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Ontology-based concept map for planning a personalised learning path

Chih-Ming Chen

Chih-Ming Chen is an associate professor of Graduate Institute of Library, Information and Archival Studies at National Chengchi University. Address for correspondence: Chih-Ming Chen, Graduate Institute of Library, Information and Archival Studies, National Chengchi University, NO.64, Sec.2, ZhiNan Rd., Wenshan District, Taipei City 116, Taiwan. Tel: +886-2-29393091 ext. 88024; fax: +886-2-29384704; email: chencm@nccu.edu.tw

Abstract

Developing personalised web-based learning systems has been an important research issue in e-learning because no fixed learning pathway will be appropriate for all learners. However, most current web-based learning platforms with personalised curriculum sequencing tend to emphasise the learner preferences and interests in relation to personalised learning services but fail to consider the difficulty level of course materials, learning order of prior and posterior knowledge and learner abilities while constructing a personalised learning path. As a result, these ignored factors thus easily lead to the generation of poor quality learning paths. Generally, learners could generate cognitive overload or fall into cognitive disorientation owing to inappropriate curriculum sequencing during learning processes, thus, reducing the learning effect. With the advancement of artificial intelligence technologies, ontology technologies enable a linguistic infrastructure to represent conceptual relationships between course materials. Ontology can be served as a structured knowledge representation scheme, capable of assisting the construction of a personalised learning path. This study thus proposes a novel genetic-based curriculum sequencing scheme based on a generated ontology-based concept map, which can be automatically constructed by the pretest results of numerous learners, to plan appropriate learning paths for individual learners. The experimental results indicated that the proposed approach could create high-quality learning paths for individual learners. The proposed approach thus can help learners to learn more effectively and to likely reduce learners' cognitive overloads during learning processes.

Introduction

With the rapid growth of the Internet, various personalised e-learning platforms have been proposed to provide adaptive curriculum sequencing services for individual learners in web-based learning environments (Fung & Yeung, 2000; Brusilovsky, 1998; Chen, Lee & Chen, 2005; Chen, Liu & Chang, 2006; Lee, 2001; Papanikolaou & Grigoriadou, 2002; Tang & Mccalla, 2003). Although information technologies enable learners to easily access a large number of learning materials without geographical boundaries, this phenomenon has caused several serious problems, including self-learning control, learning disorientation and cognitive overload among learners (Alomyan, 2004; Eppler & Mengis, 2004). Generally, self-learning control among learners implies that learners should take the initiative in their learning. However, learners can deviate or learn inefficiently when they receive unsuitable instruction and scaffold. This phenomenon will result in great differences with the original goals of the instructors (Rasmussen & Davidson-Shivers, 1998). Moreover, the disorientation problem derives from most web-based learning systems being flooded with complex courseware structures because of excessive quantities of hyperlink-based learning materials, leading learners to easily suffer learning disorientation and making them vulnerable to learning disorientation and the inability to construct complete and systematic domain knowledge during learning (Calvi, 1997; Lin & Davidson-Shivers, 1996). Cognitive overload is also a serious problem that affects learner learning in hypermedia learning systems. This problem emerges from the freedom of navigation offered by hypermedia systems; moreover, it may also be compounded by the vast quantities of easily accessible information, much of which is only peripherally relevant (Paolucci, 1998).

To deal with these problems, a few researchers have developed the notion of using learning path as a control method for guiding the learning direction for individual learners. A growing number of studies attempt to create intelligent learning systems that can arrange the curriculum sequence more flexibly to provide learners with more adaptive and personalised learning services (Fung & Yeung, 2000; Brusilovsky, 1998; Chen *et al*, 2005, 2006; Lee, 2001; Papanikolaou & Grigoriadou, 2002; Tang & Mccalla, 2003). However, these intelligent learning systems are not so adaptive to individual learners because learner abilities, difficulties of course materials and the learning sequence of prior and posterior knowledge implied by the sequential arrangement of the course materials are not considered in these systems. In a previous study (Chen, 2008), we presented the genetic-based personalised learning path generation scheme capable of providing a near-optimal learning path for individual learners online based on course material difficulty, concept relation degree between course materials and learner abilities. However, our previous study ignored the learning order of prior and posterior knowledge. This leads to illogical learning paths while planning a personalised learning path for individual learners.

Ontology (Brewster & O'Hara, 2007; Gruber, 1993; Song, Song, Hu & Allen, 2007; Yang, Chen & Shao, 2004; Yang, Yu, Chen, Tsai & Lee, 2005) is a hierarchically structured set of terms for describing domain knowledge that can provide a structure for a knowledge base system. If an ontology is effectively implemented for a specific field and used to describe related knowledge such as terminology or associated notions, it can help identify useful or connected information related to exploring such structured knowledge (Swartout, Patil, Knight & Russ, 1996). This study thus attempts to improve the shortcomings of the genetic-based personalised learning path generation scheme presented in our previous study (Chen, 2008) to enable the learning order of prior and posterior knowledge to be considered while planning personalised paths. This study attempts to establish authentic and near-optimal learning paths that can help individual learners reduce the effects of cognitive overload and disorientation. Experimental results indicate that the proposed genetic-based learning path generation scheme based on the ontology-based concept map is superior to the genetic-based learning path generation scheme proposed in our previous study in terms of learning path quality because it simultaneously considers course materials' difficulties, prior and posterior knowledge of learning concepts and learner abilities during personalised path planning.

Weaknesses of the genetic-based personalised learning path generation scheme

Because the study aims to improve the genetic-based personalised learning path generation scheme presented by our previous study (Chen, 2008), this section briefly presents the previous approach. The genetic-based personalised learning path generation scheme, which can simultaneously take into account the difficulty level of course material and the conceptual continuity of successive course materials based on incorrect pretest responses, was proposed to support personalised web-based learning for individual learners. To evaluate the concept continuity of learning paths, each course material in the courseware database has a corresponding extensible markup language binding file for recording important Sharable Content Object Reference Model (SCORM) metadata, which conveys the main course material concept. The concept continuity of learning paths can be assessed by analyzing the corresponding SCORM metadata between successive course materials. This study first employed the Chinese word segmentation system to preprocess SCORM metadata in the form of separated words and then applied the cosine similarity measures to calculate the concept relation degrees among course materials. Restated, the genetic-based personalised learning path generation scheme is a semantic approach, and the learning concepts with high conceptual relation degree are successively recommended during a learning process while simultaneously considering course material difficulty.

To assess whether the proposed learning mode of curriculum sequencing recommendation based on the genetic-based personalised learning path generation scheme is superior to the freely browsing learning mode, 220 third-grade elementary school learners who were majoring in the 'Fraction' unit in a mathematics course were invited to participate in the experiment. Among 220 elementary school students, there were 92 students who served as the control group to perform the freely browsing learning mode, while the remaining students served as the treatment group to perform the proposed learning mode of curriculum sequencing recommendation only for course materials to which incorrect responses were provided in a pretest. Both the learning modes simultaneously perform a pretest and posttest to compare the difference of learning performance before and after learning. The independent sample *t*-tests were employed to analyse whether the freely browsing or proposed learning mode of the curriculum sequencing recommendation provides benefit in terms of learning performance promotion based on pretest and posttest scores. Compared with the freely browsing learning mode used in most web-based learning systems, the statistically confirmed experimental results indicated that the learning mode of curriculum sequencing recommendation is superior to the freely browsing learning mode in promoting learning performance. Meanwhile, the investigation results of questionnaires revealed that most learners agreed that the learning mode of curriculum sequencing recommendation is superior to the freely browsing learning mode in terms of learning efficiency. An important advantage is that the learning mode of curriculum sequencing recommendation customises learning for those with extremely specific needs and not much time or patience to complete topics they have learned.

However, the genetic-based personalised learning path generation scheme ignores the learning order of prior and posterior knowledge while planning personalised learning paths because the conceptual relation degrees among course materials are served as being symmetrical. That is, the curriculum sequence pattern 'A→B' is identical to the curriculum sequence pattern 'B→A'. This outcome is inconsistent with real-world learning situations (Hsu, Tu & Hwang, 1998). Generally, prior knowledge that refers to a range of knowledge, skills and ability should be significantly considered in the learning process. Past studies also indicated that learners with more knowledge about specific domains exhibit better understanding, memory and effectiveness of cognitive learning (McCormick & Pressley, 1995). With regard to this issue, numerous researchers have found that the related prior knowledge affects the learning performance (Papanikolaou & Grigoriadou, 2002). This study thus develops a novel genetic-based personalised learning path generation scheme based on an ontology-based concept map automatically constructed by numerous learner pretest results to plan appropriate learning paths for individual learners. The proposed approach is also semantic-based, while the ontology-based concept map is based on the concept relationships between course materials based on learner responses in testing question examinations. In the proposed approach, the learning order of prior and posterior knowledge of course materials is implied by the generated ontology-based concept map, thus, providing useful information to assist the genetic algorithm in planning logical learning paths for individual learners.

System design

This section is organised as follows: First, an overview of system architecture is introduced in 'System architecture'. The next section then explains the proposed ontology-based concept map generation scheme. Finally, the application of the generated ontology-based concept map to personalised learning path generation is described in the last section.

System architecture

In this study, the previously proposed genetic-based personalised learning path generation scheme (Chen, 2008) is improved to enhance the qualities of generated personalised learning paths for the personalised e-learning system via an automatically constructing ontology-based concept map. In the enhanced personalised e-learning system, the results of the pretests are first extracted and preprocessed to serve the needs of constructing the concept map, after which the concept relationships between course materials are constructed through the proposed concept relation measure and fuzzy clustering scheme. After that, the constructed ontology-based concept map is adopted as the source of the constraint conditions of prior and posterior knowledge of learning course materials and enables the employed genetic algorithm to plan an appropriate learning path for individual learners. Figure 1 shows the system architecture. The following explains the function of each component.

First, the courseware construction module, shown as the left rectangle framed by a dotted line in Figure 1, aims to provide a teacher interface for establishing the difficulty parameters of course materials and course contents for personalised courseware generation. The remaining system components are detailed as follows:

- **Learner account database.** The database aims to record learner account information for each learner.
- **Learning interface agent.** The agent offers a friendly user interface with personalised learning path guidance to individual learners for personalised learning services and stores learner learning processes in the user portfolio database.
- **User portfolio database.** The database is in charge of storing tracks of all detailed learning processes for individual learners.
- **Concept map generation agent.** The agent primarily makes use of the computing correlation between course materials and fuzzy clustering method to automate the construction of the ontology-based concept map.
- **Ontology-based concept map database.** The database stores a total of 17 designed course materials and the constructed ontology-based concept map to support personalised learning path generation based on the genetic algorithm.
- **Learning path recommendation agent.** The agent utilises the genetic algorithm together with the generated ontology-based concept map to construct adaptive learning paths for individual learners and to receive learners' testing responses from the learning interface agent.

Next, the system operation procedure based on the system architecture is described as follows:

Steps 1–4. The course experts first designed test items for each corresponding course material then examined the test items to estimate the difficulty parameters for each corresponding course material according to computerised adaptive testing theory. In this study, more than 600 records of elementary school examinees who participated in the exam of the unit 'Fraction', including 17 testing items covering those learning concepts, are preprocessed to construct an ontology-based concept map.

Step 5. The ontology-based concept map of the 'Fraction' unit is constructed by the employed fuzzy clustering method and concept correlation measure, which can group course materials with high correlation into the same cluster. The generated

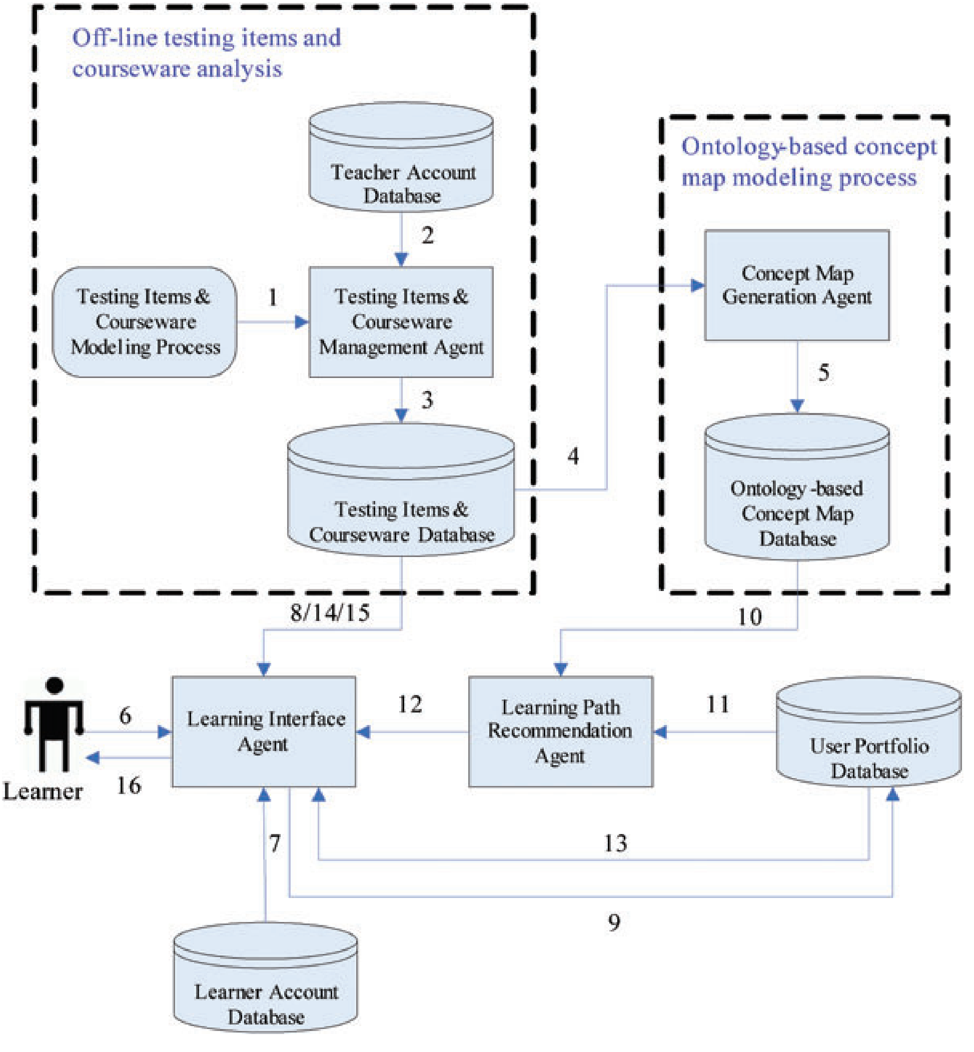

Figure 1: The system architecture of the personalised e-learning system based on ontology-based concept map

concept map is then stored in the ontology-based concept map database for supporting personalised learning path generation.

Step 6. Learners log into the system via a legal account to access personalised learning services.

Step 7. Once the learner logs in the system, the learner account database will offer legal account information to assist learners in checking their IDs.

Steps 8–9. The learning interface agent checks learner ID to determine whether the learner is a beginner or an experienced learner. If the learner is a beginner, the testing items and courseware database will provide a pretest, enabling him or her to assess which concepts he or she has still failed to learn well based on incorrect testing responses. If the learner is an experienced learner, then he or she will proceed to **Step 13** for unfinished learning processes; otherwise, he or she will proceed to the next step. Meanwhile, the learning states of each learner are also stored in the user portfolio database during learning processes.

Steps 10–12. The generated ontology-based concept map in **Step 5** is used to support the learning path recommendation agent in planning a near-optimal learning path based on the outcome of the learner pretest, after which the generated learning path is transmitted to the learning interface agent to provide adaptive learning guidance for individual learners. The functionalities of the learning interface agent for adaptive learning guidance of individual learner are detailed in 'The Implemented System for Personalised Web-Based Learning' section.

Steps 13–14. If the learner is identified as an experienced learner, his or her learning portfolio is first downloaded from the user portfolio database. The learner, thus, has to learn all the unfinished course materials recorded in the download learning path before performing the posttest.

Step 15. After the learner completes course material learning, the proposed system provides a posttest to assess the learner's learning performance.

Step 16. The learner completes all the learning procedures and logs out of the system.

The proposed ontology-based concept map generation scheme

The designed course materials in the course unit 'fraction' for exploring the ontology-based concept map

The proposed system contains one course unit 'Fraction' and includes 17 course materials designed by several mathematics teachers based on four different mathematics textbooks (ie, Han Lin, Nani, Jenlin and Kang Hsuan) used in Taiwan's elementary schools. In this study, Web pages with flash animation and synchronous voice comments for conveying some mathematical concept of course unit 'Fraction' are viewed as a course material. Moreover, each course material has a corresponding difficulty parameter initially determined via statistical analysis according to a pretest, and each course material corresponds to several testing questions used to examine the comprehensibility of the learned course material. This study uses a learning portfolio database including test records of more than 600 elementary school students who participated in the exam in the 'Fraction' unit. In the examination, the learned course materials with wrong answers will be served as 'focused concept' to evaluate the correlation with the other course materials with wrong answers as well for the proposed ontology-based concept map generation scheme. All course materials designed for the learning process and their corresponding difficulty parameters are listed in Table 1.

The computing method of concept correlation for exploring ontology-based concept map

According to the results of a testing question examination, this study proposes a computational formula of correlation to calculate the conceptual relationships between course materials. The following mathematical formula is then adopted:

Table 1: The contents of the designed course materials and the difficulty levels of the corresponding course materials in the course unit 'Fraction'

Course material	*Concept description*	*The difficulty level of course material*
C1 (Equal parts)	To understand the meaning of 'equal parts' is to divide a unit into *n* equal parts.	−1.8
C2 (Division as sharing)	To use the concept of 'equal parts' solves the problem of 'division as sharing'. Division as sharing means that a given set is partitioned into a specified number of groups to determine how many partitions are in each equal group.	−1.5
C3 (Division as separating)	To use the concept of 'equal parts' solves the problem of 'division as separating'. Division as separating means that a given set is partitioned by a specified amount to determine the number of equal groups.	−1
C4 (Sharing with a remainder)	To use the concept of 'equal parts' solves the problem of 'division as sharing with remainder'.	−0.1
C5 (Separating with a remainder)	To use the concept of 'equal parts' solves the problem of 'division as separating with remainder'.	0
C6 (Parts of a whole)	Identifying the numerator and denominator of a fraction and expressing improper fractions as whole	0.1
C7 (Improper fractions)	Identifying proper and improper fractions	0.2
C8 (Sequence of fractions)	Ordering the fractions and finding the fractional value on a number line.	0.4
C9 (Comparing proper fractions with the same denominator)	To compare fractions with the same denominator, look at their numerators. The larger fraction is the one with the larger numerator.	0.5
C10 (Comparing proper fractions with different denominators)	To compare fractions with different denominators	0.7
C11 (Adding and subtracting fractions)	Adding and subtracting fractions when the denominators are the same	1.2
C12 (Adding fractions)	Adding fractions with the same denominator	0.8
C13 (Subtracting fractions)	Subtracting fractions with the same denominator	1
C14 (Missing addend)	Perform missing addend fraction problems with the same denominator	1.3
C15 (Missing subtrahend)	Perform missing subtrahend fraction problems with the same denominator	1.5
C16 (Missing summand)	Perform missing subtrahend fraction problems with the same denominator	1.6
C17 (Missing minuend)	Perform missing minuend fraction problems with the same denominators	1.8

$$R_{C_i,C_j} = P(C_j|C_i) = \frac{N(C_i \cap C_j)}{N(C_i)}, \tag{1}$$

where R_{C_i,C_j} denotes the concept relation between the ith and jth learning concepts, $N(C_i)$ represents the number of the learners who gave wrong answers to the corresponding testing question conveying the ith learning concept and $N(C_i \cap C_j)$ stands for the number of learners who simultaneously gave wrong answers to the corresponding testing questions conveying both the ith and jth learning concepts.

Restated, the concept relationships between course materials are assessed based on learner responses in a testing question exam. All correlations among the 17 designed course materials in the 'Fraction' unit can be assessed and represented in the form of a concept correlation table, as shown in Table 2. Moreover, the threshold chosen for filtering out weak concept correlations is heuristically set to 0.132 in this study. The goal is to filter out the concept connections with weak correlation to each other. This process can simplify the generated ontology-based concept map. However, the optimal method of determining an appropriate threshold for filtering out weak concept correlations is a trade-off issue. Basically, setting a low threshold will lead to the construction of an overcomplex ontology-based concept map, thus, generating too many teaching sequence patterns of course materials. This will seriously reduce the convergence speed in planning personalised learning path based on the genetic algorithm. In fact, planning a personalised learning path for individual learners that has an acceptable run-time is also a critical consideration for a web-based learning system. In contrast, setting a high threshold will lead to the filtering out of most meaningful concept connections, thus, generating few teaching sequence patterns of course materials for planning personalised learning path. This will seriously affect the quality of planning personalised learning path. Therefore, heuristically setting the threshold in the study involves a trade-off based on the convergence speed and the quality of planning personalised learning path. To aid heuristic determining an appropriate parameter for filtering out weak concept correlations, a practicable strategy is providing an administrator interface that can help instructors to dynamically set this parameter based on teaching specialty in the proposed system before performing personalised learning service. Table 3 illustrates the revised concept correlations of the 17 designed course materials after filtering out the weak concept correlations.

The proposed ontology-based concept map generation scheme based on the computing concept correlations and fuzzy clustering scheme

Concept map generation based on fuzzy clustering scheme. This section describes how the fuzzy clustering analysis scheme (Zimmermann, 1991) is used to group course materials with high correlation into different clusters. In the employed fuzzy clustering analysis scheme, the clustering result is influenced by different α-cuts (Zimmermann, 1991). To optimise the clustering result, the concept correlations within the same cluster are expected to be as high as possible, but the correlations between different

Table 2: *The concept correlations between the 17 designed courseware items*

Courseware	*C1*	*C2*	*C3*	*C4*	*C5*	*C6*	*C7*	*C8*	*C9*	*C10*	*C11*	*C12*	*C13*	*C14*	*C15*	*C16*	*C17*
C1	1	0.23	0.153	0.153	0.192	0.269	0.346	0.423	0.192	0.653	0.307	0.23	0.307	0.461	0.307	0.269	0.384
C2	0.162	1	0.108	0.108	0.189	0.351	0.243	0.297	0.297	0.54	0.243	0.189	0.162	0.189	0.108	0.162	0.135
C3	0.307	0.307	1	0.23	0.538	0.384	0.384	0.538	0.307	0.846	0.23	0.307	0.307	0.384	0.153	0.23	0.153
C4	0.058	0.058	0.044	1	0.161	0.161	0.117	0.132	0.235	0.294	0.058	0.058	0.147	0.132	0.058	0.058	0.058
C5	0.172	0.241	0.241	0.379	1	0.241	0.206	0.31	0.275	0.517	0.137	0.172	0.172	0.206	0.137	0.103	0.137
C6	0.063	0.117	0.045	0.099	0.063	1	0.063	0.171	0.189	0.333	0.108	0.099	0.054	0.153	0.072	0.072	0.072
C7	0.2	0.2	0.111	0.177	0.133	0.155	1	0.244	0.311	0.466	0.177	0.155	0.111	0.311	0.133	0.155	0.177
C8	0.189	0.189	0.112	0.155	0.155	0.327	0.189	1	0.31	0.465	0.206	0.155	0.137	0.155	0.224	0.172	0.137
C9	0.045	0.1	0.036	0.146	0.073	0.192	0.128	0.165	1	0.284	0.165	0.082	0.073	0.1	0.045	0.073	0.036
C10	0.098	0.115	0.063	0.115	0.086	0.213	0.121	0.156	0.179	1	0.127	0.098	0.115	0.208	0.086	0.098	0.092
C11	0.153	0.173	0.057	0.076	0.076	0.23	0.153	0.23	0.346	0.423	1	0.153	0.25	0.326	0.192	0.23	0.211
C12	0.193	0.225	0.129	0.129	0.161	0.354	0.225	0.29	0.29	0.548	0.258	1	0.225	0.483	0.29	0.225	0.258
C13	0.235	0.176	0.117	0.294	0.147	0.176	0.147	0.235	0.235	0.588	0.382	0.205	1	0.382	0.294	0.382	0.441
C14	0.166	0.097	0.069	0.125	0.083	0.236	0.194	0.125	0.152	0.5	0.236	0.208	0.18	1	0.166	0.208	0.222
C15	0.258	0.129	0.064	0.129	0.129	0.258	0.193	0.419	0.161	0.483	0.322	0.29	0.322	0.387	1	0.354	0.387
C16	0.233	0.2	0.1	0.133	0.1	0.266	0.233	0.333	0.266	0.566	0.4	0.233	0.433	0.5	0.366	1	0.4
C17	0.322	0.161	0.064	0.129	0.129	0.258	0.258	0.258	0.129	0.516	0.354	0.258	0.483	0.516	0.387	0.387	1

Table 3: The revised concept correlations between the 17 designed courseware items after setting the weak concept correlations as zeros

Courseware	*C1*	*C2*	*C3*	*C4*	*C5*	*C6*	*C7*	*C8*	*C9*	*C10*	*C11*	*C12*	*C13*	*C14*	*C15*	*C16*	*C17*
C1	1	0.23	0.153	0.153	0.192	0.269	0.346	0.423	0.192	0.653	0.307	0.23	0.307	0.461	0.307	0.269	0.384
C2	0.162	1	0	0	0.189	0.351	0.243	0.297	0.297	0.54	0.243	0.189	0.162	0.189	0	0.162	0.135
C3	0.307	0.307	1	0.23	0.538	0.384	0.384	0.538	0.307	0.846	0.23	0.307	0.307	0.384	0.153	0.23	0.153
C4	0	0	0	1	0.161	0.161	0	0.132	0.235	0.294	0	0	0.147	0.132	0	0	0
C5	0.172	0.241	0.241	0.379	1	0.241	0.206	0.31	0.275	0.517	0.137	0.172	0.172	0.206	0.137	0	0.137
C6	0	0	0	0	0	1	0	0.171	0.189	0.333	0	0	0	0.153	0	0	0
C7	0.2	0.2	0	0.177	0.133	0.155	1	0.244	0.311	0.466	0.177	0.155	0	0.311	0.133	0.155	0.177
C8	0.189	0.189	0	0.155	0.155	0.327	0.189	1	0.31	0.465	0.206	0.155	0.137	0.155	0.224	0.172	0.137
C9	0	0	0	0.146	0	0.192	0	0.165	1	0.284	0.165	0	0	0	0	0	0
C10	0	0	0	0	0	0.213	0	0.156	0.179	1	0	0	0	0.208	0	0	0
C11	0.153	0.173	0	0	0	0.23	0.153	0.23	0.346	0.423	1	0.153	0.25	0.326	0.192	0.23	0.211
C12	0.193	0.225	0	0	0.161	0.354	0.225	0.29	0.29	0.548	0.258	1	0.225	0.483	0.29	0.225	0.258
C13	0.235	0.176	0	0.294	0.147	0.176	0.147	0.235	0.235	0.588	0.382	0.205	1	0.382	0.294	0.382	0.441
C14	0.166	0	0	0	0	0.236	0.194	0	0.152	0.5	0.236	0.208	0.18	1	0.166	0.208	0.222
C15	0.258	0	0	0	0	0.258	0.193	0.419	0.161	0.483	0.322	0.29	0.322	0.387	1	0.354	0.387
C16	0.233	0.2	0	0.133	0	0.266	0.233	0.333	0.266	0.566	0.4	0.233	0.433	0.5	0.366	1	0.4
C17	0.322	0.161	0	0	0	0.258	0.258	0.258	0	0.516	0.354	0.258	0.483	0.516	0.387	0.387	1

Table 4: The result of concept clustering by the fuzzy clustering scheme

The clustering results based on concept correlations among courseware	*The clustered set of courseware*
Cluster 1	C4 (Sharing with a remainder), C5 (Separating with a remainder), C9 (Comparing proper fractions with the same denominator), C1 (Equal parts), C17 (Missing minuend), C12 (Adding fractions)
Cluster 2	C6 (Parts of a whole)
Cluster 3	C3 (Division as separating)
Cluster 4	C8 (Sequence of fractions)
Cluster 5	C2 (Division as sharing)
Cluster 6	C7 (Improper fractions)
Cluster 7	C10 (Compare proper fractions with different denominators)
Cluster 8	C11 (Add and subtract fractions), C15 (Missing subtrahend), C13 (Subtracting fractions)
Cluster 9	C16 (Missing summand)
Cluster 10	C14 (Missing addend)

clusters are expected to be as low as possible. Thus, the cost function, which integrates maximising the concept correlations in the same cluster and minimising the concept correlations among different clusters, was employed for optimising the number of clusters. The final clustering outcome when considering the optimal number of clusters is listed in Table 4.The ontology-based concept map can be depicted using the clustered course materials via the fuzzy clustering algorithm and the asymmetric concept correlation table shown in Table 3. Figure 2 shows the complete ontology-based concept map. The following descriptions detail the construction of a concept map:

Step 1. Construct the inner correlations.
In this step, it is only necessary to consider clusters that contain more than one course material, such as Clusters 1 and 8. Taking Cluster 1 as an example, it is possible to first identify all correlations between the six courses then draw connections via which their weights can be indicated based on the asymmetric concept table listed Table 3. To simplify the generated ontology concept map, this study only considers connecting the concepts with the five highest correlation values. The ontology concept map of Cluster 1, thus, can be shown in Figure 3. The same method can be applied to construct the ontology concept map in Cluster 8.

Step 2. Construct the outer correlations and calculate the weights of correlations between pairs of clusters.
In this step, the main idea of constructing the ontology concept map is similar to **Step 1**. Based on the clustering results of Table 4, the total required number of connections for linking each cluster is nine because the case involves ten concept clusters. Next, this study employed a similarity measure to estimate the weights of the correlations between two clusters, formulated as follows:

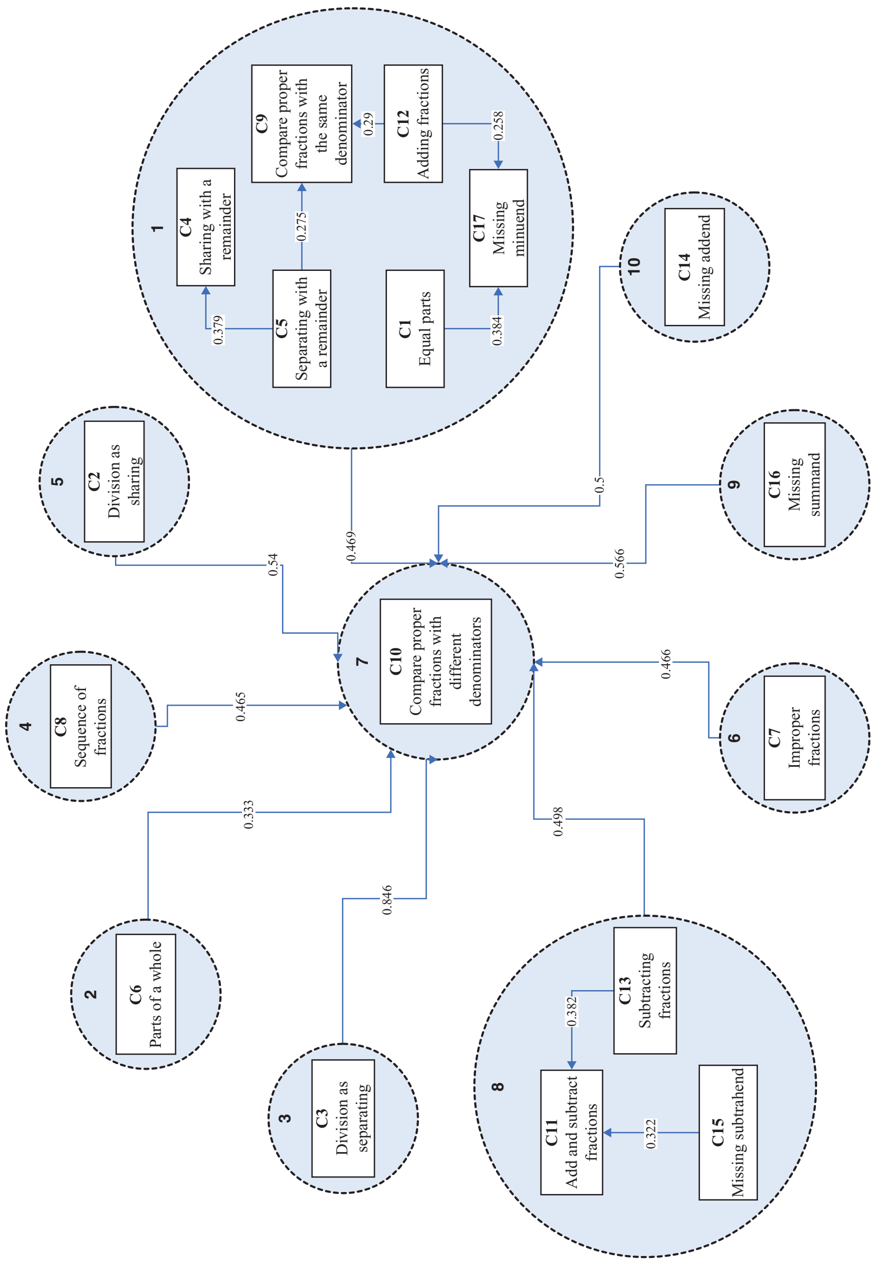

Figure 2: The generated ontology-based concept map for the 17 designed courseware items

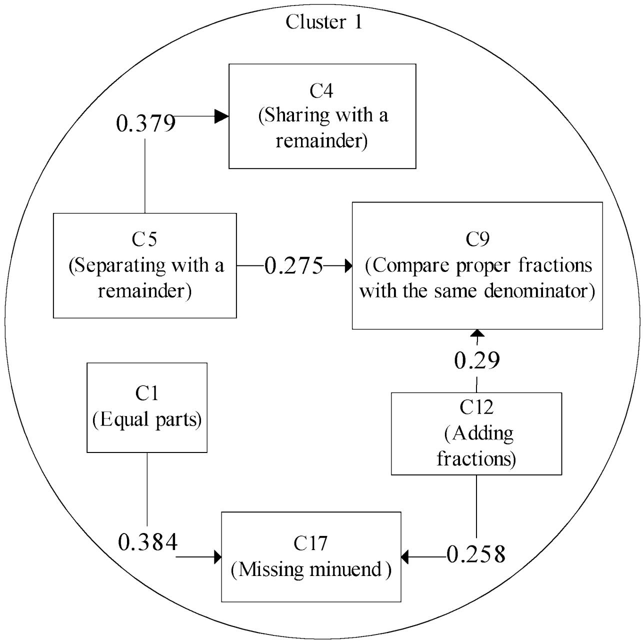

Figure 3: The generated ontology concept map of Cluster 1

$$weight_{i,j} = \frac{\sum_{p=1}^{n_i}\sum_{q=1}^{n_j} rel(C_{i,p}, C_{j,q})}{n_i \times n_j}, \quad where\ 0 \le weight_{i,j} \le 1, 1 \le i, j \le n, \tag{2}$$

where $weight_{i,j}$ denotes the correlation between the ith and jth clusters, n_i represents the number of course materials in the ith cluster, n_j is the number of course materials in the jth cluster and rel $(C_{i,p}, C_{j,q})$ denotes the correlation between the pth course material in the ith cluster and the qth course material in the jth cluster.

Teaching sequence pattern of course material derived from the ontology-based concept map
Based on the generated ontology-based concept map shown in Figure 2, 23 teaching sequence patterns of pair course materials are summarised and listed in Table 5. In the teaching sequence of each pair course material, the premise part can be considered prior knowledge of the conclusion part. This property is useful in planning a logical learning path while providing curriculum sequencing for personalised learning services.

Applying an ontology-based concept map to personalised learning path generation
To plan a better learning path than that in our previous study (Chen, 2008), the curriculum structure contained in the generated ontology-based concept map was adopted as the constraint conditions of the employed genetic algorithm for planning

Table 5: The courseware teaching sequence pattern derived from ontology-based concept map

No.	Courseware teaching sequence pattern	No.	Courseware teaching sequence pattern
1	C1 (Equal parts) → C10 (Comparing proper fractions with different denominators)	13	C11 (Add and subtract fractions) → C10 (Comparing proper fractions with different denominators)
2	C1 (Equal parts) → C17 (Missing minuend)	14	C12 (Adding fractions) → C9 (Comparing proper fractions with the same denominator)
3	C2 (Division as sharing) → C10 (Comparing proper fractions with different denominators)	15	C12 (Adding fractions) → C10 (Comparing proper fractions with different denominators)
4	C3 (Division as separating) → C10 (Comparing proper fractions with different denominators)	16	C12 (Adding fractions) → C17 (Missing minuend)
5	C4 (Sharing with a remainder) → C10 (Comparing proper fractions with different denominators)	17	C13 (Subtracting fractions) → C10 (Comparing proper fractions with different denominators)
6	C5 (Separating with a remainder) → C4 (Sharing with a remainder)	18	C13 (Subtracting fractions) → C11 (Add and subtract fractions)
7	C5 (Separating with a remainder) → C9 (Comparing proper fractions with the same denominator)	19	C14 (Missing addend) → C10 (Comparing proper fractions with different denominators)
8	C5 (Separating with a remainder) → C10 (Comparing proper fractions with different denominators)	20	C15 (Missing subtrahend) → C10 (Comparing proper fractions with different denominators)
9	C6 (Parts of a whole) → C10 (Comparing proper fractions with different denominators)	21	C15 (Missing subtrahend) → C11 (Add and subtract fractions)
10	C7 (Improper fractions) → C10 (Comparing proper fractions with different denominators)	22	C16 (Missing summand) → C10 (Comparing proper fractions with different denominators)
11	C8 (Sequence of fractions) → C10 (Comparing proper fractions with different denominators)	23	C17 (Missing minuend) → C10 (Comparing proper fractions with different denominators)
12	C9 (Comparing proper fractions with the same denominator) → C10 (Comparing proper fractions with different denominators)		

personalised learning paths for individual learners. That is, a learning path planned by the genetic algorithm must be evaluated whether it satisfies the curriculum sequence implied in the generated ontology-based concept map. If a learning path created using the genetic algorithm conflicts with the order of prior and posterior knowledge in the sequence of course materials, it is treated as an inappropriate learning path. To measure the quality of planning learning paths, this study proposes a penalty term α to calculate the violated value by comparing the rules of prior and posterior knowledge derived from the ontology-based concept map with the generated learning path, thus, enabling learning paths that conflict with the order of prior and posterior knowledge to reduce corresponding fitness function values. The penalty value obtained by a high-quality learning path, thus, can be minimised. The proposed penalty term is defined as:

$$\alpha = \sum_{k=1}^{n} MAX(P_{k1} - P_{k2}, 0) \tag{3}$$

where α denotes the proposed penalty term, n represents the total number of prior and posterior knowledge rules, P_{k1} and P_{k2} are the corresponding position index values in planning a learning path that violates with the antecedent and consequent parts of the kth rule of prior and posterior knowledge derived from the ontology-based concept map respectively.

To define a fitness function, which can simultaneously consider the proposed penalty term and the difficulty parameter of course material for assessing generated learning path quality, both the considered parameters are normalised between 0 and 1 and combined by an adjustable weight. Restated, the planning learning path will satisfy the condition that the difficulty levels of course materials range from easy to hard and that the curriculum sequence follows the order of prior and posterior knowledge where possible. In the proposed method, a learning path constructed by the genetic algorithm only considers the mapped course material in which the learner provides incorrect pretest results. Furthermore, the easiest course material is always ranked first in a generated learning path. The proposed fitness function for planning high-quality personalised learning path has the following form:

$$f = (1-w) \times (1-\alpha_n) + w \times \sum_{i=2}^{m} (b_{i(n)} - b_{i-1(n)}), \tag{4}$$

where f denotes the proposed fitness function used to assess generated learning path quality, α_n represents a normalised penalty term for assessing the violated value of a generated learning path based on the rules of prior and posterior knowledge obtained from ontology-based concept map, $b_{i(n)}$ is the normalised difficulty level of the ith course material, m denotes the total number of course materials considered for personalised learning path generation and w represents an adjustable weight.

Experiments

The experimental analysis primarily focuses on comparing the performance of the proposed genetic-based learning path generation scheme supported by the ontology concept map with the genetic-based learning path generation scheme presented in our previous study (Chen, 2008).

Parameter setting of fitness function

In the study, the parameter setting for the proposed fitness function affects the quality of the generated learning paths. In our experiments, the termination condition for the genetic algorithm is set to 150 generations, the population size is set to 50, the mutation rate is set to 0.1 and the duplication rate is set to 1. Additionally, several optimal search algorithms, such as the golden section search and simplex search algorithms (Reklaitis, Ravindran & Ragsdell, 1983), can be employed to appropriately determine the adjustable weight of the proposed fitness function for planning high-quality personalised learning paths. However, optimising the adjustable weight for planning personalised learning path is time consuming and costly because various weight combinations must be repeatedly evaluated based on the quality evaluation by the proposed fitness function. Therefore, to efficiently determine the appropriate weight of the proposed fitness function for planning personalised learning path, several parameter combinations were heuristically assessed by setting different ratios of course material difficulty level to the penalty level of measuring the degree of violation of the teaching sequence based on the sequence of prior and posterior knowledge obtained from the constructed ontology-based concept map. Based on the experiments presented here, the adjustable weight for planning personalised learning paths is set to 0.7 in this study because comparison of several different weight combinations reveals that this weight can obtain the learning path with the better quality and faster convergence speed when using the genetic algorithm. Although we cannot guarantee that this setting is optimal, this study found that this weight can stably obtain high quality result in 20 independent runs while using the employed genetic algorithm for planning personalised learning path.

Quality evaluation of the personalised learning path generated by the proposed scheme

In an educational adaptive learning system, a high-quality learning path attempts to maximise the combination of learner understanding of courseware and learning efficiency. However, identifying a high-quality learning path for individual learners is difficult because no standard solution exists for accurately evaluating learning path success. Therefore, applying the teaching sequences of textbooks and the teaching sequences suggested by experienced teachers as a baseline for evaluating learning path quality is a reasonable approach because the teaching sequences mainly consider textbook unit formation or teacher teaching processes. The present experiments used the two methods described previously to measure learning path quality when the adjustable weight is set to 0.7. First, the learning paths of the 'Fraction' unit generated by the proposed genetic-based personalised learning path generation scheme supported by the ontology-based concept map are compared with the teaching sequences of four subject elementary textbooks used in Taiwan's elementary schools. In this work, the teaching sequences of the planned learning paths were respectively examined by using the teaching sequences from the four mathematics textbooks. Secondly, the learning paths associated with the teaching sequences are also compared with those suggested by three experienced mathematics teachers to examine the validity of the planned learning path. To evaluate the quality of the generated learning path, the total violated distance of the teaching sequence is defined and formulated as follows:

$$\gamma = \sum_{i=1}^{n-1} \sum_{j=(i+1)}^{n} MAX(P_i - P_j, 0), \tag{5}$$

where γ denotes the total value of violated distance of a planned learning path, n represents the total number of course materials in a course unit, P_i is the corresponding position index value in planning a learning path that violates with the antecedent part of the ith rule of prior and posterior knowledge derived from the ontology-based concept map and P_j is the corresponding position index value in planning a learning path that violates with the consequent part of the jth rule of prior and posterior knowledge derived from the ontology-based concept map.

Table 6 lists the individual teaching orders and integrated teaching order of 17 designed course materials in the course unit 'Fraction' based on four selected textbooks. Furthermore, Table 7 presents an example illustrating how to compute the total violated distance of the planned learning path with the teaching sequence in the Han Lin version textbook. In Table 7, the course material ID is marked with parentheses when the planned learning path violates the teaching sequence of the compared textbook. Finally, the total violated distance of a generated learning path can be obtained by summing all the violated distances. According to the proposed quality evaluation formula, two experiments were designed to evaluate the quality of the learning paths generated by the proposed genetic-based learning path generation scheme supported by the ontology-based concept map, which is described as follows:

Comparing the generated learning path with the teaching sequences of four version textbooks to examine the quality of the planned personalised learning path

In this study, one course unit 'Fraction' for the third-grade elementary school students in Taiwan, which includes 17 course materials with various difficulty levels to convey the concept of the 'Fraction', was employed to evaluate the quality of the planned personalised learning path. This study assumes that a learner pretests the 'Fraction' unit using 17 various course materials, and the learner makes a total of 17 mistakes in the testing items, which correspond to 17 learning concepts of the 'Fraction' unit. This case indicates that the proposed system plans a personalised learning path containing the 17 course materials to guide learners' learning process. To assess the average performance of the proposed scheme for planning personalised learning path, 20 independent runs were conducted for planning personalised learning paths, and each planned learning path was individually compared with the individual teaching sequences of the four textbooks. Table 8 lists the comparison results under an adjustable weighting of 0.7. Additionally, a further experiment was designed to compare the quality of the learning paths generated by both the personalised learning path generation schemes with the integrated teaching sequence obtained from the four version textbooks. Table 9 lists the comparison result. Based on the above experimental results, this study found that the quality of the learning paths planned using the proposed genetic-based personalised learning path generation scheme supported by the ontology-based concept map is superior to the quality of the learning paths planned using the genetic-based personalised learning path generation scheme presented by our previous work (Chen, 2008). Moreover, the learning paths generated by the proposed scheme can also be adopted as a valuable reference in developing the teaching sequence for textbooks. In a manner, this case can logically infer that the proposed system can plan adaptive learning paths for learners who exhibit various combinations of incorrect testing responses in the 'Fraction' unit because any planned personalised learning paths based on different combinations of incorrect testing responses in the 'Fraction' unit are a subset of the personalised learning path containing all 17 course materials.

Table 6: Summarisation of the individual teaching sequences and integrated teaching sequence of the 17 designed courseware items obtained from four selected textbooks

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Han Lin	1	3	2	5	4	6	16	8	7	17	15	9	10	11	13	12	14
Nani	1	2	4	3	5	6	11	7	9	17	16	8	10	12	14	13	15
Jenlin	1	3	2	4	5	6	12	7	8	13	11	9	10	14	16	15	17
Kang Hsuan	1	2	4	3	5	6	15	7	16	17	10	8	9	11	12	13	14
Total ranking value	4	10	12	15	19	24	54	29	40	64	52	34	39	48	55	53	60
Average teaching order in the four version textbooks	1	2.5	3	3.75	4.75	6	13.5	7.25	10	16	13	8.5	9.75	12	13.75	13.25	15
The integrated teaching order for the 17 designed courseware	C1→C2→C3→C4→C5→C6→C8→C12→C13→C9→C14→C11→C16→C7→C15→C17→C10																

Table 7: An example for computing the total violated distance of the learning path generated by the proposed genetic-based learning path generation scheme supported by ontology-based concept map with the teaching sequence of Han Lin version textbook

The teaching sequence of the generated learning path in Han Lin version textbook	*The violated status of the generated learning path with the teaching sequence of the Han Lin version textbook*	*Computing violated distance by comparing the learning path sequence of the Han Lin version with the learning sequence of the generated learning path*
3→2	(2)→(3)→17→9→16→8→14→4→10	2 − 1 = 1
4→8	2→3→17→9→16→(8)→14→(4)→10	8 − 6 = 2
4→9	2→3→17→(9)→16→8→14→(4)→10	8 − 4 = 4
4→14	2→3→17→9→16→8→(14)→(4)→10	8 − 7 = 1
4→16	2→3→17→9→(16)→8→14→(4)→10	8 − 5 = 3
4→17	2→3→(17)→9→16→8→14→(4)→10	8 − 3 = 5
8→16	2→3→17→9→(16)→(8)→14→4→10	6 − 5 = 1
8→17	2→3→(17)→9→16→(8)→14→4→10	6 − 3 = 3
9→17	2→3→(17)→(9)→16→8→14→4→10	4 − 3 = 1
14→16	2→3→17→9→(16)→8→(14)→4→10	7 − 5 = 2
14→17	2→3→(17)→9→16→8→(14)→4→10	7 − 3 = 4
16→17	2→3→(17)→9→(16)→8→14→4→10	5 − 3 = 2
The total violated distance in the generated learning path		29

Comparing the generated learning path with the teaching sequences from course experts' suggestion to examine the validity of the planned personalised learning path

To further assess the quality of the learning path generated using the proposed novel scheme, this study invited three experienced mathematics teachers from Kuan-Hua elementary school in Hualien, Taiwan, to make suggestions regarding the learning sequence of the 17 course materials related to the course unit 'Fraction'. Table 10 lists the teaching sequence of the 17 course materials in the course unit 'Fraction' suggested by three experienced mathematics teachers from Kuan-Hua elementary school and the integrated teaching sequence suggested by these three mathematics teachers. Similarly, 20 independent runs were conducted and respectively compared with the individual teaching sequences suggested by three experienced mathematics teachers of Kuan-Hua elementary school for the 17 course materials in the 'Fraction' unit. Tables 11 and 12 respectively show the comparison results of the quality of the learning paths generated by both the personalised learning path generation schemes with the individual learning paths and the integrated learning path suggested by the three experienced mathematical teachers. The experimental results also demonstrated that the quality of the learning paths planned using the proposed genetic-based personalised learning path generation scheme supported by the ontology-based concept map exceeds those planned using the genetic-based personalised learning path generation scheme presented in our previous study.

Finally, given experimental results are summarised in Table 13. Based on these results, this study demonstrates that the learning paths planned via the proposed genetic-based

Table 8: Comparison of the quality of the learning paths generated by both the personalised learning path generation schemes with the individual teaching sequences obtained from four versions of textbooks

Independent run	Genetic-based personalised learning path generation scheme (Chen, 2008)				Genetic-based personalised learning path generation scheme supported by ontology-based concept map			
	The Han Lin version textbook	The Nani version textbook	The Jenlin version textbook	The Kang Hsuan version textbook	The Han Lin version textbook	The Nani version textbook	The Jenlin version textbook	The Kang Hsuan version textbook
1	459	491	535	477	200	154	221	172
2	503	497	563	513	229	216	280	187
3	383	438	467	420	153	129	192	151
4	471	466	539	477	224	182	250	200
5	449	486	529	468	240	174	240	230
6	463	458	531	471	152	146	129	69
7	453	491	541	474	207	187	218	180
8	452	490	535	471	223	235	287	184
9	459	431	487	465	234	180	239	183
10	459	491	535	477	144	113	145	152
11	471	466	539	477	252	191	284	197
12	383	438	467	420	214	249	307	237
13	449	486	529	468	237	213	303	216
14	459	431	487	465	245	249	345	240
15	373	433	461	411	239	244	278	184
16	459	431	487	465	202	180	259	209
17	469	436	493	474	222	198	353	316
18	459	491	535	477	287	240	317	274
19	373	433	461	411	216	200	260	234
20	449	486	529	468	231	198	249	175
Total violated distance	8895	9270	10 250	9249	4351	3878	5156	3990
Average violated distance	471				217			

Table 9: Comparison of the quality of the learning paths generated by both the personalised learning path generation schemes with the integrated teaching sequence obtained from four version textbooks

Independent run	*Genetic-based personalised learning path generation scheme (Chen, 2008)*	*Genetic-based personalised learning path generation scheme supported by ontology-based concept map*
1	509	146
2	496	119
3	318	256
4	496	216
5	434	240
6	478	209
7	344	228
8	353	181
9	434	263
10	282	145
11	496	158
12	519	167
13	504	211
14	486	137
15	504	237
16	478	284
17	506	117
18	508	248
19	544	179
20	357	185
Total violated distance	9046	3926
Average violated distance	452	196

personalised learning path generation scheme supported by the ontology-based concept map are more accurate and reliable than those constructed via the previously proposed scheme.

The implemented system for personalised web-based learning

This section introduces the implemented system in detail. Figure 4 shows the layout of the user's learning interface. As a learner logs into this system, he or she must conduct a pretest if he or she is a beginner; otherwise, the system will guide the learner to learn the course materials based on the previously unfinished learning procedure. Figure 5 illustrates the interface of performing a pretest for a beginner. Following the pretest, the system will plan a near-optimal learning path based on the course materials for which the learner fails to give correct answers in the pretest to support the adaptive learning guidance for the learner. Figure 6 displays the user interface for personalised learning. In the left frame of Figure 6, the course materials are ordered according to the learning sequence of the planned learning path. Next, when learners click on the course material with the highest learning priority in the left frame of Figure 6, the proposed learning system will yield the corresponding learning content for individual learner learning. Figure 7 shows the learning content of the course material with the highest

Table 10: Summarisation of the individual teaching sequences and integrated teaching sequence of the 17 designed courseware items suggested by three experienced mathematics teachers of Kuan-Hua elementary school

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Course expert A	1	2	3	4	5	6	9	10	7	8	13	11	12	14	16	15	17
Course expert B	1	2	3	6	7	4	8	9	5	10	14	11	12	13	17	15	16
Course expert C	1	2	3	4	5	6	9	8	7	17	16	10	13	11	14	12	15
Total ranking value	3	6	9	14	17	16	26	27	19	35	43	32	37	38	47	42	48
Average teaching order from three course experts	1	2	3	4.6	5.6	5.3	8.6	9	6.3	11.6	14.3	10.6	12.3	12.6	15.6	14	16
The integrated teaching order for the 17 designed courseware	C1→C2→C3→C4→C6→C5→C9→C7→C8→C12→C10→C13→C14→C16→C11→C15→C17																

Table 11: Comparison of the quality of the learning paths generated by both the personalised learning path generation schemes with the individual teaching sequences suggested by three experienced mathematics teachers

	Genetic-based personalised learning path generation scheme (Chen, 2008)			*Genetic-based personalised learning path generation scheme supported by ontology-based concept map*		
Independent run	*Course expert A*	*Course expert B*	*Course expert C*	*Course expert A*	*Course expert B*	*Course expert C*
1	542	562	501	300	308	217
2	219	207	279	310	277	204
3	538	556	508	300	294	224
4	484	505	437	288	298	228
5	539	558	498	469	449	350
6	458	436	426	212	187	173
7	212	205	270	227	240	181
8	415	393	377	359	331	252
9	511	508	467	348	350	278
10	216	203	276	258	265	183
11	535	552	505	228	222	148
12	483	503	447	289	281	204
13	480	499	444	279	294	210
14	461	440	429	197	189	118
15	535	552	505	252	233	153
16	247	212	299	203	219	190
17	506	502	449	288	267	210
18	514	512	470	307	297	228
19	535	552	505	249	240	167
20	516	520	485	309	298	231
Total violated distance	8946	8977	8577	5672	5539	4149
Average violated distance		442			256	

Table 12: Comparison of the quality of the learning paths generated by both the personalised learning path generation schemes with the integrated teaching order suggested by three experienced mathematics teachers

Independent run	*Genetic-based personalised learning path generation scheme (Chen, 2008)*	*Genetic-based personalised learning path generation scheme supported by ontology-based concept map*
1	540	193
2	532	223
3	270	423
4	532	323
5	477	296
6	435	341
7	268	321
8	365	336
9	477	388
10	213	291
11	532	198
12	539	198
13	535	335
14	438	185
15	535	325
16	435	361
17	491	159
18	536	373
19	541	310
20	276	261
Total violated distance	8967	5840
Average violated distance	448	292

learning priority in the generated learning path. To adaptively guide individual learner learning, the learning interface agent of the proposed system will temporally disable the course materials that their ranking priorities are less than the priority of the current learning material until the current learning material has been acquired. Moreover, one randomly selected testing item related to the current learning course material is arranged in the bottom-right window to help assess whether the learner acquires the learned course material. If a learner can pass the test question regarding the current course material, then the learning interface agent permits the learner to learn the next course material in the planned learning sequence. If a learner cannot pass two randomly selecting testing questions for some learning course material, the learning interface agent will guide the learner to conduct the remedy learning. In this work, the testing items and courseware database contain course materials with easier difficulty level than the current learning course material used for supporting remedy learning. The remedial course materials convey similar learning concepts with the current learning course material, but they contain different learning content. The remedy learning mechanism aims at improving the learning performances of individual learners for the course materials that they cannot acquire well through the normal course materials.

Table 13: The entire quality evaluation of the learning path generated by both the personalised learning path generation schemes

	Learning mode	
Comparison items	*Genetic-based personalised learning path generation scheme (Chen, 2008)*	*Genetic-based personalised learning path generation scheme supported by ontology-based concept map*
The average violated distance of the generated learning path with the individual teaching sequences of the four versions of textbooks	471	217
The average violated distance of the generated learning path with the integrated teaching sequence of the four versions of textbooks	452	196
The average violated distance of the generated learning path with the individual teaching sequences of the three course experts	442	256
The average violated distance of the generated learning path with the integrated teaching sequence of the three course experts	448	292

Figure 4: The logon user interface

Figure 5: The user interface of pretest

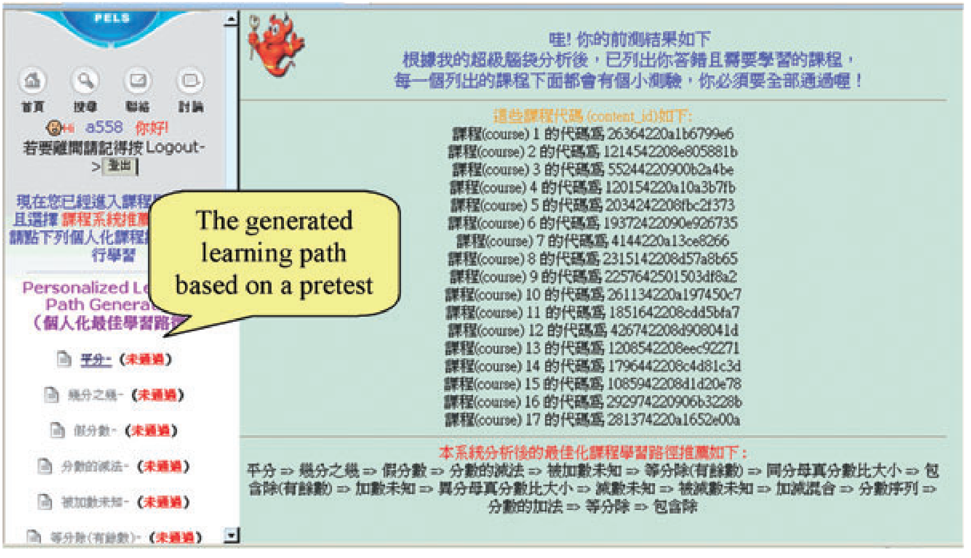

Figure 6: The user interface with personalised learning path guidance

Learning performance assessment for the proposed system

The study also performed an experiment to assess whether the proposed genetic-based personalised learning path generation scheme supported by ontology-based concept map is superior to the genetic-based personalised learning path generation scheme presented by our previous study (Chen, 2008). In the experiment, 86 third-grade

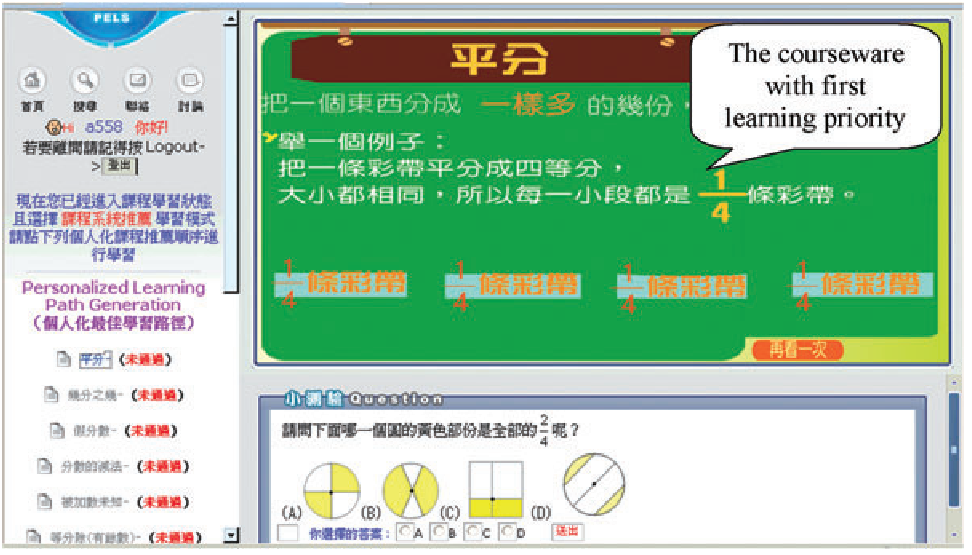

Figure 7: The courseware with first learning priority in the generated learning path

elementary school students who were majoring in the 'Fraction' unit in a mathematics course were invited to participate in the experiment. Among 86 elementary school students, there are 43 who were served as the control group to perform the genetic-based personalised learning path generation scheme, and the remaining students were served as the treatment group to perform the genetic-based personalised learning path generation scheme supported by ontology-based concept map. Both the learning modes simultaneously perform a pretest and posttest for comparing the difference of learning performance before and after learning. In the experiment, teachers first detailed the system operation procedures for all participants in the first hour, then all participants logged in the system to perform the planned learning process according to two different experimental groups for the next 2–4 hours. Each participant must follow three learning stages to complete the entire learning process, ie, pretest process, learning process and posttest process, no matter what learning modes were used. Table 14 displays the statistics information of learning performance for both the control and treatment groups.

First, the independent samples t-test was adopted to assess whether the mathematical abilities of two participating groups in the 'Fraction' unit are equivalent before performing the experiment process based on pretest. The result indicates that these two participating groups do not reach significant difference on the pretest score ($t = -6.82$, $p = 0.497 > 0.05$). Therefore, the mathematical abilities of two participating groups in the 'Fraction' unit can be viewed as equivalent before performing the experiment process. Next, the posttests of two participating groups were also analysed by using independent samples t-test. The t-test result ($t = -1.001$, $p = 0.320 > 0.05$) shows that

Table 14: The statistics information of learning performance for both the control and treatment groups

Learning mode	Pretest			Posttest		
	Number of learners	Mean	Standard deviation mean	Number of learners	Mean	Standard deviation mean
The control group performed the genetic-based personalised learning path generation scheme presented by our previous study (Chen, 2008)	43	76.67	5.41	43	78.23	5.26
The treatment group performed the genetic-based personalised learning path generation scheme supported by ontology-based concept map	43	77.51	5.96	43	79.47	6.12

the two participating groups do not reach significant difference on the posttest score. Thus, this study further compared the pretest and posttest for each group using the paired samples t-test. The statistical analysis result on the control group shows that the difference of the mean scores of pretest and posttest is −1.56, and the result of paired samples t-test reaches the significant level ($t = -2.204$, $p = 0.033 < 0.05$). In addition, the pretest and posttest scores of the treatment group were also assessed by using the paired samples t-test. In the statistical analysis result, the difference of the mean scores between pretest and posttest is −1.96, and the result of paired samples t-test ($t = -3.508$, $p = 0.001 < 0.05$) shows that the treatment group also achieves significant difference. The results reveal that both the learning modes provide benefit in terms of the promotion of learning performance, but the statistical analysis cannot prove that the treatment group is obviously superior to the control group. However, the mean progressive score of the treatment group is superior to that of the control group in this experiment. Importantly, the proposed genetic-based personalised learning path generation scheme supported by ontology-based concept map can plan more logical learning paths than the genetic-based personalised learning path generation scheme presented by our previous study (Chen, 2008) for individual learners.

Conclusions

This study presents a novel genetic-based personalised learning path generation scheme based on an ontology-based concept map capable of simultaneously considering the difficulty level of course material and the concept relations of prior and posterior knowledge between course materials in planning personalised learning paths according to the incorrect testing responses in a pretest. Experimental results indicate that the proposed scheme can create higher quality learning paths than the previously proposed genetic-based personalised learning path generation scheme for individual learners. Meanwhile, the statistical analysis also reveals that the proposed web-based learning system supported by the proposed ontology-based concept map for planning personalised learning paths is helpful to the promotion of learning performance. In addition, from the perspective that the proposed system can guide individual learners in conducting adaptive learning based on a personalised learning sequence for course materials with incorrect testing responses in a pretest, the proposed scheme helps reduce learner disorientation during learning processes. Actually, the proposed system can also reduce learner cognitive overload because learners learn course materials only that learners have not acquired well and follow a learning sequence based on individual learner knowledge level. More important, the personalised learning path customises learning for individuals with extremely specific needs and not much time or patience to complete topics they have learned, thus, helping enhance learning effectiveness.

Additionally, several critical issues require further investigation. First, to record the ontology-based concept map more flexibly, the database design for storing the ontology-based concept map can be replaced by Resource Description Framework (RDF) with extensible markup language syntax in the future. This improvement can not only easily extend the number of course materials but also make it more convenient to apply the ontology-based concept map to other web-based educational systems to support adaptive learning materials. Second, it is also useful to research curriculum sequencing standards for developing e-learning systems with adaptive learning guidance.

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