Enhancement of student learning performance using personalized diagnosis and remedial learning system

Ling-Hsiu Chen
Department of Information Management, Chaoyang University of Technology, 168, Jifong East Road, Wufong, Taichung County 413, Taiwan

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Abstract
Although conventional student assessments are extremely convenient for calculating student scores, they do not conceptualize how students organize their knowledge. Therefore, teachers and students rarely understand how to improve their future learning progress. The limitations of conventional testing methods indicate the importance of accurately assessing and representing student knowledge structures. The personalized diagnosis and remedial learning system (PDRLS) proposed in this study enhances the effectiveness of the Pathfinder network by providing remedial learning paths for individual learners based on their knowledge structure. The sample was 145 students enrolled in introductory JAVA programming language courses at a Central Taiwan technology university. The experimental results demonstrate that learners who received personalized remedial learning guidance via PDRLS achieved improved learning performance, self-efficacy, and PDRLS use intention. The experimental results also indicated that students with lower knowledge level gain more benefits from the PDRLS than those with higher level of knowledge and that field dependence (FD) students obtain a greater benefit from PDRLS than field independence (FI) students do.

1. Introduction

To learn effectively, students must organize and link their prior knowledge (the knowledge they have already learned or already know) with new knowledge. Students who are unable to link new knowledge with prior knowledge have problems understanding, recalling, and accessing the new knowledge later (Anderson, 1995). As Ausubel (1968) noted, “the most important single factor influencing learning is what the learner already knows.” Thus, identifying and understanding student knowledge status serves as an important work for teacher to design instructional strategies to help students learn efficiently (Carpenter, Franke, Jacobs, Fennema, & Empson, 1998; Cobb et al., 1991). Conventional assessments (e.g., evaluation and recall) are convenient means of calculating student scores and grades but provide little information regarding student knowledge status (or knowledge level) (Lau & Yuen, 2010). Therefore, alternative assessment techniques are needed to remedy the limitations of conventional assessment (Reeves, 2000).

An alternative technique of assessing student knowledge level is concept mapping, which reveals and visualizes student knowledge structures. However, concept maps are often inadequate for assessing and comparing knowledge structure for larger groups of students, and they lack scales for measuring student knowledge quality. One solution for investigating large numbers of students and indicating individual knowledge quality is the Pathfinder network. Pathfinder network applies a scaling algorithm based on graph theory to represent knowledge in a network format, which enables assessment of numerous students as well as evaluation of knowledge quality by comparing similarities in referent structure (Cooke, 1992; Cooke & Schvaneveldt, 1988). This technique obtains three measurements of individual knowledge quality: PRX index, GTD index, and PFC index (C index). Previous studies confirm that these indexes are effective for evaluating student knowledge quality in various learning domains (Chen, 1997; Davis, Curtis, & Tschetter, 2003; Goldsmith, Johnson, & Acton, 1991; Gomez, Hadfield, & Housner, 1996). However, learners with similar knowledge scores may have different understandings or misconceptions and may present different knowledge structures. Pathfinder indices have limited capability to locate specific misconceptions for individual learners (Davis et al., 2003).
Technological advances in information and network technology now enable efficient solutions for this problem. Many researchers have proposed personalized e-learning systems for enhancing individual learning efficiency (Chen, Lee, & Chen, 2005; Chen, Liu, & Chang, 2006; Chen, 2010; Lau & Yuen, 2010; Papanikolaou & Grigoriadou, 2002; Tang & Mccalla, 2003). Recent studies have investigated the use of adaptive mechanisms in personalized e-learning systems that consider learner preferences, interests and browsing behaviors. These studies, however, overlook the importance of learner ability when providing personalized service (Chen et al., 2005; Chen, Liu, et al., 2006; Papanikolaou & Grigoriadou, 2002). Therefore, numerous researchers have focused on developing personalized services based on learner ability (Chen et al., 2005; Chen, Liu, et al., 2006; Lau & Yuen, 2010; Papanikolaou & Grigoriadou, 2002). Some have focused on diagnosing groups (e.g., different gender) rather than individuals (Lau & Yuen, 2010). Others have proposed various scoring mechanisms for representing knowledge level individually (Chen et al., 2005; Chen, Liu, et al., 2006; Papanikolaou & Grigoriadou, 2002). However, none of these studies have described specific misconceptions and provided remedial service of individual learners.

To add value to personalized services in asynchronous or synchronous online learning and enhance student online learning performance, this study developed a method of personalizing remedial learning based on the knowledge structure of the individual learner. A Web-based intelligent personalized diagnosis and remedial learning system (PDRLS) was used to assess and visualize student knowledge structures and diagnose student misconceptions. Knowledge structure was measured using Pathfinder network (Schvaneveldt, 1990), which enables assessment of large numbers of students. The application of Pathfinder network was then extended to individual knowledge diagnoses and remedial learning paths.

1.1. Knowledge structure

An important step in the individual learning process is the organization of associations and relationships among previously learned knowledge or concepts that are stored in long-term memory into appropriate sequences, or “epistemological orders” (Polya, 1957). The sequence of the epistemological order can be obtained and presented topologically as a “conceptual map” or as a “knowledge structure” (Novak, Gowin, & Johansen, 1983; Plotnick, 1997). The structure of concepts in a knowledge domain is configurable, which enables measurement of knowledge structure and the identification of misconceptions held by novices.

Typically, the first step in revealing knowledge structure is eliciting knowledge, which obtains individual judgments or answers about concept relationships. The judgments or answers are then scaled and represented. Finally, the derived knowledge is compared against a referent structure or “gold standard”, which is often elicited from a domain expert. Many methods have been proposed to reveal knowledge structure. The many proposed methods of revealing knowledge structure include concept mapping (Leauby & Brazina, 1998), word association techniques (Geeslin & Shavelson, 1975), ordered recall (Cooke, Durso, & Schvaneveldt, 1986), card sorting procedures (Frederick, Heiman-Hoffman, & Libby, 1994), paired-comparison (Curtis & Viator, 2000), and the ordered tree technique (Naveh-Benjamin, McKeachie, Lin, & Tucker, 1986). Cluster analysis or multi-dimensional scaling can be used for scaling and representing knowledge structure while holistic scoring, density scoring, and validity scoring (McClure, Sonek, & Suen, 1999) are typical techniques for scoring knowledge structure. Of these methods, concept maps offer an appropriate way of visualizing learner knowledge structure and lead to a better understanding on learner’s knowledge status (Lau & Yuen, 2010; Leauby & Brazina, 1998). However, concept maps are ineffective for studying large groups, particularly in classes larger than twenty students in which the teacher must spend considerable time providing personalized suggestions to individual students.

1.2. Pathfinder network

Pathfinder network technique was proposed by Schvaneveldt (1990) to investigate individual knowledge quality in large groups of students. The Pathfinder network reveals local relations among psychologically meaningful concepts compared with other multi-dimensional scaling representations (Cooke, 1992; Cooke & Schvaneveldt, 1988). Thus, this study employed this technique to assess learner knowledge structures.

Pathfinder network applies a scaling algorithm based on graph theory to represent knowledge as a network derived from proximity matrices. The proximity matrices represent the interconnectedness (distance) between concepts and the strengths of the relationships among concepts. Concepts and relations among concepts are represented as nodes and lines. The Pathfinder algorithm uses the triangle inequality rule to search the nodes for a minimum length path among concepts and then constructs a proximity matrix. Finally, the matrix is transformed into a network structure. To ensure that the network structure is a better representation of domain knowledge, network is determined by two main parameters r and q. The r parameter determines how the weight of a path is calculated from the weights of path links while the q parameter limits the number of links permitted in the paths. This limit can be incorporated into the network generation procedure to limit the number of links in the paths for which triangle inequality is ensured in the final proximity matrix. Pathfinder analysis provides three measurements for assessing individual knowledge quality by comparing similarities among referent structures provided by experts: PRX, GTD, and FFC.

Pathfinder networks are widely used to represent knowledge structures in diverse domains, including computer programming (Cooke & Schvaneveldt, 1988; Lau & Yuen, 2010), team performance (Lim & Klein, 2006), software requirements (Kudikyala & Vaughn, 2005), flight training (Schvaneveldt, Beringer, & Lamonica, 2001), accounting education (Curtis & Davis, 2003; Rose, Rose, & McKay, 2007) and mental health (Ober & Shenaut, 1999). This technique also reveals conceptual changes before and after evolutionary changes in instruction in varying applications (D’Apollonia, Charles, & Boyd, 2004), including statistics (Geske, 2001) and police training (Braverman, 1997). Previous studies indicate that Pathfinder scores can effectively predict self-efficacy (Davis et al., 2003), achievement (Chen, 1997; Goldsmith et al., 1991), and behavior (Gomez et al., 1996). Although Pathfinder scoring mechanisms are adequate for evaluating student knowledge quality, they do not explain student misconceptions by showing inappropriate links in student knowledge structures (Davis et al., 2003). Therefore, the proposed intelligent personalized diagnosis and remedial learning system (PDRLS) extends Pathfinder network to student learning improvement in order to assess student knowledge structure and diagnose student misconceptions, and finally, to provide individual learners with remedial learning paths.
The PDRLS provides personalized service to individual students based on their learning misconceptions. This section describes the PDRLS system architecture, operation, and components.

2.1. System architecture and operation

Fig. 1 shows the PDRLS system architecture. The front-end architecture includes an interface management agent, a testing management agent, and a courseware management agent while the back-end architecture includes a knowledge acquisition agent, a misconception diagnosis agent, and a remedial learning path generation agent. The system also includes five databases: testing bank database, courseware database, learner account database, conceptual relationship database, and user profile database. Learners must perform several tasks during the learning progress. First, the concepts in each course subject and the relationship (linkage and learning level) among concepts must be defined by the experts (or instructors) and stored in the conceptual relationship database. Second, course content should be developed by the instructor and stored in the courseware database. Finally, the testing question profile, including testing question content, answers, and the weights of all possible answers to the corresponding concepts should be created and stored in the testing bank database.

The PDRLS enables all learners to browse course materials, but only registered learners have a personalized remedial learning path service. As learners log in to the PDRLS, the interface management agent checks the learner account database to identify learner status. Learners who already have accounts in the learner account database can then receive personalized learning services. Alternatively, the learner can simply browse the course material (steps 1–3). After the registered learner completes a course unit provided by the courseware management agent, the interface management agent asks the learner to complete a test and notifies the testing management agent (step 4). The testing management agent provides the learner with randomly selected test items for the corresponding learning subject, records the answers, and forwards them to the knowledge acquisition agent (step 5). The knowledge acquisition agent then searches for learner concept relationships. Accordingly, this agent implements a scaling algorithm based on network representation to generate expert knowledge based on the answers stored in the testing bank database. The learner answers are then used to present learner knowledge (step 6). The misconception diagnosis agent also compares learner and expert knowledge structures to clarify learner misconceptions, which are then forwarded to the remedial learning path generation agent (step 7). After the remedial learning path generation agent produces the personalized remedial learning path based on conceptual relationships among diagnosed misconceptions stored in the conceptual relationship database, it sends a message to the interface management agent (step 8). Finally, the courseware management agent provides the corresponding learning content followed by the suggested remedial learning path (step 9). Processes and patterns associated with the learner learning process are recorded and then stored in the user profile database.

2.2. System components

2.2.1. Front-end part

2.2.1.1. Interface management agent. The interface management agent provides a channel for communicating with agents for courseware management, testing management, and remedial learning path generation.
2.2.2. Testing management agent. The testing management agent measures learner understanding of relationships among course concepts. This agent randomly provides a testing item to the learner, and records the answers of the learner and passes them to the knowledge acquisition agent. This study thus applied the XOR operator to identify the misconception path by comparing novice and expert knowledge structures. The XOR operator is as follows:

\[ \text{Misconception path}(N, E) = \forall (|N_i \oplus E_i|) \]

Where \( N_i \) is the novice with link in concept \( i \), \( E_i \) is the expert with link in concept \( i \) and \( \oplus \) is the XOR operator. The XOR operator can identify two different misconception paths. One is expert with link but novice without link, and another is expert without link but novice with link. Both misconceptions indicate that novices are either ambiguous or do not learn well.

2.2.2. Back-end part

2.2.2.1. Knowledge acquisition agent. The knowledge acquisition agent elicits and represents individual knowledge structure. This agent receives student answers from the testing management agent and produces a proximity matrix. This agent randomly provides a testing item to the learner, and records the answers of the learner and passes them to the knowledge acquisition agent.

2.2.2.2. Misconception diagnosis agent. This agent assesses student-derived knowledge presentation relative to some standard such as expert organization of the concepts calculated from the answers stored in the testing bank database. The Pathfinder algorithm uses the triangle inequality rule to search the nodes for a minimum length path between concepts and then transforms the proximity matrix into a network structure. To ensure that the network structure is a better representation of domain knowledge, this network is determined by two main parameters, \( r \) and \( q \). The \( r \) parameter determines how the weight of a path is calculated from the weights of path links while the \( q \) parameter limits the number of links permitted in the paths.

\[ r \text{ parameter for determining path weight.} \]

In graph theory, the distance between nodes \( i \) and \( j \) is the minimum weight of all possible paths from \( i \) to \( j \). Given a path \( P \) comprising \( k \) links with weights \( w_1, w_2, ..., w_k \), the weight of path \( P \), \( w(P) \), is

\[ w(P) = \left[ \sum_{l=1}^{k} |w_l| \right]^{1/r} \]

where \( r \geq 1 \), \( w \geq 1 \), \( i \neq j \).

When \( r = 1 \), the function corresponds to simple addition, when \( r = 2 \), it becomes the usual Euclidean metric, and when \( r \) tends to \( \infty \), the function is maximized. Restated,

\[ \lim_{r \to \infty} \left[ w_i + w_j \right]^{1/r} = \text{maximum}(w_i, w_j) \]

The perceived dissimilarity between entities increases with the value of \( r \) in the psychological interpretation. \( q \) parameter for limiting the number of links in the paths. The \( q \) parameter provides systemic control of link density in the original similarity matrix according to the equation \( \alpha = \frac{q}{2} \). This limit can be incorporated into the network generation procedure to limit the number of path links for which triangle inequality is ensured in the final proximity matrix.

This novel system sets \( r = \infty \) and \( q = n - 1 \) since these are the most common parameter values when Pathfinder is used for knowledge representation.

2.2.2.3. Remedial learning path generation agent. After diagnosis, learner misconceptions are forwarded to the remedial learning path generation agent to generate a personalized remedial learning path based on the concept learning level defined in the conceptual relationship database. The following procedure is used to generate a personalized remedial learning path:

1. Gather all misconceptions obtained from the misconception diagnose agent, e.g., A, B, C, F, G.
2. Of the misconceptions obtained in step 1, identify the highest and lowest learning level concepts stored in the conceptual relationship database. For example, in the conceptual relationship shown in Fig. 4, the highest learning level is concept A (learning level = 1), and the lowest levels are concept F and G (learning level = 4) where the larger and smaller numbers denote lower and higher learning levels, respectively.

3. Generate the individualized remedial learning path by connecting the linkage relationship stored in the conceptual relationship database from the lowest level concept to the highest level concept. Since the linkage relationship from concepts F to A is F, C, A, the first remedial learning path is A- C- F. Since the linkage relationship from concept G to concept A is G, D, B, A, the second remedial learning path is A- B- D- G.

3. Experiments

A true experimental design, i.e., a pretest-posttest control group design, was implemented to confirm the quality and effectiveness of the proposed personalized diagnosis and remedial learning system (PDRLS) for helping learners improve their learning performance. The true experimental design effectively reveals cause-and-effect relationships by randomly assigning controls for extraneous variables. Additionally, the true experimental design exhibits high internal validity. The true experimental design thus offers an excellent way for this investigation to verify the effectiveness of PDRLS.

3.1. Participants

Volunteers were recruited from a JAVA Programming Design course. One hundred forty-five first-grade students (86 males and 59 females) completed the experimental procedure. Participant age range was 18–20 years. No participants had previous knowledge of JAVA programming language.
3.2. Experimental environment

The PDRLS was implemented on a Windows XP system using PHP 4.3 for front-end script language and MySQL for the database server. The web-based design of the PDRLS included free browsing and guided learning modes. Before implementing the PDRLS, experts or instructors can apply concept management to establish the definitions and learning levels of concept relationships in each course and to develop learning materials. The expert or instructor can then use the testing question management function to establish the testing question content, answers, and the weights of individual answers relative to the corresponding concepts.

3.3. Procedure

The experimental procedure was as follows:

1. Constructing referent structure: To establish the referent knowledge structure, referent structures were obtained from three different experts. This study applied the Winslow (1996) criterion of 10 years experience for expert status. Two other criteria were a degree in Computer Science or a related discipline and at least 6 years experience using or teaching JAVA or a related object-oriented (OO) programming language.

2. Assignment of experiment and control group: Students were randomly assigned to an experimental group \(n = 72; 43\) male, 29 female) or a control group \(n = 73; 43\) male, 30 female). Students in the experimental group received personalized remedial learning path service after completing their first round of testing while those in the control group only received their scores (rate of correct answers) in first round testing.

3. Learning with the PDRLS: Students were limited to 30 min to learn the topic (i.e., OO programming design) assigned in the guided learning mode.

4. Pre-test and knowledge diagnosis. After completing the assigned topic, students were asked to complete the pre-test. The 10-item multiple-choice test was designed to assess their knowledge of "OO programming design" (see Appendix 2). The content and answer of all testing questions were established by three experts and the inter consistency value are all exceed 0.95. Finally, the PDRLS determined the individual knowledge structures for all students by analyzing their test results (Fig. 5).

5. Learning feedback and remedial learning. The PDRLS displays the remedial learning paths, the correct ratios, and the learning times for the students in the experimental group (Fig. 6). The students can then follow the learning sequence provided by the Remedial learning path generation agent for the learning process.

![Fig. 5](image_url). The screen to present student's individual knowledge structure.
Fig. 7 lists the control group interface, including correct ratio and learning times indicated on the diagnostic reports of individual students. The students can go to learning main page and browse course materials of interest.

1. Post-test. After completing the remedial learning, all students took a ten-question multiple-choice test to demonstrate their knowledge of “OO programming design”. The post-test content was identical to that of the pre-test, except that the order of questions and answer choices was rearranged (see Appendix 2).
4. Results

The SPSS for Windows version 12.0 was used for data analysis. A t-test was used to compare the pre-test and post-test scores between the experimental and control groups. A p-value less than 0.05 was considered statistically significant.

4.1. Influence of personalized remedial learning service on learning performance

Table 1 lists the t-test scores for the pre-test. The table reveals no significant difference in pre-test score between the experimental and control groups (40.47 vs 40.30, respectively; \( t = 0.048 \)). Next, post-test scores were compared. Table 2 lists the post-test scores for the experimental and control groups. The table shows that the improvement in the experimental group was significantly larger than that in the control group (68.23 vs 58.91, respectively). However, the p-value in the experimental group (0.048) was only marginally better than that of the control group.

4.2. Effect of personalized remedial learning service on student attitude

A questionnaire survey was also performed to assess student attitude towards PDRLS. Specifically, this study designed a three-item scale with responses ranging from "1" (strongly disagree) to "5" (strongly agree) to examine student attitude towards self-efficacy, satisfaction, and intention to use PDRLS. The cronbach’s alpha value of this three-item scale is 0.87, demonstrating this scale has good reliability (Nummally, 1978).

Table 3 lists the test results for different groups in the personalized remedial learning service. The table shows that the scores for self-efficacy, satisfaction, and intention to use PDRLS were significantly higher in the experimental group than in the control group. Restated, after the groups had received learning guidance via PDRLS, the experimental group perceived PDRLS more positively than the control group did.

5. Discussions

This study provides primary evidence that learner knowledge structure is important for promoting learning performance. Although the analytical results indicate that the proposed PDRLS can help learner to achieve better learning performance, while, the efficacy of the PDRLS seems not good enough since the statistics result just present marginal significance effect (\( p = 0.048 \)) on students learning performance. The proposed explanation is that the study did not account for other important human factors that might affect how learners use the PDRLS system. For example, knowledge level (Chen, Fan, & Macredie, 2006; Mitchell, Chen, & Macredie, 2005) and cognitive style (Chen, 2010; Ford, 1995; Ford & Chen, 2001; Fullerton, 2000) are reportedly relevant to student interaction in the Web-based learning system.

5.1. Knowledge level and learning performance

Learning strategies reportedly differ among students with different knowledge levels. Compared to experts (individuals with high knowledge levels), novices (individuals low knowledge levels) often suffered more disorientation. Therefore, students with low knowledge level gain more benefits from the online tutorial system than those with high knowledge level in a guidance style context (Chen, Fan, et al., 2006).
learning. Among the different measures of cognitive style, more bene-

48.33; 7.693

5.2. Cognitive style and learning performance

Rayner, 1998). Although these preferred modes of processing information differ among individuals, a given individual consistently uses

effectiveness. Further analyses indicated that students with low knowledge levels obtain a greater bene-

detailed information representing the conceptual properties of student misconceptions and more guidance for optimizing their future

Table 4

Comparison of post-test scores of the two groups in various knowledge level.

<table>
<thead>
<tr>
<th>Bracket</th>
<th>Group</th>
<th>N</th>
<th>Mean</th>
<th>S.D.</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low-score (n = 72)</td>
<td>Experimental group</td>
<td>34</td>
<td>58.88</td>
<td>6.68</td>
<td>3.565</td>
<td>0.014*</td>
</tr>
<tr>
<td></td>
<td>Control group</td>
<td>38</td>
<td>48.33</td>
<td>7.693</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High-score (n = 73)</td>
<td>Experimental group</td>
<td>38</td>
<td>69.30</td>
<td>5.542</td>
<td>1.100</td>
<td>0.272</td>
</tr>
<tr>
<td></td>
<td>Control group</td>
<td>35</td>
<td>67.29</td>
<td>4.545</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*p < 0.05.

Table 5

Comparison of post-test scores of the two groups in various cognitive styles.

<table>
<thead>
<tr>
<th>Bracket</th>
<th>Group</th>
<th>N</th>
<th>Mean</th>
<th>S.D.</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>FD (n = 49)</td>
<td>Experimental group</td>
<td>27</td>
<td>55.55</td>
<td>6.86</td>
<td>6.565</td>
<td>0.001*</td>
</tr>
<tr>
<td></td>
<td>Control group</td>
<td>24</td>
<td>50.86</td>
<td>7.08</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FI (n = 44)</td>
<td>Experimental group</td>
<td>15</td>
<td>70.21</td>
<td>5.38</td>
<td>0.473</td>
<td>0.624</td>
</tr>
<tr>
<td></td>
<td>Control group</td>
<td>27</td>
<td>68.50</td>
<td>6.77</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IM (n = 52)</td>
<td>Experimental group</td>
<td>30</td>
<td>58.65</td>
<td>7.84</td>
<td>3.022</td>
<td>0.025*</td>
</tr>
<tr>
<td></td>
<td>Control group</td>
<td>22</td>
<td>94.0</td>
<td>7.58</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

FD: field-dependent; FI: field-independent; IM: intermediate.

*p < 0.05.

2006; Mitchell et al., 2005). To determine the influence of knowledge level on learning performance, each student group was further subdivided by pre-test scores into high-score and low-score groups. The grouping standard was as follows: the top 50% (73 students) were assigned to the high-score bracket and the bottom 50% (72 students) were assigned to the low-score bracket. Table 4 compares the post-test scores between experimental and control groups in each bracket. Table 4 indicates that, in the high-score bracket, the average post-test scores of the experimental group was higher than that of the control group (69.30 vs 67.29). However, the difference did not reach statistical significance (t = 1.100). The low-score bracket of the experimental group was significantly higher than that of the control group (56.88 vs 48.33; t = 3.565). These statistical results support previous researchers’ opinion (Chen, Fan, et al., 2006; Mitchell et al., 2005). Thus, PDRLS is more beneficial for students with low knowledge levels than for those with high knowledge levels.

5.2. Cognitive style and learning performance

Cognitive style is the approach that an individual habitually and preferentially uses to organize and represent information (Riding & Rayner, 1998). Although these preferred modes of processing information differ among individuals, a given individual consistently uses the same approach (Witkin, Moore, Goodenough, & Cox, 1977). Individuals with different cognitive styles adopt different approaches to learning. Among the different measures of cognitive style, “Field Dependence (FD)/Field Independence (FI)” is the most common measure of cognitive style used in education research (Messick, 1976; Witkin et al., 1977). Field dependent individuals are typically heavily influenced by format-structure (Jonassen & Grabowski, 1993) and prefer guidance in their learning processes (Chou, 2001). Conversely, FI individuals tend to rely on internal references rather than format-structure and are usually independent thinkers (Goodenough, 1976; Jonassen & Grabowski, 1993). That is, FI individuals prefer analytical and active learning approaches (Chou, 2001; Frank & Keane, 1993). Previous investigations of cognitive styles also indicate that learning is significantly more efficient in matched conditions than in mismatched conditions (Ford, 1995; Ford & Chen, 2001; Fullerton, 2000; Lee, 2000). Therefore, matching the cognitive styles of learners with the Web-based learning program design is an important factor in learning outcome.

To discover how cognitive style affects learning performance, this study applied the Cognitive Style Analysis (CSA) to identify the cognitive styles of learners. This study applied the scale developed by Riding (1991), i.e., WA scores of 1.36 and above denote field independence, scores below 1.03 indicate field-dependence, and scores between 1.03 and 1.35 are intermediate. Fifty-two students in this study were intermediate (WA score: Mean = 1.07, SD = 0.090), 44 were FIs (WA score: Mean = 1.896, SD = 0.554), and 49 were FDs (WA score: Mean = 0.927, SD = 0.258). Table 5 compares the post-test scores for the experimental and control groups of FD and FI students. Table 5 indicates that the average post-test score of the FI bracket of the experimental group was higher than that in the control group, although the difference did not reach statistical significance (70.21 vs 68.50; t = 0.473). In the FD bracket, the experimental group was superior to the control group, and the difference was statistically significant (55.55 vs 50.86; t = 4.565). Also in the intermediate bracket, the experimental group was superior to the control group, and the difference was statistically significant (58.65 vs 54.0; t = 3.022). Thus, is clearly more beneficial for FD and intermediate students than for FI students.

6. Conclusions

To improve student learning performance, this study extended the application of the Pathfinder network and designed a personalized diagnosis and remedial learning system (PDRLS) to provide personalized misconceptions regarding the diagnosis and remedial learning service based on student knowledge structure. Compared to conventional assessment procedures, the PDRLS provides more precise and detailed information representing the conceptual properties of student misconceptions and more guidance for optimizing their future learning progress. The experimental results clearly indicate that learner knowledge structure is an important factor in learning performance. Besides knowledge structure, this study also discovered that two human factors, knowledge level and cognitive style, may influence learning effectiveness. Further analyses indicated that students with low knowledge levels obtain a greater benefit from PDRLS than students with high knowledge levels do and that PDRLS is more beneficial for FD students than for FI students.
Meanwhile, the analyses of learner attitudes about the personalized remedial learning service revealed that self-efficacy, satisfaction, and intention to use PDRLS was considerably higher in students who received the service than in students who did not. Restated, the study confirmed that PDRLS provides learners with valuable learning information and appropriate guided learning paths. Further, the PDRLS provides information (i.e., flawed concepts and clustered concepts) that instructors can use to enhance their teaching effectiveness.

This study demonstrated that multiple human factors should be considered when developing personalized Web-based learning systems. These experimental results can be used to construct robust user models for customized Web-based learning systems that accommodate individual preferences and abilities (Chen, 2010). Future studies may adapt the PDRLS to different content presentation approaches (e.g., non-linear approach) or to the design of various navigation tools (e.g., hierarchical maps and alphabetical indexes) to support the requirements of different learners (e.g., expert learners or Fl learners). Chen (2010) proposed a design model that Web-based learning program designers can use to tailor programs to different cognitive styles. Therefore, future studies can extend the Chen model by including other human factors (i.e., knowledge level) to obtain user models that are more robust and comprehensive.

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Appendix. Supplementary material

Supplementary data associated with this article can be found in the online version, at doi:10.1016/j.compedu.2010.07.015.

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