in this work covers these three dimensions of competency.

The review of related work highlights the potential of knowledge graphs to facilitate student learning through knowledge graph-based systems. It also shows that current approaches to knowledge graphs have limitations in developing learners' ability to apply knowledge in real-life situations and meet practical requirements. To address the authentic learning demands, this study proposes a learning approach featuring the use of a knowledge graph based on students' multidimensional competency requirements. An experimental evaluation was carried out to assess the effects of the proposed learning approach.

3 Development of a knowledge graph-based learning system

This study examined the effects of a knowledge graph-based learning approach on students' study performance as well as their learning experience in this approach. A learning system based on a knowledge graph was developed for the study. Figure 1 provides an overview of the process for knowledge graph construction and the learning system design.

Figure 1 Knowledge graph construction process and learning system design

3.1 Knowledge graph construction

The study utilised a bottom-up approach for the construction of knowledge graphs. This approach begins from an entity layer where entities and relationships are extracted from various data sources. Next, a schema layer is established and continually refined based on the consolidated data from the entity layer (Mo et al., 2024).

3.1.1 Knowledge acquisition and integration

The data for the knowledge graph system was gathered from course materials in various forms, such as course syllabuses, textbooks, course videos, PowerPoint slides, and digital text resources. To convert the data into a structured format, optical character recognition and speech-to-text tools were employed to process printed documents as well as audio and video data.

The data was further processed to extract entities from it. The term frequency-inverse document frequency (TF-IDF) technique, a statistical method commonly used in NLP, was employed for this process. It helped to identify the entities from the data based on the frequency of each word in a document in relation to the proportion of documents the word appears in (Ramos, 2003). The raw entitles were then reviewed and consolidated by two experts in academic reading and writing in English to remove incorrect entitles and eliminate duplicate ones.

The relationships among the extracted entities were then identified and categorised. They were represented in the format of an ontology as a structured framework that categorises and defines the relationships between various entities and concepts within a specific domain (Agrawal et al., 2022; Hitzler and Janowicz, 2013). As illustrated in Table 1, the relationships were divided into three categories. Finally, a knowledge graph covering multiple dimensions of competency (i.e., knowledge, skill, and ability) was created.

In this study, the knowledge graph is on the topic of English academic reading. Figure 2 shows a portion of the knowledge graph.

Table 1 Relationships in the knowledge graph

Type of relationship	Name of relationship	Description
Subordinate relationship	Subclass	It denotes that one knowledge point is a subclass of another. The arrow points to the subclass knowledge point.
Sequential relationship	Apply to concept; apply to skill; apply to task	It denotes that the former knowledge point is a prerequisite for the subsequent one. The arrow points to the subsequent knowledge point.
Coordinating relationship	individual	It denotes that the two knowledge points are related in a coordinating manner. The arrow signifies the recommended learning sequence.

Figure 2 A portion of the multidimensional competency-based knowledge graph

3.1.2 Knowledge storage

The knowledge storage stage focuses on the storage and retrieval of triple data. The Neo4j graph database was utilised for knowledge storage in this study, taking into consideration the simplicity and adaptability of incorporating new types of knowledge into the database. This graph database offers the flexibility in storing multiple properties for both nodes and edges of a knowledge graph (Agrawal et al., 2022). Figure 3 illustrates the structure of a knowledge graph generated from the database.

3.2 Design of the knowledge graph-based learning system

3.2.1 System architecture

Based on the knowledge graph, a prototype learning system was developed for presenting knowledge organised in a graph-based structure. The system was deployed as an online platform and can be used in mobile environments. Figure 4 shows the system architecture, which consists of three major components:

- a Knowledge graph database It stores the knowledge points and relationships for supporting search queries and generation of learning paths.
- b System backend This component is tasked with generating learning paths and delivering them to the system interface.
- c System interface It serves as an online platform for interaction with learners.

The system backend receives, analyses, and processes data. Based on a user's input, the system searches for knowledge points in the graph database and presents knowledge points through the online interface.

Figure 4 Architecture of the knowledge graph-based learning system

For evaluation purposes, a 'knowledge graph mode' and a 'list mode' were designed for the system interface. Figure $5(a)$ shows the 'knowledge graph mode' which presents search results in the form of knowledge points and relationships, with nodes containing links to learning resources. Users can easily learn how the various knowledge points are related, and access corresponding learning resources based on their interest and progress for specific learning points. Figure 5(b) shows the 'list mode' which displays the topics and links to learning resources presented in a conventional textbook-like linear structure. The two system interface modes were made for comparison, as detailed in the evaluation section below.

Figure 5 (a) Interface of the learning system (knowledge graph mode) (b) Interface of the learning system (list mode) (see online version for colours)

Figure 5 (a) Interface of the learning system (knowledge graph mode) (b) Interface of the learning system (list mode) (continued) (see online version for colours)

(b)

3.2.2 System operation

Figure 6 depicts the operation of the learning system. The system first receives the user's input and matches the keywords in the query with the knowledge points in the knowledge graph. It then extracts learning paths that contain relevant knowledge points and relationships based on the query, and generates a learning resource pack. Finally, the system presents the learning resource pack to the user in the form of a knowledge graph.

4 Evaluation methodology

4.1 Evaluation settings

An evaluation was conducted to examine the effects of the proposed knowledge graph-based learning approach based on the system developed. The learning task used for the evaluation was about reading and comprehending an English academic paper from a course titled Academic Reading in English. Figure 7 depicts the knowledge graph developed for this task in the learning system.

The evaluation was conducted at a university in Hong Kong. A total of 96 undergraduate students majoring in language studies, social sciences, and computer science participated in the evaluation. The participants were recruited to participate on a voluntary basis. They were randomly divided into two groups of 48, with one group serving as the control group and the other as the experimental group. The experimental group used the knowledge graph mode [Figure 5(a)] of the learning system to conduct the learning task, while the control group used the list mode [Figure 5(b)] of the system, which presents learning contents in a sequential format, i.e., a traditional textbook-like structure. Both groups accessed the same learning resources through the system. The learning content was new to both groups of students.

The learning activities and evaluation were carried out in a computer lab for all the participants to ensure that their learning scenarios were consistent.

4.2 Evaluation procedures

Figure 8 illustrates the evaluation procedures. Before commencing the learning activities, both the experimental and control groups received instructions regarding the learning task, objectives, strategies, resources, and assessment methods, as well as the use of the proposed system. The students in the experimental group used the knowledge graph mode while those in the control group used the conventional list mode. The two groups then carried out the learning activities using the corresponding mode (i.e., knowledge

graph mode or list mode) of the system assigned to them. During the learning activities, guidance and support regarding the use of the system were provided to both groups.

After completing all the learning activities, both groups took a performance test to assess the knowledge and skills they acquired from the activities, as well as their ability to synthesise and apply what they had learned. Furthermore, the students in the experimental group were asked to complete a questionnaire to gauge their experience in learning with the system.

4.3 Evaluation instruments

A performance test was devised to evaluate the students' knowledge, skills, and abilities after the learning activities. The knowledge dimension assessed the students' understanding and retention of basic concepts related to the learning content. The skill dimension tested their proficiency in applying reading skills and operating the system. The ability dimension addressed their understanding of an academic article. Two experienced teachers of the relevant course were invited to review and revise the test items. The finalised version of the performance test contains a total of 23 items with a maximum of 68 scores.

To investigate the students' experience in the learning system, a questionnaire survey was developed for the students in the experimental group. The questionnaire was adapted from the one developed by Yang and Tan (2022), which surveyed students' experience with a knowledge graph-based learning resource recommendation system. The adapted questionnaire consists of 12 items which cover three sections:

- 1 experience in the knowledge graph-based learning approach
- 2 presentation of learning resources in the system
- 3 overall experience with the learning system.

A five-point Likert scale was used, with responses ranging from 'strongly disagree' (1) to 'strongly agree' (5). An open-ended question was included at the end of the questionnaire to collect the students' suggestions (if any) for the learning system.

5 Results

5.1 Learning performance

Table 2 reports the results of the students' learning performance test after the learning activities. The scores of the experimental group are higher than that of the control group in all of the three dimensions. The mean differences in the scores for the knowledge, skill, and ability dimensions are 0.42, 2.42, and 2.42, respectively. The mean values and standard deviations of the total scores for the experimental group are 43.40 and 7.32, respectively, compared with 38.14 and 11.54, respectively, for the control group. The results suggest that the experimental group performed better and more consistently than the control group.

An independent sample t-test was performed to examine the statistical differences between the mean values of the two groups. The results show that the experimental group's ability score and total score are significantly higher than those of the control group. This implies that the students who learned with the knowledge graph-based learning approach demonstrated better learning outcomes overall than those who learned through the conventional mode.

Dimension	Group	N	M	SD	MD	
Knowledge	Experimental	48	7.38	2.83	0.42	0.743
	Control	48	6.96	2.71		
Skill	Experimental	48	24.52	5.60	2.42	1.758
	Control	48	22.10	7.72		
Ability	Experimental	48	11.50	3.92	2.42	$2.616*$
	Control	48	9.08	5.07		
Total	Experimental	48	43.40	7.32	5.26	$2.667*$
	Control	48	38.14	11.54		

Table 2 Results of t-test for learning performance scores

Notes: $N =$ number of participants, $M =$ mean, $SD =$ standard deviation, $MD =$ mean differences. $*_p < 0.05$.

5.2 Learning experience

Table 3 shows the average time spent by the two groups on the system during the learning process. The experimental group spent an average of 3.44 hours on the system, which is slightly longer (by 0.06 hours) than that of the control group (3.38 hours). The amount of time spent on using the learning system suggests the students' level of engagement with the learning content (Lo et al., 2012).

Table 4 shows the results of each section of the questionnaire survey, which contain 48 valid responses from all members of the experiment group. Regarding the students' experience in learning with the knowledge graph-based approach, the students most strongly agreed that the knowledge graph effectively highlighted the key points of learning tasks, thereby enhancing their learning efficiency (mean $= 4.17$, SD $= 1.03$). The relatively high ratings for item 2 ($M = 3.79$, $SD = 1.14$) and item 3 ($M = 3.81$, $SD = 1.02$) suggest that the students found the knowledge graph to be well-formatted and efficient in presenting learning content. Their interest in the proposed knowledge graph was only moderate $(M = 3.71, SD = 1.00)$, indicating that the majority of participants had a similar level of interest in the proposed knowledge graph.

Group		M	
Experimental	48	3.44 hours	.02
Control	48	3.38 hours	0.86

Table 3 Time spent on using the learning systems

Table 4 Results of the questionnaire survey

Regarding the presentation of learning resources, the students gave the highest rating on the item in which the system significantly reduced the time they needed to spend searching for relevant learning resources ($M = 4.29$, SD =1.00). They also strongly agreed that the knowledge graph provided reasonable learning suggestions in reference to the sequence of knowledge ($M = 4.15$, SD = 0.96), and they followed the sequence recommended by the knowledge graph system during their learning process ($M = 4.27$, $SD = 0.93$). They generally agreed that the recommendation of learning resources was simple and easy to understand ($M = 3.92$, SD = 1.02). The students showed a slight preference for the way the knowledge graph presented learning resources compared to the tools they had used before $(M = 3.73, SD = 1.02)$.

Regarding their overall experience with the learning system, the students highly recognised the usability of the learning system ($M = 4.25$, SD = 0.95). They generally agreed that the learning system improved their learning efficiency $(M = 4.06, SD = 1.01)$. However, they rated item 11 as the lowest among all 12 items ($M = 3.52$, $SD = 1.04$), indicating that the learning system was not very effective at increasing their learning interest.

5.3 Suggestions from students

Table 5 lists the suggestions provided by the students from the experimental group for improving learning strategies and the design of the learning system and knowledge graph. A total of 14 students offered suggestions. In terms of learning strategies, the students showed an interest in the learning strategy employed in the experiment and indicated their wish to have more opportunities to learn through this method. The other two suggestions highlight the students' preference to personalise their learning path and have a more comprehensive learning guide.

Regarding the learning system design, the students recommended making the user interface more visually appealing and intuitive, which could help them understand the relationships between different pieces of information more easily. Two students put forward a suggestion for recording relevant data to help track and analyse their interaction with the learning system.

In terms of knowledge graph design, two students suggested organising learning content in a more structured and detailed manner.

Suggestion	Freg.
Learning strategies	
Increase opportunities for learning through the knowledge graphs.	3
Provide students with the opportunity to explore their own learning path.	2
Offer a more comprehensive learning guide.	2
Learning system design	
Enhance the aesthetic design of the interface to clearly and explicitly show the connections between knowledge points.	3
Incorporate recording and analysis of learning behaviour data.	2
Knowledge graph design	
Increase the hierarchy of knowledge points to make the content more refined.	2

Table 5 Suggestions from the students

6 Discussion

This study examined the effects of a knowledge graph-based learning approach on students' learning performance and experience. The results show that the students who learned with the proposed approach using a knowledge graph-based system outperformed those who used the conventional learning system. The students provided overall positive feedback for their learning experience, suggesting that the proposed learning approach was well-received. These findings support the use of knowledge graphs to benefit student learning.

The performance test results underscore the advantages of knowledge graphs, demonstrating their usefulness for ability acquisition. Knowledge graphs can support diverse data sources, convert fragmented knowledge into a structured form, and augment knowledge visualisation through a graphical representation (Hoffart et al., 2013; Paulheim, 2017; Sheth and Thirunarayan, 2012). This integration, organisation, and visualisation of knowledge can reduce learners' cognitive load, promote knowledge internalisation, and facilitate a comprehensive understanding of complex knowledge structures and relationships, thereby fostering deep learning (Mayer, 2001; Sweller, 1988). The learning system's hierarchical knowledge points allow learners to complete learning tasks following their personalised learning paths, achieving multiple stages of learning objectives. As Bransford et al. (1999) noted, the ability to reason and solve problems relies on well-organised knowledge that reflects a deep understanding of the subject matter. The knowledge graph-based learning approach contributes to providing a structured and visualised learning environment to support the development of students' abilities.

The students' positive perception of their learning experience with the knowledge graph-based learning approach also reveals the benefits of this approach. Specifically, the system provides learners with a clear and systematic overview of knowledge points and learning resources, allowing them to sort through knowledge and search for learning content more efficiently. Learners using the traditional approach may need to structure and understand knowledge by drawing their own concept maps manually, which prompts constructive thinking by linking new knowledge and experiences with prior knowledge through self-checking in an organisational approach (Hwang et al., 2013; Novak and Cañas, 2008). This process is time-consuming and could potentially lead to misunderstandings. Teachers, on the other hand, are capable of organising knowledge points in a structured manner (Shulman, 1986). By preparing the knowledge graph for learners, their learning efficiency could be improved (Chen et al., 2015). Additionally, knowledge graphs can link learning resources to knowledge points, allowing for efficient information retrieval. As shown in Cui and Yu (2019), compared to other knowledge organisational structures such as a concept map, the knowledge graph had greater positive impacts on students' effective learning.

The students' suggestions provide insights for the future development of the knowledge graph system. They expressed a desire for more personalised learning, detailed instructions, a visually appealing and intuitive user interface, data tracking and analysis features, and structured and detailed learning contents. Their suggestions reveal the potential of incorporating the knowledge graph learning approach in mobile environments to provide more learning opportunities, timely insights from learning records, and an enhanced ubiquitous learning experience (Li et al., 2019; Li and Wong, 2020). They also align with contemporary learner-centred educational paradigms which

emphasise the importance of addressing students' individual needs, experiences, and preferences, and empowering them by giving them responsibility and autonomy in their learning (Li and Wong, 2021, 2022; Mäkelä et al., 2018). While it is impractical for teachers to create a unique knowledge graph for each student, or to design one that suits all students, a potential development could involve students in the process of co-designing knowledge graphs with teachers. This may help the system to be more engaging and better suited to individual learning needs. The co-designing process may also increase student interest, which is an issue to address with the current system as per student feedback.

There are some limitations of this study that should be acknowledged. First, the experimental results were limited to a small sample size. These results should be explored further in future studies at a larger-scale, and a longitudinal study design could be used to observe the effects of the knowledge graph learning approach with a longer period of time. Second, the experiment did not consider the potential influence of student background factors, such as gender and academic major, on the efficacy of the learning approach. Finally, the experimental content was confined to the subject of academic reading in English. For a more comprehensive understanding of the effectiveness of the proposed learning approach, future work should address other disciplines where learners' needs for knowledge visualisation may differ.

7 Conclusions

This study contributes to proposing and examining a knowledge graph-based learning approach to support competency development. The findings demonstrate the effects of knowledge visualisation achieved through knowledge graphs in terms of enhancing learners' acquisition of knowledge. The proposed learning system provides evidence of being able to facilitate a more efficient and effective learning process. The findings also reveal the potential of the knowledge graph-based learning approach to address the increasing volume of information, which can be overwhelming for learners.

Student feedback for the proposed system has suggested future developments for refining and adapting the system to meet the evolving needs and preferences of learners. The students' suggestions underscore the need for a learner-centred approach in their learning process. Future development of the system could involve students in co-designing, which would not only make the system more tailored to their needs, but also increase their sense of ownership and motivation to learn.

The implications of this study lie in the potential for educators and instructional designers to enhance the effectiveness of teaching approaches. The knowledge graph-based learning approach proposed in this study offers a promising solution to address the challenges of information overload and cognitive load in the learning process. By visualising knowledge in a structured and interconnected manner, learners can better understand the relationships between concepts and retain information more effectively. The findings of this study also highlight the importance of a learner-centred approach in designing effective learning systems. By involving learners in the co-design process, educators can create more personalised and engaging learning experiences that cater to the unique needs and preferences of individual learners. Overall, this study provides valuable insights into the benefits of knowledge graph-based learning approaches to support competency development and improve the quality of education.

The findings of this study also highlight the potential areas for future research. The effects of the proposed learning approach on areas not covered in this study, such as reducing cognitive load, require empirical examination in future studies. Moreover, the implementation of learning analytics, utilising data encompassing aspects such as learning behaviours and learner backgrounds, should be pursued to bolster the provision of personalised learning with the system.

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