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Crowdsourcing mode-based learning activity flow approach to promote subject ontology generation and evolution in learning

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ABSTRACT

Subject ontology can help implement the structured organization of knowledge for online learners and thus plays an important role in the learning process. However, building ontologies by experts is time-consuming, and the adaptation of such ontologies to different contexts might be a problem. Crowdsourcing, which allows users to build and refine ontologies during their learning process, has exhibited potential for solving this problem. In this study, a crowdsourcing mode-based learning activity flow approach is proposed to guide the learning of online learners while promoting the generation and evolution of subject ontologies using the learners' contributions to the learning content. This flow makes full use of the learners' wisdom during the learning process to promote self-regulated learning as well as the generation and evolution of the ontology. Based on the proposed approach, a learning support system was developed and an experiment conducted involving a Chinese lesson on "The Liangzhou Poem". In the experiment, student participants built 722 triples, of which 584 evolved as formal items in the subject ontology. Moreover, all learners were able to construct a well-organized knowledge graph. Students in both high- and low-scoring groups contributed valuably to the knowledge generation and evolution of the subject ontology. Furthermore, while the widths of the knowledge constructed by students in high- and low-scoring groups were similar, their depths were substantially different. During this process, the crowdsourcing-based activity flow system achieved satisfactory technique acceptance, which means that the proposed approach and system are useful for the effective generation of subject ontologies while helping learners acquire knowledge.

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Subject ontology generation and evolution; crowdsourcing; learning activity flow; learning mode; learning cell knowledge community system

Introduction

In an online learning environment, learners are able to access learning resources without being limited by locations, time, or even devices (Motiwalla, 2007; Yu, 2007). During the online learning process, learners may feel uncertain or confused when facing a large amount of information. A well-organized knowledge structure could make the learning process much easier for them. A subject ontology, which is a resource network with semantic descriptions of concepts, the relations between these concepts, and instances (Antoniou & Vanharmelen, 2008), is a good structure for organizing knowledge. With a well-organized knowledge structure, learning systems can provide users with more relevant information instead of inundating them with a large number of online search results. This then helps learners learn more accurately and efficiently (Wang, Mendori, & Xiong,

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2014). As massive amounts of knowledge and a large number of learning resources are now available for online learning, it is important to organize these learning resources well for learners (Chi, Qin, Song, & Xu, 2018; Xu, Song, Yu, & Tavares, 2017). Therefore, building subject ontologies for knowledge representation and description is an important task in online learning.

In the past decade, researchers have defined the domain ontology for several fields to improve students' learning efficiency and accuracy (Alomari, Hussain, Turki, & Masud, 2015; Chen, 2009; Ouf, Ellatif, Salama, & Helmy, 2017; Zeng, Zhao, & Liang, 2009). Although most of these researches have yielded good results and shown that ontology-based learning systems can help promote efficient online learning, a given ontology cannot be reused in another context adaptively because its representation changes and evolves with respect to time and context. A previously defined ontology is thus only useful in specific contexts. However, it is time-consuming to manually build complete subject ontologies, especially when considering the rapid generation and evolution of knowledge. To build a complete subject ontology that can adapt to changing contexts and the evolution of knowledge, researchers must devise a method to help the ontology evolve with these changes once it has been built.

Crowdsourcing has been recognized as an effective approach for generating and improving subject ontologies (Wohlgenannt, 2016; Zhitomirsky-Geffet, Erez, & Judit, 2017). It has been shown that crowdsourcing can help improve ontologies based on the practice of Wikipedia (Niederer & van Dijck, 2010). However, most of this improvement is not achieved by employing the users' own work, for example, by employing the activities of users during the process of learning instead of requiring additional time specifically for ontology generation. Therefore, in this study, we focus on the dynamic features of knowledge acquisition and the flow of users' learning activities and use them to propose a crowdsourcing mode-based learning activity flow approach. With this approach, learners can help generate and evolve subject ontologies while they are immersed in learning. Moreover, they can achieve their learning goals through interactive activities. Accordingly, a system for ontology generation and evolution is developed as a subsystem of the Learning Cell Knowledge Community System in which the subsystem constructs a knowledge base to support the parent system (Yu, Yang, Cheng, & Wang, 2015). To examine the impacts of the proposed approach on subject ontology generation and evolution as well as learners' knowledge, an experiment was conducted in a Chinese lesson on "The Liangzhou Poem" with 34 fifth-graders.

Literature review

Ontology, subject ontology, and their roles in online learning

Ontology is a concept derived from philosophy. It represents the original form of things. In the 1980s, the term "ontology" was introduced to the field of artificial intelligence to describe entities, relations, and properties in the Semantic Web (Chandrasekaran, Josephson, & Benjamins, 1999). Ontologies have been used to provide a shared or common understanding of facts about a given domain; moreover, an ontology is sufficiently dynamic to capture the change in specific concepts (Ding & Foo, 2002). When using an ontology to represent things or concepts, scholars usually use triples to define the concepts, properties, instances, and relations between them, e.g. the triple <Sheep, has, feet> means that the concept of "Sheep" has the property of "feet." By adding other rules, such as the number of feet the sheep has, the kind of species to which it belongs, and its other attributes, a concept can be defined (Benchcapon, 2002).

Subject ontology is used to represent knowledge or conceptualization in specific domains in education (Kunkel, 2015; Miranda, Orciuoli, & Sampson, 2016). In online learning, subject ontology has been used in several contexts for tasks, such as supporting learning activities, annotating or organizing learning resources, providing an overview of the knowledge graph, and acting as an assessment tool by describing the concepts and relations involving learners' competence (Allert, Markannen, & Richter, 2006; Dicheva, Sosnovsky, Gavrilova, & Brusilovsky, 2005). In these scenarios, subject ontology can help correctly identify the boundary or scope of the user's requirements and contribute to algorithms that provide personalized learning resources (Marzano & Notti, 2014). However, to build subject ontologies in these scenarios, an effective approach is needed.

Methods for promoting the generation and evolution of subject ontology

There are several ways to build subject ontologies. If the subject ontology is not large scale, it can be built using manual tools, such as Protégé and the NeON Toolkit. However, in most studies, the target ontology is quite complex and researchers cannot create a summary manually. Many automated methods using recent technologies have thus been proposed to help build subject ontologies (Capuano, Dell'Angelo, Orciuoli, Miranda, & Zurolo, 2009; Gruber & Olsen, 1994; Miranda et al., 2016). Capuano et al. (2009) proposed a method to automatically build a subject ontology based on SCORM (Sharable Content Object Reference Model) packages. They used an algorithm to extract knowledge from SCORM packages, following which a program distinguished elements in the extracted package and saved them according to the standard structure defined in SCORM. Hatala, GašEvić, Siadaty, Jovanovic, and Torniai (2012) proposed a method that uses existing domain ontology to provide recommendations to ontology builders to help with their work. Zouaq and Nkambou (2010) used a similar method to help build ontologies. Some researchers have also used natural language processing to extract concepts and relations from textual sources in specific areas, and reused this technology to identify the quality of the extracted concepts or relations before finalizing the ontology (Serra & Girardi, 2011).

Using these methods, researchers and practitioners can build subject ontologies for different disciplines. However, given the continual development in most areas of human endeavor, knowledge in a subjects evolves, and the previously built ontologies may not be able to adapt in practice. To solve this problem, researchers have provided methods for ontology evolution, such as ontology mapping (Martins & Silva, 2009), Ontologging (Maedche, Motik, Stojanovic, Studer, & Volz, 2002) and data mining (Cao & Zhang, 2007). N. Stojanovic and Stojanovic (2002) proposed a method that allows users to annotate and control the details of an ontology. Ontologies can thus be rendered consistent with use. Chen and Huang (2014) used an annotation system to represent the difference between knowledge at any given time and past knowledge, and integrate the different attributes and concepts. Another study controlled the evolution process automatically by applying users' interactive data to other platforms to make use of their workflows. During this process, researchers tracked changes to titles, keywords in related wikis, blogs, and other websites through algorithm, and updated the ontology using algorithms (Juffinger et al., 2009).

Although the above methods can help the generation and evolution of subject ontologies, they consumes either resources or time, or they cannot guarantee high quality output. Moreover, these methods are used mainly to build ontologies to support users, and have rarely been aimed at the development and evolution of subject ontologies through employing users' compulsory work.

Crowdsourcing (Collective wisdom) in problem solving

From the above, we can see that users' work or crowdsourcing could be employed to promote the generation and evolution of subject ontologies if we design reasonable crowdsourcing learning activity flows and embed them into the learning process.

Crowdsourcing uses collective wisdom to help solve complex problems in specific areas (Howe, 2006). Many organizations have applied this idea, especially in medicine and on the Internet, with great success. In the last decade, Wikipedia has increased significantly in terms of the number of articles as well as the size of pages. This can be attributed to crowdsourcing's effectiveness (Niederer & van Dijck, 2010). In medicine, scientists designed a game called "FoldIt" which involved a problem that had puzzled them for decades. Weeks later, the problem had been solved by crowd gamers (Cossins, 2013). In other areas, the image website "Flickr"used crowdsourcing to help annotate pictures, which made it easier to organize them. Ahn et al. (2008) used crowdsourcing to help computers recognize text in the "reCAPTCHA" system. The system scans all text into a computer and extracts the words it cannot recognize. Then it generates a user validation code using this text and employs users to recognize it when they are performing other operations. Using this method, researchers have almost completely solved the text recognition problem. Other researchers have also used crowdsourcing to annotate videos (Gadgil, Tahboub, Kirsh, & Delp, 2014).

The above are all uses of crowdsourcing to solve complex problems. The success of crowdsourcing suggests that it might be useful for solving learning problems, especially those related to ontology generation and evolution (Hills, 2015), which require significant effort. Although researchers can use computer algorithms to automate these tasks and validate them through experts, this still does not guarantee an evolved ontology of satisfactory quality (Zouaq & Nkambou, 2009). Learners are the subjects of the learning process. There are large numbers of learners for each subject who have the cognitive ability to help promote the generation and evolution of subject ontologies if the generation and evolution work can be seamlessly embedded into their learning process. From their collective wisdom we can determine the legitimacy of the generated knowledge in the subject ontology. Moreover, many studies have shown that activity-based learning can guarantee engaged participation and promote learning if the activities are designed well (Hewitt, 1995; Nudzor, Dare, Oduro, Bosu, & Addy, 2015; Zahirović Suhonjić, Despotović-Zrakić, Labus, Bogdanović, & Barać, 2018). Therefore, in this study, we designed a crowdsourcing approach based on the learning activity flow and embedded it into an online learning platform to support the learning process. In this way, we expect to promote the generation and evolution of subject ontologies while online learners complete their compulsory learning.

Crowdsourcing mode-based learning activity flow approach

Structure of the approach

To promote the generation and evolution of subject ontologies, and improve learners' organization and acquisition of their knowledge, a crowdsourcing mode-based learning activity flow approach is proposed in this study, The proposed approach consists of a learning process composed of three logically successive learning activities (see Figure 1): Semantic Annotation as a content learning process, the Knowledge Graph as a reflection process, and the Reverse Quiz as an evaluation process.

As a whole learning process, learners need to construct their knowledge using the Semantic Annotation activity. In the Knowledge Graph activity, learners can overview the organization of knowledge they have constructed and supplement it. Finally, to test the learning outcomes based on the relations annotated by the students in the two preceding activities, questions are generated for the learners in the Reverse Quiz activity. Afterwards, all relations created during the three activities

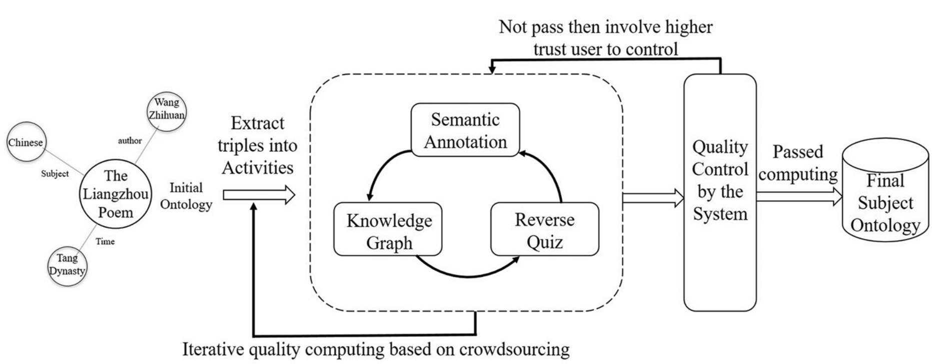

Figure 1. Flow of crowdsourcing mode-based learning activity.

are verified by a Quality Control Module that uses the participants' trust, which is measured by his/her scores and operations in specific subjects on the platform, to compute the authority of the created relations. If the computed authority is high, the relation is preserved. Otherwise, the relation is sent to the previous procedure to be voted on by users with higher trust value(a measurement to decide if we can trust the user's operation in specific subject). Using these three learning activities embedded in the learning process, on the one hand, online learners can learn knowledge and, on the other, they can help promote the generation and evolution of subject ontologies using crowdsourcing (collective wisdom).

Process and role of each activity

The aim of this study is to engage learners in promoting the generation and evolution of subject ontologies during their learning process. Hence, learning activities are needed. Therefore, we designed and implemented the three learning activities with the help of experienced teachers for them to be effective. These three activities, Semantic Annotation, Knowledge Graph, and Reverse Quiz, are closely related to the learning process and can help both learners and learning management. The Semantic Annotation activity helps learners discover and annotate knowledge which is useful in their learning. The annotated knowledge can be used in the following two activities as components of unverified triples. The Knowledge Graph activity then presents the knowledge annotated in the first activity as an initialized knowledge structure for learners and so that they may improve and personalize it according to their understanding of the structure. This process can also generate some new relations or knowledge. Most of the generated relations or knowledge in the two activities can be validated through algorithms while the ones which algorithm cannot decide are sent to Reverse Quiz activity for further validation. This activity uses relations and knowledge generated in the previous two activities to generate questions. During this process, not only the validated relation can be used to generate questions, but relations waiting to be verified are also used. Once the questions have been generated, we present them to the learners as a test. Learners' answers to questions generated by the unverified relations are used to check and determine if the relations can be evolved. If more than five learners choose the same answer to a question, it means the relation can be evolved. Relations cannot be verified this way, are sent to teachers or high-trust users for validation. At the end of the three activities, both the unverified and verified relations are placed into the Quality Control Module for quality revalidation, where the system extracts the trust values of all users who have contributed to the specific relation. The module then normalizes all trust values and determines if the relation created by the learners has high authority. For verified relations that have been evolved as the formal subject ontology, the system just labels it with the trust value. For unverified relations, this process determines whether it is likely to evolve and be included in subject ontology. The trust-computing formula is as follows:

$$\mathrm{Trust}(\mathrm{relation_s}) = w_1 * \sum_1^n (\mathrm{Trust(i,\ s)}/n) + w_2 * \sum_1^m (\mathrm{Trust(\,j,\ s)}/m) + w_3 * \sum_1^k (\mathrm{Trust(t,\ s)}/t),$$

where "$\mathrm{relation_s}$" represents the relation created by learners and $\mathrm{Trust(relation_s)}$ represents the trust value of $\mathrm{relation_s}$. The trust value of $\mathrm{relation_s}$ is composed of three parts: the weighted average of users who annotated this relation in the first activity, weighted average of users who added it in the second activity, and the weighted average of users who validated it in the third activity. Here, Trust(i, s) represents the trust value of $\mathrm{user_i}$ who created $\mathrm{relation_s}$ in the first activity, and w1 is the weight assigned to the first activity. The meanings of Trust(j,s), Trust(t,s), w2, and w3 are analogous. For an unverified $\mathrm{relation_s}$, if its trust value exceeds the system's critical value, the relation evolves as the formal subject ontology relation. Otherwise, it is sent for further validation with higher-trust users, such as experts and teachers. The initial critical value is set to 0.5 according to experts' discussion and experts' trust value in the platform. After using for a period, the value can be adaptively changed according to the users' practice.

Logic of semantic annotation activity

Learners participate in the Semantic Annotation activity when they start learning the material. During this process, each learner studies all the materials to identify problems with descriptions or concepts. Figure 2 shows an example of semantic annotation. Here, the learner is reading an article titled "Wang Anshi," about a famous litterateur from Chinese history.

When the learners read the first sentence, they can annotate the term "Wang Anshi" by choosing it before the system shows the annotation layer if they have difficulty understanding the term. If "Wang Anshi" is already a concept or relation in the subject ontology, the annotation layer provides an explanation of it at the top, such as "Wang Anshi is a poet." This can help the learners understand the concept or relation more easily. If there is no related concept or relation in the subject ontology or the provided concept does not satisfy the learner's need, the learners can search for "Wang Anshi" by themselves and annotate it using the annotation function at the bottom of the annotation layer. For example, the learners can add the new annotation, "Wang Anshi is a politician." The annotation will then be saved as a unverified triple <"Wang Anshi", "is", "a politician">. This process helps them go through the learning material more easily, especially when faced with complex articles full of difficult terms. Furthermore, the new annotations constitute knowledge accumulation for them and can be used to form the initial knowledge graph in the Knowledge Graph activity. The activity flow is as shown in Figure 3.

Logic of knowledge graph activity

The Knowledge Graph activity follows the Semantic Annotation activity, and is conducted as a reflection task on the learning content they have generated in the first task. It provides them with an overview of the initial knowledge structure of the learning content using the concepts or relations annotated by the learners themselves during the Semantic Annotation activity. The activity requires that all learners use the initial knowledge graph to supplement their own knowledge graph according to their comprehension of the content, as shown in Figure 4.

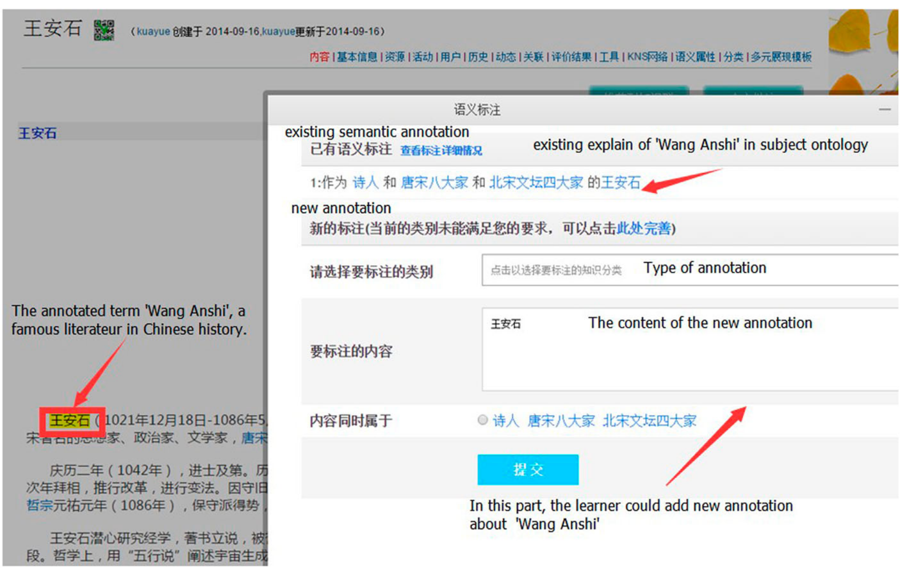

Figure 2. Semantic annotation.

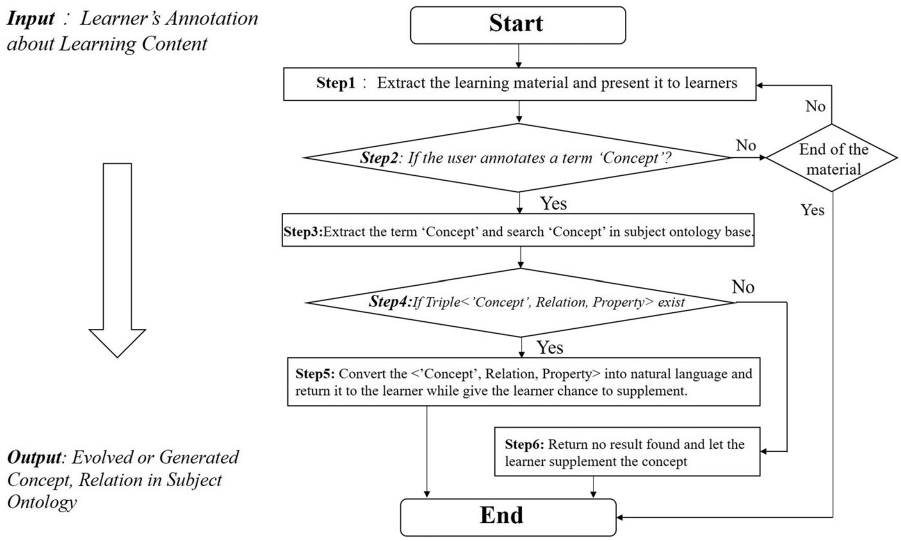

Figure 3. Process of semantic annotation activity.

When the learners find that the initial graph is inconsistent with their view, they can click on a specific concept and add another relation to it. For example, assume that the title of the learning content is "Introduction to Love" created by the creator. There are two common personages, "Confucius" and "Mencius," who have view on "love". If the learners think there is a new litterateur to add, they can click on the icon for "love" and add a node (sentence) at the bottom. The system then sends the triple < "Love", "Relation", "Another sentence"> to the server; following validation the triple is saved in the subject ontology. During validation, the program uses three methods to validate the quality of the triple: a dependency parser, Word2Vec and Doc2Vec. These methods are used because, when judging if a sentence is reasonable, we first determine the dependency relations of the subject, predicate, and object. Then we determine if the subject, predicate, and object are often present in a sentence or document. To complete the first task, the Stanford Parser (Dozat, Qi, & Manning, 2017) is often used and performs well. To determine the second characteristic, Word2Vec and Doc2Vec can be used(Hu et al., 2018).

Figure 4. Knowledge graph activity.

Dependency parser. The system first extracts the generated triple <ON, R, NN> and recombines the triple as a sentence S'. Word segmentation tools are then used to obtain the subject, verb, and object of the sentence. If a sentence formed by the three words is not reasonable according to the algorithm, zero is returned as value; otherwise, the Stanford Parser is executed for S' using to obtain the dependency parser tree S'->Tree. If the central word "root" does not exist, zero is returned; otherwise, if "root" is consistent with R in the triple, the subject (SS') and object (SO') of the sentence S' are obtained. The similarities between SS' and SO', and the similarities between ON and NN in the triple are compared. If they are identical, one is returned; otherwise, the similarity output by the dependency parser is returned (M1).

Word2Vec. The system then uses Word2Vec to validate the relations among the subject, predicate, and object of this sentence. During this procedure, for each triple <ON, R, NN> generated by the learners, the system first obtains the related word collection W{w1, w2, … , wn} of ON using Word2Vec, and then extracts NN from the triple to determine if it exists in W. If NN exists in W, one is returned; otherwise, zero is returned (M2).

Doc2Vec. The system uses Doc2Vec to validate the similarity of the sentence with respect to existing sentences. It firstly obtains the generated triple <ON, R, NN> and combine ON, R and NN to form a new sentence NS. Then the system uses Doc2Vec to obtain a collection of sentences SS{s1, s2, … , Sn} that are similar to NS. It retrieves the sentences in SS and obtain the sentence (MS) that is most similar to NS. If the similarity(measured by Doc2Vec) between NS and MS exceeds 0.5, one is returned; if the similarity is between 0 and 0.5, return the similarity; otherwise, zero is returned as the result of this method (M3).

The quality of the generated triple is measured by summing the results of the above three methods. The value of function Quality(triple), is used to determine whether the triple can be evolved and saved as a formal ontology. Function Quality(triple) is calculated as follows:

$$\text{Quality(triple)} = \frac{(M1 + M2 + M3)}{3}$$

The process of the Knowledge Graph activity is shown in Figure 5. If any of the three terms in the Quality calculation return 0, the triple doesn't pass the machine validation and it would not be saved or evolved as the formal ontology. However, this triple can be saved in the learner's own knowledge graph as a part of his/her own accumulation of knowledge. If the triple passes the three-term validation and the value of Quality(triple) exceeds 0.5, the triple could be saved and evolved.

Logic of reverse quiz activity

In the two preceding activities, learners help annotate some concepts and create new ones. The system designates some of these as having high authority and saves them in the formal subject ontology. For the concepts and relations not validated by the system, learners are asked to assess their authority using their collective wisdom in the form of a quiz. In this activity, the system first queries all triples related to the title of the learning content, verified and unverified. The extracted triples(<Subject, verb, Object>, e.g. <"The Liangzhou Poem", "isComposedBy", "Wang Zhihuan">) are used to generate questions according to a question template, such as the following: (1) "The Liangzhou Poem is composed by ()?", (2) "Who composed Liangzhou Poem", (3) "Is the Liangzhou Poem composed by Wang Zhihuan? ", (4) "Wang Zhihuan is the composer of ()?". Once the questions are generated, they are presented as a reverse quiz to the learners (Figure 6).

For verified questions, feedback is provided immediately. For unverified questions, a crowdsourcing process is used to determine the correctness of the result proposed by the learner. To do this, the system collects all learners' answers to unverified questions and calculates the frequency of each answer. If the frequency of answer exceeds a given threshold (the value is five), the answer is considered verified; if the value is below the threshold, the creator or a teacheras an expert is asked to determine the result and return it to the learners. If the experts think the answer is correct and authentic, the answers as well as the unverified questions are saved as a verified

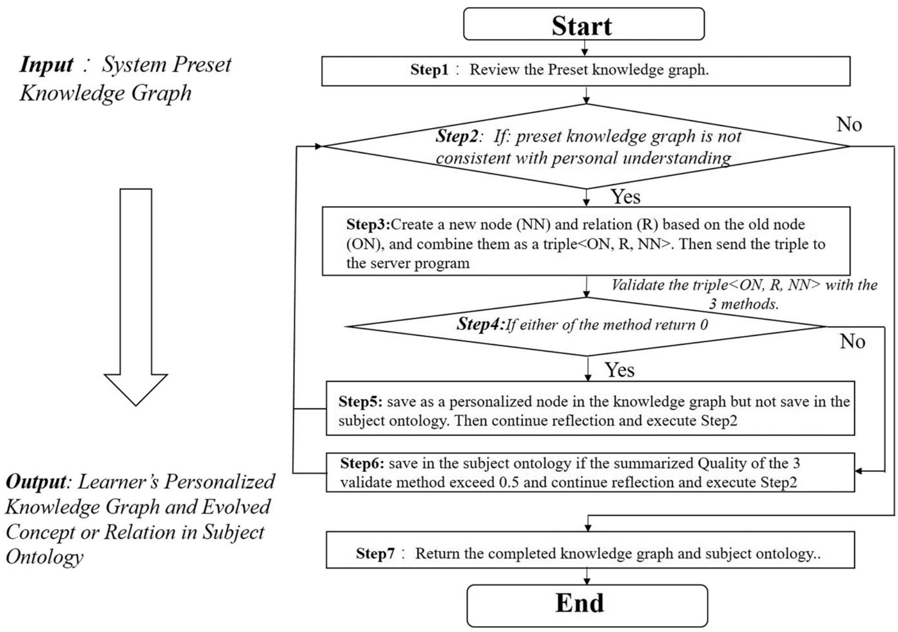

Figure 5. Process of knowledge graph activity.

triple in the subject ontology, Otherwise the triple will not be evolved. The entire process is shown in Figure 7.

Development of a learning system based on the proposed approach

According to the crowdsourcing mode-based learning activity flow approach, we designed and implemented a subsystem based on an online learning platform called the "Learning Cell Knowledge Community System" in which the subsystem constructs knowledge base to support the parent system. In the newly designed subsystem, we use the learning activities in the learning process to support the generation and evolution of subject ontology while promoting learners' knowledge

Figure 6. Reverse quiz activity.

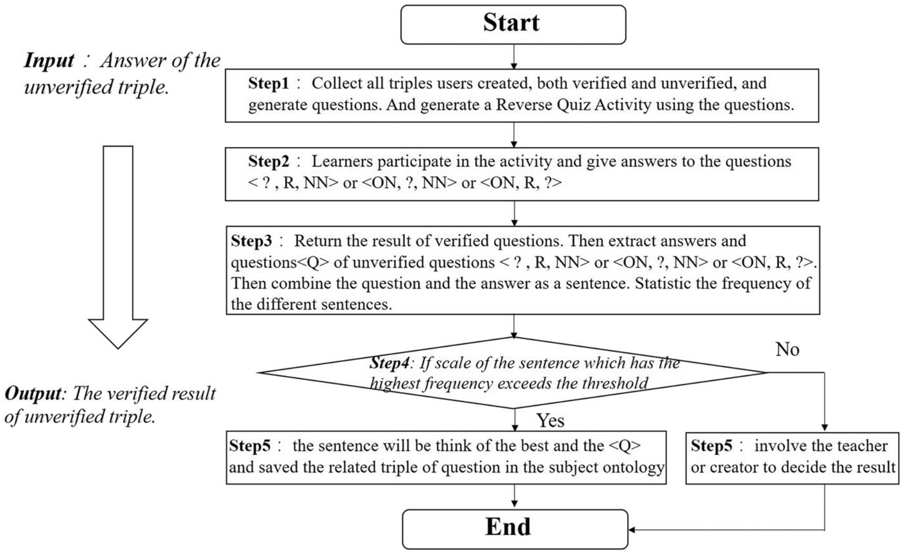

Figure 7. Flow of reverse quiz activity.

acquisition at the same time. The system uses semantic techniques and natural language processing to guarantee the flow of the learning activity. The proposed system is composed of five layers: subject ontology storage layer, relation processing layer, quality control layer, application generation layer, and user interactive interface (Figure 8), which control user-generated data flow in the system. The details of each layer are given below.

The subject ontology storage layer is the central part of the system and stores all concepts, relations, and properties as triples. The collection of the verified triples is defined as the final subject ontology, and unverified triples are labeled as "waiting to be verified". When the learner

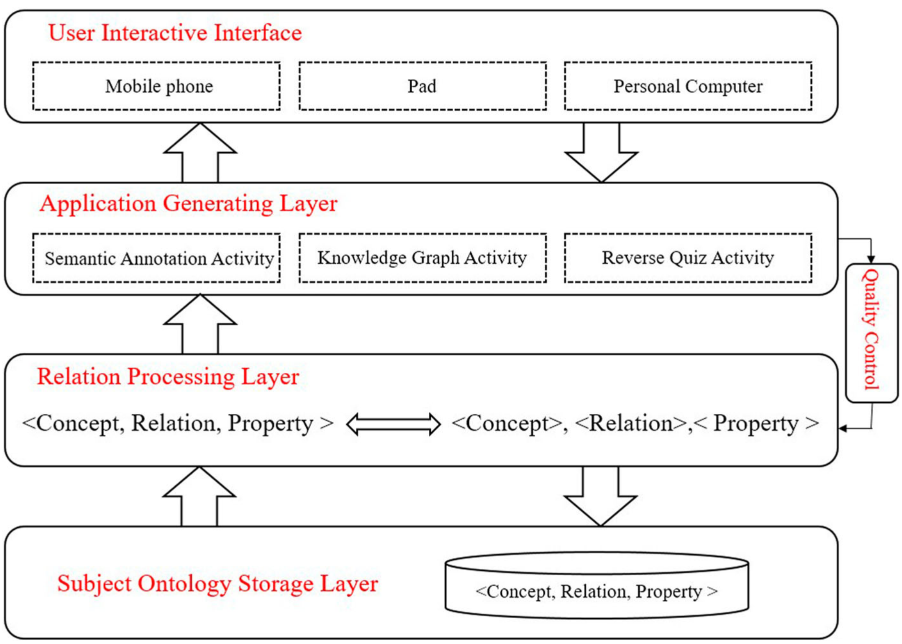

Figure 8. Infrastructure of crowdsourcing learning activity flow-based system.

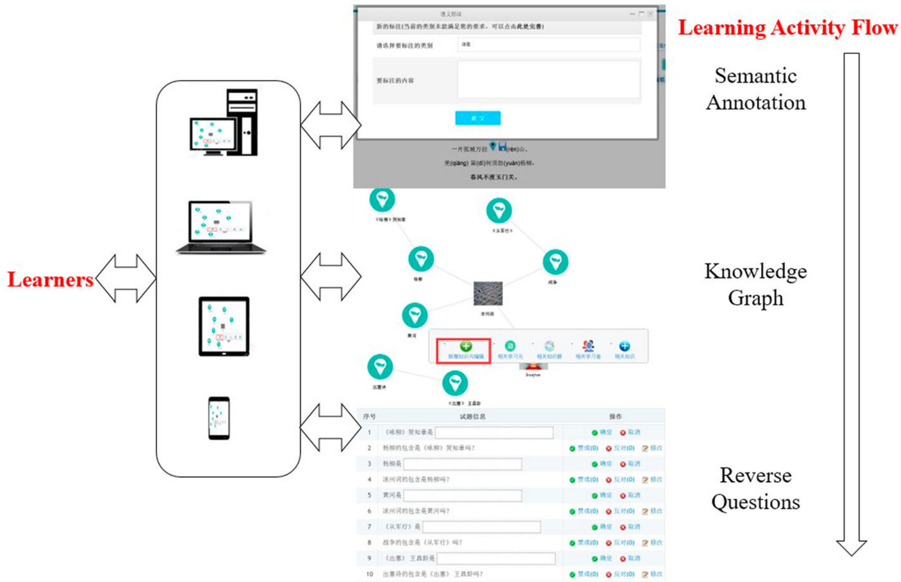

Figure 9. System-supported application.

interacts with the system, the storage layer conducts a query or a reserve processes to process the triple. We used Jena TDB to store triples and SPARQL to query the database.

The relation processing layer is a middle layer responsible for the processing of all triples. On the one hand, this layer can break up triples in the storage into separate records, e.g. <Concept>, <Relation>, and <Property> for further processing in applications. On the other hand, this layer can also recombine data from the service interface as triples that can be stored in the storage layer.

The quality control layer enables the proposed approach. It implements the automatic logic processing described in Section 3. When a new triple is inputs to this part, a natural language processing algorithm calculates its authority and determines if it should be stored as a verified triple in the subject ontology database. This guarantees the high quality of the generated subject ontology.

The application generation layer is a combination of the three learning activities: Semantic Annotation activity, Knowledge Graph activity, and Reverse Quiz activity. These activities are used as a series of methods to enable learners to participate in knowledge generation, and to promote their learning outcomes.

The user interactive interface implements all interactions through different devices, such as mobile phones, tablets, and personal computers. Figure 9 shows the system applications.

Research design

Once the approach was designed and the learning activities developed, we conducted an experiment using the proposed system in a Chinese lesson called "The Liangzhou Poem" with 34 fifth-graders. This experiment focused on the following four questions:

(1) Is the proposed approach effective in promoting the generation and evolution of subject ontologies in terms of quantity and quality compared with traditional online learning?
(2) Is there any difference between learners in high-scoring and low-scoring group in terms of the quantity and quality of knowledge generated under the proposed approach?
(3) Are there differences between learners from high-scoring and low-scoring groups in terms of self-constructed knowledge graphs with respect to construction depth, width, and the integration of depth and width?

(4) Does the proposed support system perform well on the technique acceptance (TAM) dimensions of usefulness and ease of use? The first dimension indicates whether the proposed system can help knowledge ontology generation and evolution, as well as facilitate learning. The second dimension indicates whether the system is easy to use.

Instruments

"The Liangzhou Poem": For the learning content, we chose the "The Liangzhou Poem" for students of grade 5. This poem was written by "Wang Zhihuan". It has rich relations, and was easy for learners to extend the ontology on this subject.

Pre-test instrument: We use pre-tests to distinguish different levels of learners with respect to knowledge building and generation. The content of the test was proposed by Chinese teachers in the school of the participants. The test contained three parts: basic knowledge, reading, and writing. The first part consisted of 10 questions, including multiple choice and true or false questions, gap filling questions, and matching questions. In the second part, there were two passages of text, and the learners were asked to read them and answer 12 questions. In the last part, the learners were asked to write an essay. The total score for the test was 100.

To verify the authority of the knowledge evolved through this experiment, two subject experts were asked to score all the generated concepts with scores of zero or one. The results were compared with the final results of the system's evolution. Moreover, the experts scored the personalized knowledge graphs created by all learners. They used a scale of 1–5 to represent the quality of the knowledge graphs on dimensions of construct depth, construct width, and the integration of both. Depth was measured according to whether the relation added was rich and good quality (scores of 1–5 represented few relations and low quality, relatively few relations and low quality, medium, relatively rich relations and good quality, the relation was rich and the quality was good). For construction width, we measured whether the relations added were extensive (1–5 represented few relations and not extensive, relatively few relations and not extensive, medium, relatively many relations and extensive, many relations and extensive). Integration was scored by the total of the above two dimensions.

TAM schema: The TAM schema is a five-point Likert scale containing two dimensions: usefulness and ease of use. There were six questions on the dimension of usefulness and five questions for ease of use (Chu, Hwang, Tsai, & Tseng, 2010).

Participants

The participants were 34 fifth graders in one class randomly selected from a cooperative school in the south area of China. Before the experiment, we classified them into two groups according to the results of the pre-test. The top 50% (17 learners) were assigned to the high-scoring group and the bottom 50% to the low-scoring group.

Experimental process

The experimental procedure is shown in Figure 10. The teacher divided learners into the high-scoring and low-scoring groups according to pre-test performance, and gave an overview of the course and the experimental process, including how to participate in the three learning activities.

The students then participated in the three learning activities (Figure 11) as follows:

(1) At the beginning, learners completed the learning of the required content thoroughly through the Semantic Annotation activity. During this process, the system helped learners conveniently find related knowledge using the existing subject ontology and learners were allowed use the annotation function to make notes about knowledge that could not be explained by existing subject ontology. This process was the knowledge learning process in the crowdsourcing mode-based approach.

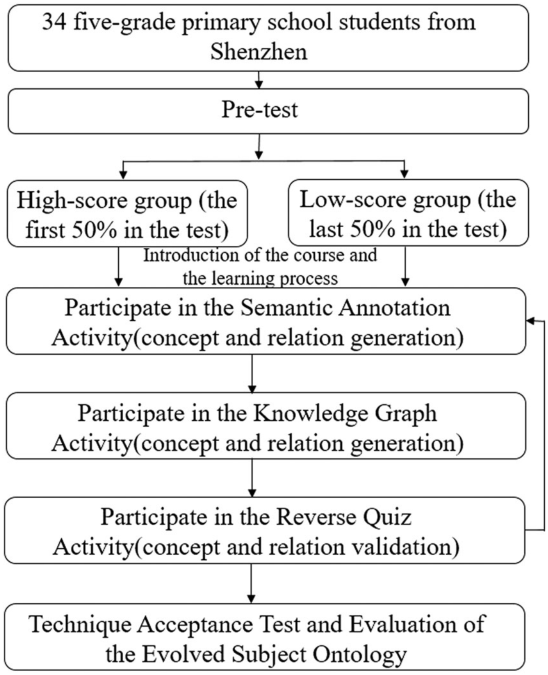

Figure 10. Process of the experiment.

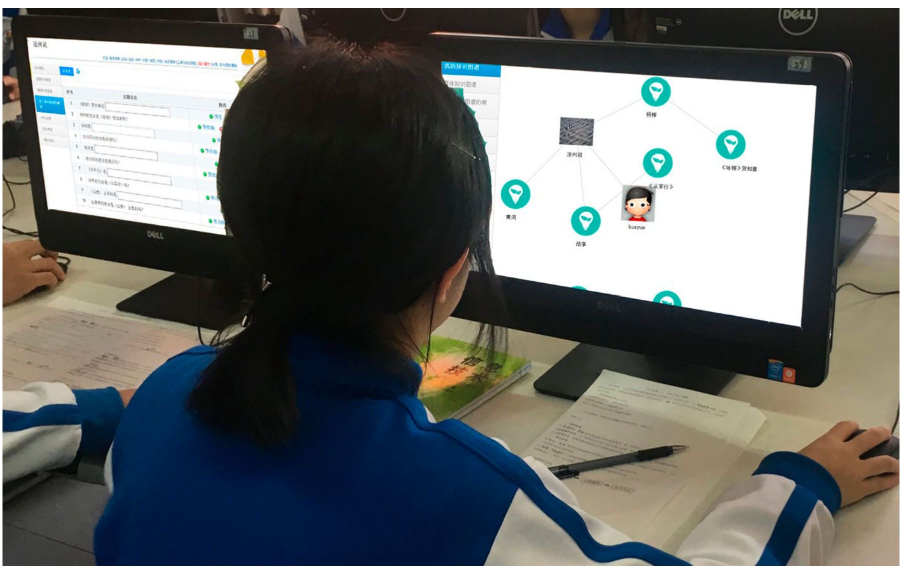

Figure 11. Picture of the learning process.

(2) Once the learners had completed the first procedure, the knowledge structure the learners created was presented as a Knowledge Graph activity. They were asked to review the constructed knowledge graph and improve it according to their comprehension of the content. This activity constituted reflection in learning.

(3) The numerous concepts and relations formed in the first two steps were recombined as questions for the Reverse Question activity. This process was used to evaluate the learners' outcomes of learning. For example, learner A generated the relation "isComposedOf" between the concepts "Yongliu" and "Hezhizhang". According to the question schema preset in the system, the question "___ is the composer of Yongliu" or "Was Yongliu composed by Hezhizhang?" could be generated. Learners were asked to complete the test and answer the questions. Using these answers, the system determined the authority of the generated concepts and relations.

During the three stages, numerous concepts and relations were generated and were saved in the database as triples. When the learner submitted a new edit, the system extracted the concept and relation the learner had created. For example, suppose a learner clicked on the concept "The Liangzhou Poem" and related it to a new concept "War Poem" using the relation "type." The system would then extracts the source concept "The Liangzhou Poem", the target concept "War Poetry" and the relation "type". Then, the three extracted objects would be combined as a triple <"The Liangzhou Poem", "type", " War Poem">. The triple was then transmitted to the storage layer and saved in the database.

When the experiment was complete, we summarized all learners' personalized knowledge graphs and analyzed the triples they had generated. The results are shown and analyzed below.

Results and discussion

We first quantitatively analyze the results of the knowledge generation by learners at different levels. Of the 34 students, 32 completed the learning process. Although the other two participated in the learning activities, they did not perform any operations, and thus were not considered. During the learning processes of the 32 learners, 722 new triples were generated, of which 584 were verified as authorized and stored in the subject ontology. To determine whether the system's evolution was authorized, we asked two subject experts in the area to review all generated concepts and relations, and assign them zero (unauthorized) or one (authorized). The kappa value of the two experts was 0.834, which means that they could code items with good consistency. We then compared the consistency of the results of evolution generated by the experts and the system using the kappa test. The kappa value was .693, which means that the results were consistent (as shown in Table 1). This also shows that the evolved subject ontology by the system was satisfactory in terms of quality.

When analyzing the quantity and quality of the knowledge generated by the high- and low-scoring groups, we found that in the high-scoring group, students generated 418 triples (26.13 per person), of which 347 (21.69 per person) were verified. The success rate was 83%. In the low-scoring group, 304 triples (19 per person) were generated, of which 237 (14.81 per person) were verified, yielding at a success rate of 78%. The results are shown in Table 2.

To determine the differences in the knowledge graphs constructed by different groups, the experts scored all personalized knowledge graphs with respect to construction depth, construction width, and integration. Scores of 1–5 were used to represent the quality of the knowledge graph. The results of the differences between the high- and low-scoring groups are shown in Table 3.

The number of items of knowledge generated indicates that of the 32 learners, more than 700 triples were created and 584 were evolved into the subject ontology. This is a large number for a single lesson compared with traditional online learning, where learners always learn using knowledge points provided in the learning material but cannot extend or help create more relations (Clarke,

Table 1. Kappa test of the evolution.

	Unauthorized (Annotate as 0)	Authorized (Annotate as 1)	kappa	sig
Expert	158	562	.693	.000***
System	136	584		

***$p < .001$.

Table 2. Independent *t*-test of knowledge generation in different groups.

	Group	*N*	Mean	SD	*t*	*p*
Evolve	High-score	16	21.69	9.96	1.81	0.080
	Low-score	16	14.81	11.44		
Generate	High-score	16	26.13	10.04	1.71	0.098
	Low-score	16	19.00	13.35		

2003). This approach can thus help knowledge generation, and the construction and evolution of subject ontologies at least in terms of quantity. With regard to the quality of the knowledge generated by learners, Table 1 shows the results of validation by both experts and the system during system evolution. A total of 584 triples of the generated 722 were evolved in the final subject ontology. The results of assessment by the expert show that 562 of the 720 validated triples were authorized to evolve. The Kappa consistency value between the results of the system and the expert was .693, which is high. This approach can thus help high-quality knowledge evolution. This result answers the first research question and demonstrates the effectiveness of crowdsourcing activity in learners' learning (Hills, 2015).

To answer the second research question, we classified the triples generated by different levels of learners (high- and low-scoring learners) and conducted an independent sample t-test. The results are shown in Table 2. From the number of knowledge items generated by learners at different levels, we see that high-scoring learners generated more triples than the low-scoring group, and had a larger number of triples that evolved into the subject ontology. This matches the results obtained by other researchers, whereby learners from high-scoring groups tend to perform more positively and contribute more valuably during the learning process (Hsu, Hwang, & Chang, 2013; Yang, Li, Guo, & Li, 2015). Learners of the high-scoring group thus created more high-quality triples; the more they created the more were likely to evolve. However, we see from the t-test that there is no difference between the high- and low-scoring groups in terms of the number of triples generated ($t = 1.71$, $p = 0.098$) and evolved ($t = 1.81$, $p = 0.080$). This shows that low-scoring learners in the crowdsourcing mode-based learning activity can also help implement our targets. This is the advantage of crowdsourcing, where all participates can play a role in the group (Poetz & Schreier, 2012). We can use this method in future research to help the generation and evolution of subject ontologies. Moreover, with respect to the quality of the triples, the rates of evolution of both the high-scoring group (83%) and low-scoring group (78%) were high, and the evolution quality was very good. This result is consistent with other studies that have used a crowdsourcing mechanism to facilitate learning(Way, Ottenbacher, & Harrington, 2011; Zahirović Suhonjić et al., 2018). Hence, different levels of learners are able to participate in this approach.

To answer the third research question, the results in Table 3 are helpful. All learners generated their own knowledge graphs. This activity flow can thus involve all learners in the process. The depth, width, and integration scores of the personalized knowledge graphs show that a significant difference between the high- and low-scoring groups in terms of depth and integration. There was no difference in terms of width. The high-scoring group was thus more likely to construct better knowledge graphs because this method relies on learners' personal knowledge and engagement. This result is in accordance with our expectations. Hence, in order to promote learning for all

Table 3. Differences in the quality of knowledge graphs on 3 dimensions.

	Group	*N*	Mean	SD	*t*	*p*
Depth	High-score	16	3.69	1.30	2.09	0.046*
	Low-score	16	2.75	1.24		
Width	High-score	16	3.88	1.36	1.51	0.142
	Low-score	16	3.13	1.45		
Integration	High-score	16	3.87	0.92	2.63	0.014*
	Low-score	16	2.81	1.28		

*$p < .05$.

Table 4. TAM test.

dimension	Questions	*N*	Mean	SD
Usefulness	1、This strategy is helpful in my online learning	38	4.32	0.81
	2、This strategy is helpful in finding the knowledge point	38	4.34	0.71
	3、This strategy can improve my learning efficiency	38	4.34	0.75
	4、I can learn better with the help of the strategy than traditional method	38	4.03	1.00
	5、This strategy can promote the build of my knowledge structure	38	4.16	0.82
	6、This strategy is helpful in completing the subject knowledge	38	4.03	0.79
Ease of use	7、I can master the use of this system quickly	38	4.08	0.82
	8、It take me little time to fluently use this system	38	3.87	1.04
	9、It is easy to use this system to learn	38	3.92	0.94
	10、This system could guide me to complete the learning task	38	4.11	0.86
	11、In all, I think the system is easy to use	38	4.03	0.89

learners instead of only high-scoring learners, we can provide low-scoring learners some supplementary materials to help knowledge construction.

For the final research question, we use the results of the TAM test, as shown in Table 4. The mean scores for the first dimension (usefulness) were all higher than 4.0, as were those for the second dimension (ease of use), apart from questions 8 and 9. This indicates that the crowdsourcing mode-based learning activity flow approach promotes learning while aiding the generation and evolution of subject ontologies. Moreover, the method and system are relatively easy to use. Although the responses to questions 8 and 9 were relatively low, they still nearly scored 4.0. We can conclude that the system is useful in assisting learning and is an effective and easy way to promote knowledge generation and evolution by learners as well as adding to the knowledge in the learning content. This is easy to understand because in the crowdsourcing mode-based learning activity flow, learners can learn a large number of knowledge items and concepts. On the one hand, learners can learn the content as on any other platform; on the other, they can use annotations to create relations according to their understanding. This can help knowledge divergence (Besemer, 1981). When they learn content, they can reflect the learning process in the Knowledge Graph activity. In this activity, they can also improve the scope of their knowledge and build a personalized knowledge structure. Concepts and relations created but not validated by the system in the first two activities are sent to learners for verification according to their answers. This encourages implement a process of learn–reflect–strengthen that is helpful for learning. The results show that most learners found the system easy to use.

Conclusions

In this study, we proposed a crowdsourcing mode-based learning activity flow approach consisting of three learning activities (Semantic Annotation activity, Knowledge Graph activity, and Reverse Quiz activity) embedded in the learning process to help promote the generation and evolution of subject ontologies. Based on this approach, we designed and developed a system to support online learning. After the system was published, a fifth grade class participated in an experiment to evaluate the effectiveness of the system including whether the system can help subject ontology generation and evolution, whether there are differences between different level learners in subject ontology generation and evolution and if the system is useful and easy to use. A total of 34 learners participated in the experiment and 32 completed the learning process. With the data generated by the users, the system helped built 722 triples, of which 584 of were evolved into the formal subject ontology. The results were consistent with the expert's review. The proposed strategy is thus helpful for the generation and evolution of subject ontologies.

With regard to the operation of learners at different levels, we found that those in the high-scoring group could construct more triples, and more of them were accepted and evolved in the subject ontology. However, an independent sample t-test showed no difference between different levels of learners in terms of the amount of knowledge triples the learners generated and evolved. This indicates that all learners can be involved in knowledge generation process. This result can be attributed to the quality control mechanism. Each learner has his/her own advantage in terms of knowledge and, and was able to contribute as much as he/she could. This is the meaning of crowdsourcing, and this approach makes full use of crowdsourcing method to promote the generation and evolution of subject ontologies.

With regard to graph construction by different learners, learners from the high-scoring group were more likely to create a better knowledge graph that represents a deeper knowledge comprehension of the subject because they had better knowledge structures. However, all learners generated their personalized knowledge graphs with a similar knowledge breadth that satisfactorily reflected their prior knowledge. This enlightens us that learners of different levels have a similar knowledge breadth even though they could not comprehend knowledge from a similar depth. Hence, in order to make learning more effective, high-scoring learners can be given more freedom in knowledge construction, whereas low-scoring learners can be provided supplementary materials to scaffold their deeper understanding.

Finally, we tested the technique acceptance (TAM) of the system. The questionnaire had two dimensions, usefulness and ease of use. All learners in the experiment reported that the system was useful for improving their learning efficiency, knowledge discovery and complete their knowledge structures (which can be seen as the subject ontology in the system). Moreover, when learners used the system, they found it easy to master and use for learning. So this system is very helpful for learners' learning processes.

These results and conclusion are helpful for our future studies because they show that this system enables two important and difficult work integrate together and work successfully: promote the generation and evolution of subject ontology and guide the learner's learning process. Subject ontology is quite important in online learning. However, building sufficient subject ontology for all fields is time-consuming and difficult work. Considering the potential of crowdsourcing in building subject ontology, this research proposed a crowdsourcing mode-based learning activity flow embedded in learners' learning process to help the generation and evolution of subject ontology. This study is a novel trial both in the fields of learning and subject ontology construction. This research demonstrates that with respect to building a subject ontology, learners can promote the generation and evolution of subject ontology within their learning process if the learning activity is well designed. Moreover, learners of different knowledge levels can participate in this process with no difference. Hence, this verifies the main idea and advantage of crowdsourcing in subject ontology construction. In the future, the crowdsourcing mode based learning activity flow could help us more, not only with subject ontology construction, but also with other time-consuming tasks in the field of education.

In future work, we will experiment with more users to assist the generation and evolution of subject ontologies. Using the constructed subject ontologies, we can help implement intelligent recommendations in other learning contexts.

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