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Mobile formative assessment tool based on data mining techniques for supporting web-based learning

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ABSTRACT

Current trends clearly indicate that online learning has become an important learning mode. However, no effective assessment mechanism for learning performance yet exists for e-learning systems. Learning performance assessment aims to evaluate what learners learned during the learning process. Traditional summative evaluation only considers final learning outcomes, without concerning the learning processes of learners. With the evolution of learning technology, the use of learning portfolios in a web-based learning environment can be beneficially adopted to record the procedure of the learning, which evaluates the learning performances of learners and produces feedback information to learners in ways that enhance their learning. Accordingly, this study presents a mobile formative assessment tool using data mining, which involves six computational intelligence theories, i.e. statistic correlation analysis, fuzzy clustering analysis, grey relational analysis, *K*-means clustering, fuzzy association rule mining and fuzzy inference, in order to identify the key formative assessment rules according to the web-based learning portfolios of an individual learner for the performance promotion of web-based learning. Restated, the proposed method can help teachers to precisely assess the learning performance of individual learner utilizing only the learning portfolios in a web-based learning environment. Hence, teachers can devote themselves to teaching and designing courseware, since they save a lot of time in measuring learning performance. More importantly, teachers can understand the main factors influencing learning performance in a web-based learning environment based on the interpretable learning performance assessment rules obtained. Experimental results indicate that the evaluation results of the proposed scheme are very close to those of summative assessment results and the factor analysis provides simple and clear learning performance assessment rules. Furthermore, the proposed learning feedback with formative assessment can clearly promote the learning performances and interests of learners.

1. Introduction

Assisted learning tools on e-learning systems have increasingly been presented due to the popularization of computers and networks. Learning performance assessment approaches are essential in the web-based learning field, owing to the rapid growth of e-learning systems globally, and lack of assisted learning performance assessment tools for assessing web-based learning process. Gagnés' research on the internal process of learning has indicated that the complete learning process should assess learning performance (Gagnés, 1997). Learning performance evaluation instruments can generally be broken down into two broad categories, summative and formative (Margaret, 2003; Torrance & Pryor, 1998). Summative evaluation is generally performed towards the end of a course (Nuhfer, 1996). It stands in contrast to the formative evaluation, which is provided while the course is ongoing so as to permit improvements (Scriven, 1967; Tessmer, 1993). The aim of summative assessment is to judge learner competency after an instructional phase is complete. Conversely, formative assessment helps teachers to obtain feedback about how well learners are learning and particular difficulties that they might be having. In other words, the formative assessment can help teachers to accumulate information and adopt information as feedback in order to adjust their teaching strategies and enhance learners' learning outcomes.

A web-based learning portfolio can be collected, stored and managed automatically by computers when learners interact with an e-learning platform. Consequently, the learning portfolios not only provide true and rich information for reflecting and assessing the true

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performances and achievements of learners, but also help learners to engage in meaningful learning. Therefore, learning performance assessment using a web-based learning portfolio has recently received significant attention (Lankes, 1995; Rahkila & Karjalainen M., 1999). Lankes (1995) stated that computer-based learner assessment portfolios are innovative in that they are an authentic demonstration of accomplishments that enable learners to take responsibility for their tasks. Several studies have emphasized that the learning portfolio assessment is supported by the cognitive–constructive theory of learning (Bruner, 1996; Rahkila & Karjalainen, 1999). Wang, Weng, Su, and Tseng (2004) noted that learning behavior information, commonly referred to as a learning portfolio, can help teachers to understand why a learner obtained a high or low grade.

However, developing a precise learning performance assessment scheme using a web-based learning portfolio is a challenging task for web-based learning systems. Data mining had been regarded as a suitable method of knowledge discovery to excavate the implicit information (Margaret, 2003). Romero and Ventura (2007) surveyed that there is an increasing interest in data mining and educational systems, making educational data mining as a new growing research community. Additionally, Romero, Ventura, and Garcia (2008) also proposed the full process for mining e-learning data step by step as well as how to apply the main data mining techniques used, such as statistics, visualization, classification, clustering and association rule mining for Moodle data. Thus, this study presents a data mining approach that combines six computational intelligence schemes, i.e. the statistical correlation analysis (Johnson & Wichern, 1998), fuzzy clustering algorithm (Gath & Geva, 1989), the grey relational analysis (Chen, Chang, & Liao, 2000; Deng, 1989), *K*-means clustering (Krishna & Murty, 1999), fuzzy association (Delgado, Martín, Sánchez, & Vila, 2003; Hong, Kuo, & Chi, 1999) and fuzzy inference (Lin & Lee, 1996), to measure online learning behavior and learning performance. The six computational intelligence schemes were adopted to perform independence and importance analyses of the considered learning factors to extract the key factors that contribute to learning performance, and to discover the useful fuzzy association rules relating to the learning performance assessment.

Based the proposed assessment method, the analytical results can help teachers to perform precise formative assessments based on the learning portfolios of individual learners collected from a web-based learning system and mobile formative assessment tool implemented on PDAs for teachers. The inferred learning performance can be adopted as a reference guide for teachers and as learning feedback for learners. The feedback mechanism allows all learners to understand their current learning status and make appropriate learning adjustments. Hence, all learners can play an active role in their learning (Black, 2001). Additionally, teachers can observe the main factors influencing learning performance in a web-based learning environment from mobile formative assessment tools according to the interpretable learning performance assessment rules. Moreover, teachers can alter their teaching strategies according to these main learning factors affecting the learning performance. Meanwhile, because teachers save much time in evaluating learning, they can devote more time to teaching and designing courseware. Experimental results indicate that evaluation results of the proposed formative assessment scheme are very close to those of summative assessment results, and that the proposed factor analysis scheme can simplify learning performance assessment rules. Furthermore, the experimental results also demonstrate that the learning feedback of formative assessment can assist web-based learning, significantly improve the learners' learning achievements and promote their learning interests.

2. System design

Learning assessment is typically the most appropriate process to evaluate the learning performance and teaching effects regardless of the traditional classroom or web-based learning environment. This section aims to present the proposed formative assessment system and scheme. First, the system architecture is presented in Section 2.1. Next, the considered learning factors for assessing learning performance is explained in Section 2.2. Finally, the proposed formative assessment approach based on learning portfolios of individual learners is detailed in Section 2.3.

2.1. System architecture

The personalized e-learning system (PELS) based on item response theory was presented for adaptive learning services of individual learners in our previous study (Chen, Lee, & Chen, 2005; Chen, Liu, & Chang, 2006). Fig. 1 shows the learning interface of the personalized e-learning system. However, the PELS mainly focuses on performing adaptive learning. The learning performance assessment is lacked feature in this system. In this study, the PELS is extended to include the learning assessment and feedback module and the teacher formative assessment module for assisting learning performance assessment and learning feedback using the gathered learning portfolios of individual learners. The PELS can automatically gather the useful learning portfolios of individual learners for the learning performance assessment during learning processes. The proposed personalized e-learning system with formative assessment mechanism is shown as Fig. 2. The primary functions of the extended formative assessment modules will be described in Sections 2.1.1 and 2.1.2, respectively.

Based on the system architecture, the details of system operation procedure are described and summarized as follows:

Step 1. Learners login the system through the learning interface agent by the legal learners' accounts.
Step 2. After a learner logins the system, the learning interface agent will check whether his account stored in the user account database.
Step 3. If the learner has already owned a registered account, the system will get his learning profile from the user profile database for personalized learning services.
Step 4. The system guides the learner to perform the personalized courseware learning based on the course materials stored in the courseware database and the user profile information stored in the user profile database.
Step 5. The teacher uses PDA to assess the learning states of individual learners during the learning process, including the attendance statuses, question and answer responses for teacher questions, concentration degree on learning, and learning comments for individual learners. All learning records will be stored in the user profile database through wireless network communication.
Step 6. The learning side formative assessment and feedback agent gets the learning portfolios from the user profile database and analyzes the key formative learning assessment rules.
Step 7. The learning side formative assessment and feedback agent stores those discovered formative learning performance assessment rules into the learning rule database for inferring learning performances of individual learners.

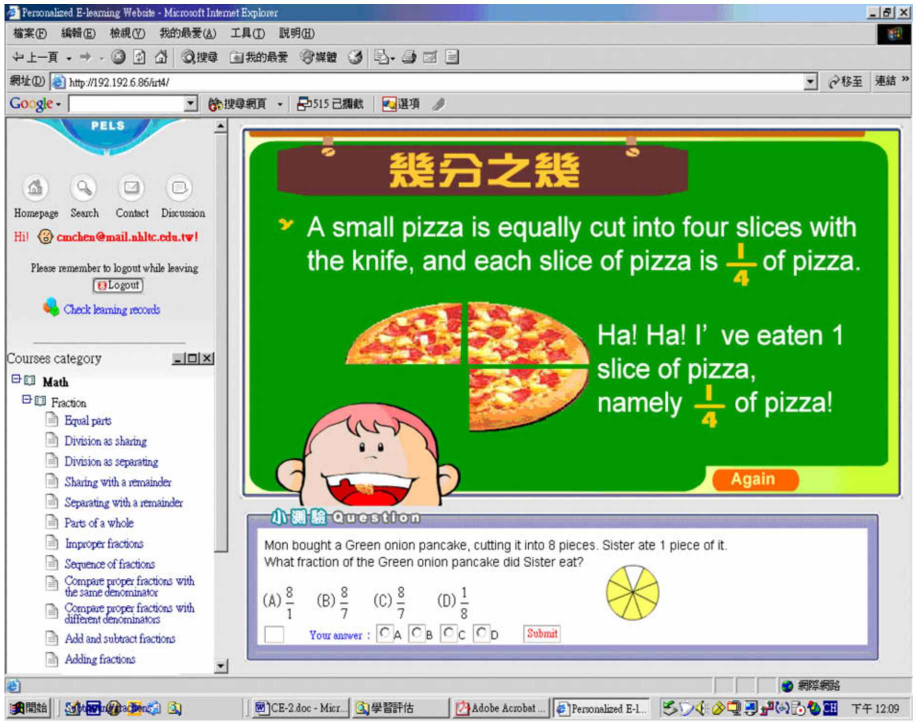


Fig. 1. The learning interface on PELS.

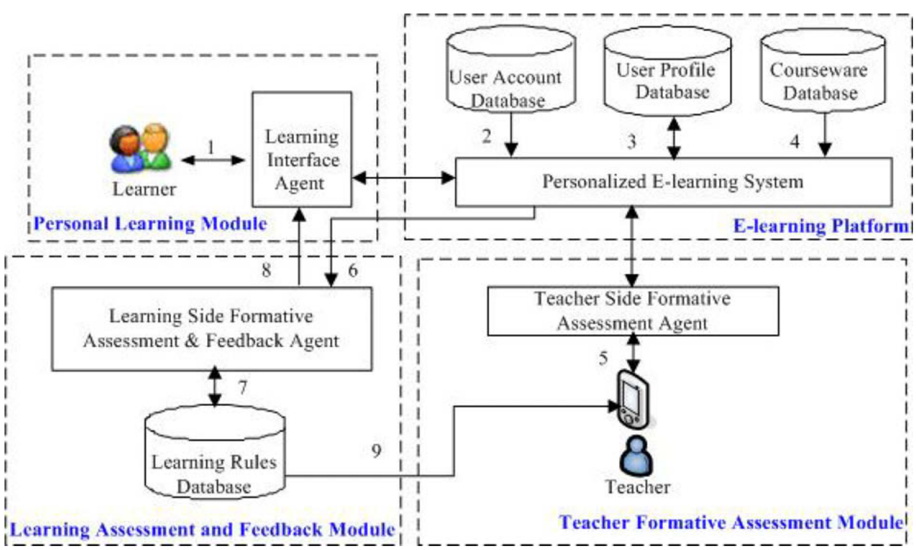


Fig. 2. The system architecture of the proposed personalized e-learning system with formative assessment mechanism.

Step 8. The learning side formative assessment and feedback agent predicts the learning performances of individual learners according to the learning portfolios of individual learners and conveys the evaluating results to the individual learners in order to assist learning reflections and adjust learning strategies.

Step 9. The teacher can also get the discovered learning performance assessment rules from the learning rules database through PDA. Based on the results, the teacher can adjust his/her teaching strategies. The user then returns to Step 4 for the next learning cycle or logs out, terminating the learning process.

2.1.1. Teacher formative assessment module

Formative assessment is a new trend of assessment both in the classroom and in web learning environments. This study performed formative assessment in a classroom with a computer-assisted learning environment, and mainly focused on evaluating each individual learner's learning situation. Thus, teachers must evaluate the learning process of each individual learner based on several formative learning factors (discussed later), such that learners can improve their performance by reflecting on their learning strategies during learning processes. Conversely, teachers also have to know the learning situations of the entire class, and what the class needs to work on. Learning feedback from formative assessment helps learners improve their performance, and allows teachers to adjust their teaching strategies if necessary. Hence, the teacher's formative assessment agent assists teachers to record learners learning processes, including the attendance statuses, concentration degree, question and answer response and learning comments to the learners, and provides a friendly interface to aid teachers to view learners' learning statuses on the PDA.

2.1.2. Learning assessment and feedback module

Nicol and Macfarlane-Dick (2006) indicated that formative assessment with feedback benefits learners and lecturers simultaneously. Feedback allows learners to restructure their understanding/skills, and to build more powerful ideas and capabilities. Ramaprasad (1983), Sadler (1989) also noted that feedback given as part of formative assessment helps learners become aware of gaps existing between their desired learning goals and current knowledge. Learning, assessment and feedback form the learning cycle improving teaching and learning. In the personalized e-learning system, all learners' interaction with learning system can be recorded automatically in the web learning portfolios. Therefore, this study examines turning the massive learning portfolio data into meaning educational information, and giving effective feedback for teachers and online learners. To solve the problem of formative assessment, statistical theory and data mining techniques are employed to analyze learners' online learning behavior based on web learning portfolios.

In the learning assessment and feedback module, the learning side formative assessment and feedback agent is utilized to mine the main learning factors influencing learning performance according to the web learning portfolios and the learning records in the classroom with computer-assisted learning environment from teachers. Moreover, the agent was adopted to produce the results of the formative learning assessment. Learning feedback not only predicts learners' learning performance in the learning procedure, but also provides benefits in terms of teachers' teaching and learners' learning. The agent provides assessment feedback simultaneously to the learners who were performing learning activities on the PELS, and to the teachers with PDA mobile formative assessment tool who were performing teaching activities on the PELS.

2.2. Considered learning portfolio in the user profile database

This section describes the learning portfolio information collected by PELS and PDA for the proposed learning performance assessment approach. The ten gathered learning factors are detailed as follows:

2.2.1. Learning factors gathered by PELS

(1) Reading rate of course materials (RR)
The reading rate of course materials is defined as the rate of studying course materials in a course unit, and the notation RR is employed to represent the learning factor.
(2) Total accumulated reading time of all learned course materials (RT)
The total accumulated reading time of each learner is calculated by summing up the reading time of all learned course materials on the PELS system, and the notation RT is used to represent the learning factor in this study.
(3) Learner ability evaluated by PELS (LA)
After learning the recommended courseware, the PELS (Chen et al.,2005, 2006) can dynamically estimate a learner's ability according to the item response theory (Baker, 1992) by collecting the replied responses of the learner to the randomly selected testing questions in the learned course unit. The range of learner's ability and difficulty parameter of courseware is limited from -3 to +3. The notation LA is used to represent the learning factor of learner ability in this study.
(4) Correct response rate of randomly selecting testing questions (CR)
After a learner has studied the recommended course material, the PELS tests the learner on his understanding by randomly selecting a relevant question from the testing item database. The rate of correct responses to test questions helps to determine the learner's degree of understanding for all learned courseware, and the notation CR is used to represent the learning factor in this study.
(5) Effort level of studying course materials (EL)
Since each course material in the PELS system is assigned a required minimum reading time by course experts based on the courseware content, the effort level is defined as the actual reading time compared with the required minimum reading time for the learned courseware, and the notation EL is used to represent the learning factor in this study.
(6) Final test grade (GRADE)
This study measures the final test grade through the summative assessment scheme of fixed-length testing examination after the entire learning process is completed, and the notation GRADE is used to represent the learning factor in this study.

2.2.2. Learning factors gathered by PDA

(1) Attendance rate (AR)
The attendance rate is defined as the rate of participating in courseware learning in a course unit, and the notation AR is employed to represent the learning factor.
(2) Accumulated score of question and answer (QA)
The teacher side formative assessment agent defines various scores for the different qualities of question and answer responses. Teachers can give different scores predefined by the system as 1 point, 3 points and 5 points based on the qualities of learner question-or-answer responses. The accumulated score of question and answer responses denotes the level of active interaction with teachers, and the notation QA is used to represent the learning factor in this study.
(3) Concentration degree (CD)
If a learner does not concentrate on the learning activity during learning processes, then the teacher deducts 1 point, 3 or 5 points from the learner's score depending on the degree of the learner's distraction. The summation of the score assessed by the teacher can be regarded as the distraction degree. Hence, the concentration degree is an inverse score based on the score of the degree of distraction, and the notation CD is used to represent the learning factor.

(4) Accumulated score based on teacher's comments (SC)
The teacher side formative assessment agent implemented on PDA provides an interface for teachers to edit some default comments before performing learning activities. In this study, positive and negative comments obtain +3 points and −3 points, respectively. The teacher gives a comment score based on assessing each learner's learning behavior during learning processes, and the total score of teacher's comments is accumulated automatically. The notation SC is used to represent the learning factor.

2.3. The proposed formative assessment approach based on web-based learning portfolios

2.3.1. The flowchart of formative assessment

Fig. 3 shows the entire flowchart of the proposed learning performance assessment scheme. Initially, the factor analysis procedure attempts to identify the main learning factors, which are independent and important factors affecting the final learning outcome. To identify the independence between learning factors, a statistical correlation analysis and the fuzzy clustering method are primarily employed, and then the grey relational analysis is used to measure the importance of factors. The *K*-means clustering algorithm (Krishna & Murty, 1999) is then used to determine logically the fuzzy membership function based on the real data distribution of learning portfolios for fuzzy association mining, and, hence, identify valuable fuzzy knowledge rules for learning performance assessment. The *K*-means clustering algorithm is a very popular, simple, useful, and unsupervised clustering method (Chinrungrueng & Sequin, 1995; Krishna & Murty, 1999; Lee, Baek, & Sung, 1997; Sarkar, Yegnanarayana, & Khemani, 1997) based on the Euclidean distance measure for numerous engineering and scientific disciplines such as image segmentation, patterns reorganization and data mining (Wu & Huang, 2006). Based on the reasons, this study employed the *K*-means clustering algorithm to logically determine the membership functions used in the fuzzy association rule mining. After the fuzzy association rule mining identifies the fuzzy rules for learning performance assessment, the fuzzy inference is employed to grade the learning performance for learners. The following sections give details for the proposed learning performance assessment scheme for individual learners.

2.3.2. Learning factor analysis

First of all, factor analysis is an essential and important step towards finding key learning factors affecting learning performance assessment (Wang & Kuo, 2004). Before mining the learning performance assessment rules from the learning portfolios, the independent and important learning factors have to be first decided. Learning factor analysis is essential to the proposed learning performance assessment scheme as it enhances learning evaluation efficiency and accuracy by filtering out dependent factors and those unimportant to learning performance assessment of learning portfolios (Chen, Chen, & Liu, 2007). The purpose of learning factor analysis aims to find the minimum number of learning factors that can represent complete information of the learning process as possible. Fig. 4 shows the proposed flowchart of the learning factor analysis.

2.3.2.1. Learning factor dependence analysis using the fuzzy clustering method. Factors are considered individually since this approach represents key learning factors better than considering all learning factors simultaneously (Wang & Kuo, 2004). Therefore, identifying the independence of learning factors is also a necessary condition of mining key formative assessment rules from the learning portfolios in the web-based learning system. Learning factor dependence analysis not only improves the efficiency of data mining by reducing the complexity of the procedure, but also helps the teacher to understand the simple and clear learning performance assessment rules. The statistical theory and fuzzy set theory, which involve correlation analysis, coefficient of determination and fuzzy clustering analysis, are adopted to analyze dependence between learning factors.

Statistical theory is a traditional method that is broadly applied to investigate the relationships among learning factors. The correlation is generally utilized to define the relationship between two factors. Hence, the independence of learning factors can be measured using pairwise correlation coefficients (Johnson & Wichern, 1998). The fuzzy clustering analysis algorithm is then adopted to cluster those learning factors based on their similarities (Behounek & Cintula, 2005). Since fuzzy theory was proposed by Zadeh (1996) in 1965, fuzzy

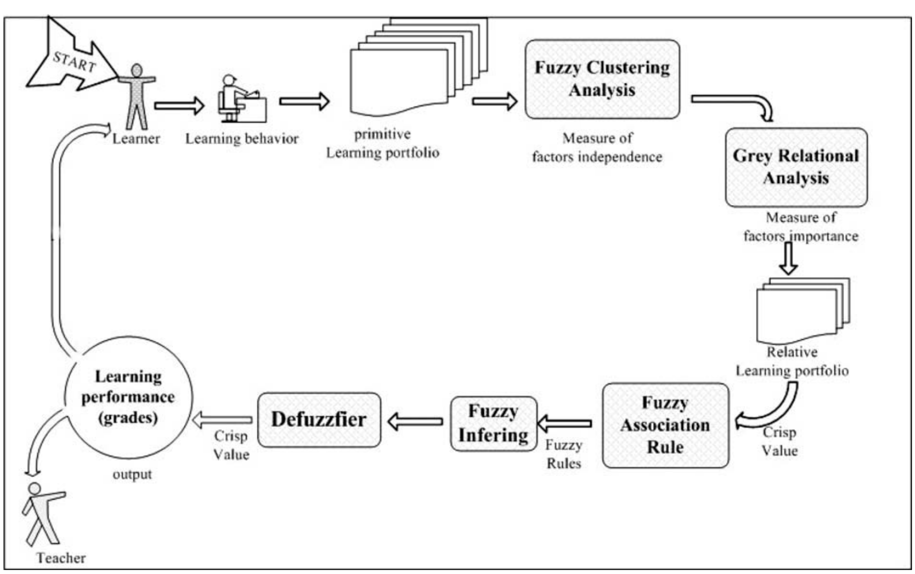


Fig. 3. The flowchart of learning performance assessment.

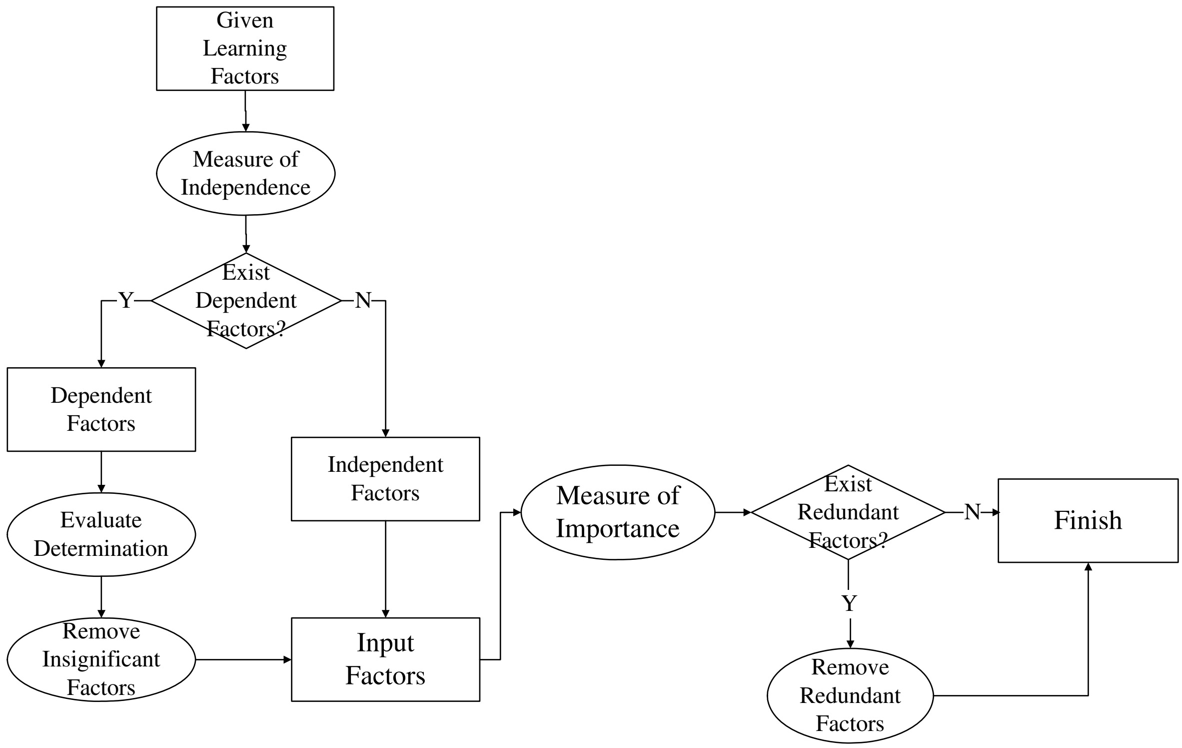


Fig. 4. The learning factor analysis flowchart.

clustering analysis algorithm had been successfully implemented in taxonomy, feature analysis, pattern recognition, image processing, medicine, geology and neural network (Bezdek, 1981; Hoppner, Klawonn, Kruse, & Runkler, 1999; Yang, 1993). Unlike most traditional clustering algorithms, fuzzy clustering analysis accepts that data belong to clusters with different degrees of membership between 0 and 1 to every datum (Kennedy, Price, & Susanto, 1997). Therefore, the learning factors belong to different clusters with different degrees, and the dependence of learning factors can be determined accordingly. The learning factors dependence analysis is be elaborated in terms of following steps:

step 1. Determining the referred and comparative sequences
The first step for adopting statistical correlation for factor dependence analysis is to determine the original referred sequence and the comparative sequence. The final test grade is regarded as the referred sequence, and the rest of nine learning factors mentioned-above are treated as the comparative sequences.

step 2. Calculating the correlation coefficient
Correlation analysis is a statistical method that can evaluate the relationships within pairs of learning factors by calculating the pairwise correlation coefficient $r_{i,j}$ of the learning factors x_i and x_j. The formula is defined as follows (Johnson & Wichern, 1998)

$$r_{i,j} = \frac{\mathrm{Cov}(x_i, x_j)}{\sqrt{\mathrm{Var}(x_i)\mathrm{Var}(x_j)}} \tag{1}$$

where $\mathrm{Cov}(x_i, x_j)$ denotes the covariance of the learning factors x_i and x_j, and $\mathrm{Var}(x_i)$ and $\mathrm{Var}(x_j)$, respectively, are the standard deviations of the learning factors x_i and x_j.The correlation coefficient always takes a value between -1 and +1, with the outer values denoting perfect correlation. A positive correlation represents a positive relation between the learning factors, while a negative correlation indicates a negative relation between the learning factors. A correlation value close to 0 indicates that no correlation exists between learning factors.

step 3. Fuzzifying the correlation coefficient
If the learning factors x_i and x_j are independent, then $r_{i,j} = 0$. However, defining any two factors as completely independent or dependent is hard. Based on the fuzzy theory (Behounek & Cintula, 2005), the relation of two factors can be treated as "degree of dependence" by fuzzifying the correlation coefficient of the learning factors x_i and x_j within the range 0–1. In this study, the membership function $\mu_{\tilde{A}}(r)$ was employed to fuzzify the correlation coefficients computed in Step 2, and formulated as follows

$$\mu_{\tilde{A}}(r) = \begin{cases} b - \frac{b}{a}\sqrt{a^2 - r^2}, & 0 \leqslant r \leqslant a \\ b + \frac{b}{a}\sqrt{a^2 - (1-r)^2}, & a \leqslant r \leqslant 1 \end{cases} \tag{2}$$

where $a, b = [0, 1]$, $r = |r_{i,j}|$.

step 4. Constructing the fuzzy relation matrix
A fuzzy relation matrix $\tilde{A}_i$ can be constructed to indicate the level of dependence within each pair of learning factors. The notation $\mu_{\tilde{A}}(r)$ in fuzzy relation matrix is the fuzzy degree computed in Step 3. The fuzzy relation matrix $\tilde{A}_i$ is represented as follows

$$\tilde{A} = \begin{bmatrix} 1 & \mu_{12} & \mu_{13} & \cdots & \mu_{1n} \\ \mu_{21} & 1 & \mu_{23} & \cdots & \mu_{2n} \\ \mu_{31} & \mu_{32} & 1 & \cdots & \mu_{3n} \\ \vdots & \cdots & \cdots & \cdots & \vdots \\ \mu_{n1} & \cdots & \cdots & \cdots & 1 \end{bmatrix} \tag{3}$$

step 5. Clustering the learning factors
For each fuzzy relation matrix, a hierarchical clustering method (Liao, 2001) with a chosen α-cut value for identifying dependence level is adopted to identify the dependent learning factors. Different α-cut values of dependence levels generate different numbers of clusters. To optimize the clustering result, the fuzzy correlation coefficients within the same cluster are maximized, while those between different clusters are minimized. Such a cost function was utilized to determine the most suitable number of clusters under considering different α-cuts in the fuzzy clustering analysis method. Namely, the cost function makes the learning factors within the same cluster as similar as possible, while making the learning factors of different clusters as dissimilar as possible.

step 6. Computing the coefficient of determination
After the dependence of learning factors clustered in the same cluster is identified, the dependent learning factors with the lower degree of importance should be removed. The factor with higher coefficient of determination indicates that the factor contains the larger amount of information to contribute the prediction of the learning performance (i.e. final test grade). Hence, the dependent factors with the lower degrees of importance are eliminated due to their unimportance, while factors with the larger degree of determination remain. The coefficient of determination of each dependent learning factor is computed as follows

$$r_{xy}^2 = \frac{SS_{yy} - SSE}{SS_{yy}} = 1 - \frac{SSE}{SS_{yy}} \tag{4}$$

$$SSE = \sum (y_i - \hat{y}_i)^2 \tag{5}$$

$$SS_{yy} = \sum (y_i - \bar{y})^2 \tag{6}$$

where r_{xy}^2 denotes the coefficient of determination of the learning factor x against the learning performance y (i.e. the final test grade), SSE denotes the deviation of the observation of the learning performance y with the predicted value $\hat{y}_i$, SS_{yy} is the deviation of the observation of the learning performance y with the mean $\bar{y}$, and $\hat{y}_i$ indicates the predicted value of the regression curve.*2.3.2.2. Learning factor importance analysis using the grey relational analysis.* The relationships between learning performance and learning factors affecting learning performance are usually unclear or relational information is incomplete. It could be difficult to analyze important learning factors related to the learning performance by the traditional statistical methods or machine learning methods. This is because these methods usually require a large amount of complete samples or data must follow a certain statistical distribution, but the grey relational analysis (GRA) method (Deng, 1982) in grey system theory throws emphasis on the problem of "small-sized data samples, poor information and uncertainty" which cannot be handled by traditional statistics (Kui, 2005; Qinbao, Martin, & Carolyn, 2005). The main reason of using the GRA is the consideration of the reference sequence. The grey relational analysis (GRA) proposed by Prof. Deng, which ranks sub-factors with each main factor by degree of relevance using the grey relational grade (Chen et al., 2000; Deng, 1989). The importance of a single data sequence can be explored by the grey relational grade.

2.3.3. Fuzzy association rule mining

Hong et al. study (1999) presented the fuzzy association rule to overcome a defect in Boolean association rules for handling quantitative transaction data. To identify the large fuzzy grids for the fuzzy association rule mining, the transaction data with quantitative value must be first transformed into fuzzy degrees. To determine the fuzzy membership function logically, the K-means clustering algorithm (Krishna & Murty, 1999) is used to determine the centers of the triangle fuzzy membership functions automatically according to the data distribution of each learning factor in the learning portfolios for the fuzzy association rules mining herein. Additionally, this study employed Hong's fuzzy association rule scheme (Hong et al., 1999) to discover whether the fuzzy knowledge rules are related to the learning performance from the learning portfolios. The employed fuzzy association rule mining procedures for mining formative assessment rules has been proposed in our previous study (Chen et al., 2007).

2.3.4. Fuzzy inference for the learning performance assessment

The discovered fuzzy production rules are formed by IF-THEN rules. A defuzzification strategy aims to convert the outcome of fuzzy inference into a crisp value. In the fuzzy set theory, the center of gravity (COG) (Lin & Lee, 1996), which is most widely used defuzzification scheme, is utilized to obtain the crisp value of a learner's learning performance.

3. Experiments

In this section, the performance of the proposed formative assessment scheme is first evaluated in Section 3.1. Section 3.2 explains the discovered learning performance assessment rules in the actual teaching scene. Next, the developed formative assessment tools for both the learner and teacher sides are introduced in Section 3.3. Section 3.4 describes the experimental design for evaluating the promotion of the learning performance with learning performance assessment feedback. Section 3.5 illustrates the evaluation results of learning performance. Finally, a discussion is drawn out for the proposed learning performance assessment scheme.

3.1. Evaluation results of the proposed learning performance assessment scheme

To verify the quality of the discovered learning performance assessment rules, the learning portfolio gathered from 583 third-grade students of Taipei County Jee-May Elementary School, who were invited to participate in the learning activity of the "Fractions" course unit in elementary school mathematics, was first used to identify learning performance fuzzy rules affecting their learning outcomes. In the experiment, the learning records of 400 out of 583 learners were used as training data to extract learning performance assessment rules, and the other learning records served as testing data to verify the accuracy of the discovered learning performance assessment rules. The experimental results are described as follows.

3.1.1. Learning factor analysis

3.1.1.1. Learning factor independence analysis. Initially, Table 1 displays the computing correlation coefficients between the seven considered learning factors including RR (reading rate of course materials), RT (total accumulated reading time of all learned course materials), LA (learner ability), CR (correct response rate of randomly selecting testing questions), PN (posted amount of articles on the forum board), AS (accumulated score on the forum board), and EL (effort level of studying course materials) presented in our previous study (Chen et al., 2007). Then, the correlation coefficients of learning factors are fuzzified for the fuzzy clustering analysis. Table 2 lists the result of fuzzy clustering analysis with different α-cut values. When the α-cut value is set 0.79, the best clustering result {{RR, RT}, {LA, CR}, {PN, AS} and {EL}} with maximum value of clustering cost function mentioned-above is obtained. Next, the coefficients of determination of those dependent learning factors in the clusters {RR, RT}, {LA, CR} and {PN, AS} are measured, and the dependent learning factors are filtered out

Table 1
The correlation coefficients between seven considered learning factors

Learning factors	RR	RT	LA	CR	PN	AS	EL
RR	1	−0.705	0.256	0.495	0.269	0.381	0.309
RT	−0.705	1	−0.242	−0.421	−0.278	−0.406	−0.240
LA	0.256	−0.242	1	0.859	0.276	0.323	−0.027
CR	0.495	−0.421	0.859	1	0.286	0.357	0.102
PN	0.269	−0.278	0.276	0.286	1	0.667	−0.033
AS	0.381	−0.406	0.323	0.357	0.667	1	−0.078
EL	0.309	−0.240	−0.027	0.102	−0.033	−0.078	1

Table 2
The fuzzy clustering results with different α-cut values

α -cut Value	Clustering Results	Dependence in the Same Cluster	Independence between Clusters	Total
0.69	{RR, RT, LA, CR, PN, AS, EL}	14.012	0	14.012
0.70	{RR, RT, LA, CR, PN, AS}{EL}	13.223	5.211	18.434
0.78	{RR, RT, LA, CR}{PN, AS}{EL}	10.645	10.633	21.279
0.79	{RR, RT}{LA, CR}{PN, AS}{EL}	9.232	13.219	*22.451
0.90	{RR, RT}{LA, CR}{PN}{AS}{EL}	8.564	13.552	22.116
0.92	{RR, RT}{LA}{CR}{PN}{AS}{EL}	7.705	13.693	21.397
0.93	{RR}{RT}{LA}{CR}{PN}{AS}{EL}	7.000	13.988	20.988

except the one with largest coefficient of determination. Table 3 shows the learning factors {RT}, {LA} and {PN} can be removed due to relatively lower coefficients of determination to the learning performance assessment. Thus, these four learning factors {RR}, {CR}, {AS} and {EL} are served as significant learning factors after performing the factor independence analysis.

3.1.1.2. Learning factor importance analysis. In the previous subsection, the four independent learning factors {RR}, {CR}, {AS} and {EL} are extracted based on the proposed learning factor analysis scheme. Next, these four learning factors are further measured by the grey relational analysis in order to figure out the degree of importance. Table 4 lists the grey relational grades between the referred sequence and various comparative sequences based on the ranking order of the grey relational grades. The results indicate that the top three considered learning factors are highly relevant to the final test score since their grey relational grades are greater than the threshold of 0.5. Thus, the three learning factors were preserved to perform the fuzzy association rule mining and to detect useful fuzzy rules for learning performance assessment, but the learning factor AS was eliminated since it has lowest relevance to the final test score among four considered learning factors.

3.1.2. The discovered fuzzy rules for learning performance assessment

To explain the discovered fuzzy association rules for learning performance assessment, the simplified representation notations VH, H, M, L and VL were employed to represent "very high", "high", "moderate", "low" and "very low" for fuzzy rules, respectively. After performing the fuzzy association rule mining procedure, fourteen fuzzy learning rules are discovered in this study. Table 5 displays the entire discovered fuzzy rules that can be employed to assess the learning performance of learners with various grade levels in the proposed learning performance assessment scheme. These interpretable fuzzy rules for the learning performance assessment of various grade levels are valuable to teachers to understand which learning factors influence the learning performance in a web-based learning environment.

3.1.3. Evaluating accuracy rate of learning performance assessment

To measure the accuracy rate of learning performance assessment for the proposed method, two methods were used to measure the predicted learning performance. First, the ±5 point method was used to evaluate the accuracy rate of the predicted learning performance. That is, if the difference between the predicted learning score and the actual final test score was in the range −5 to +5, then the predicted result is served as correct; otherwise, the predicted result is incorrect. Additionally, the score level method was used to evaluate the accuracy rate of the predicted learning performance. In this evaluation method, the each learner is assessed according to one of five score levels based on the mapping membership degrees of learning factor GRADE. For example, the score level of a learner with a final test score of 85.16 was set to GRADE.M, because the linguistic term of GRADE.M has the largest mapping membership degree among the other linguistic terms of the learning factor GRADE.

Fig. 5 illustrates the prediction accuracy rates of 183 testing data under various combinations of learning factors for the two proposed accuracy evaluation methods. The experimental results show that the proposed dependence and importance analysis scheme of learning factor can help the proposed learning performance assessment scheme to identify the key learning factors. As mentioned early, when the

Table 3
The coefficients of determination of dependent learning factors

Learning factors	*{RR}	{RT}	{LA}	*{CR}	{PN}	*{AS}
The coefficient of determination	0.168	0.090	0.281	0.459	0.032	0.063

Table 4
The grey relational grades between the referred sequence and comparative one

Factor analysis item	Grey relational grade
γ(GRADE, CR)	0.8594
γ(GRADE, EL)	0.7027
γ(GRADE, RR)	0.5883
γ(GRADE, AS)	0.4757

Table 5
The discovered learning performance assessment rules with the satisfied minium fuzzy support, confidence, and certainty factor

No.	Fuzzy rule	Support (Min Sup = 0.2)	Confidence (Min Conf = 0.5)	CF (Min CF = 0.5)
1.	CR_L ⇒ GRADE_L	0.407075	0.882605	0.565105
2.	RR_VL ⇒ GRADE_L	0.330171	0.899318	0.627017
3.	CR_L ∩ RR_VL ⇒ GRADE_L	0.202906	0.979183	0.922883
4.	CR_M ⇒ GRADE_M	0.468819	0.913054	0.637235
5.	RR_VL ⇒ GRADE_M	0.341713	0.921658	0.673133
6.	CR_M ∩ RR_VL ⇒ GRADE_M	0.259632	0.955261	0.813337
7.	CR_H ⇒ GRADE_H	0.514702	0.911135	0.616762
8.	RR_L ⇒ GRADE_H	0.286783	0.926365	0.682442
9.	CR_H ∩ RR_L ⇒ GRADE_H	0.238686	0.964525	0.847008
10.	CR_H ∩ EL_VH ⇒ GRADE_H	0.217541	0.889984	0.525543
11.	CR_VH ⇒ GRADE_VH	0.68382	0.956338	0.685182
12.	RR_H ⇒ GRADE_VH	0.257372	0.967798	0.767812
13	CR_VH ∩ RR_H ⇒ GRADE_VH	0.22981	0.979792	0.854291
14.	CR_VH ∩ EL_VH ⇒ GRADE_VH	0.400021	0.960917	0.718194

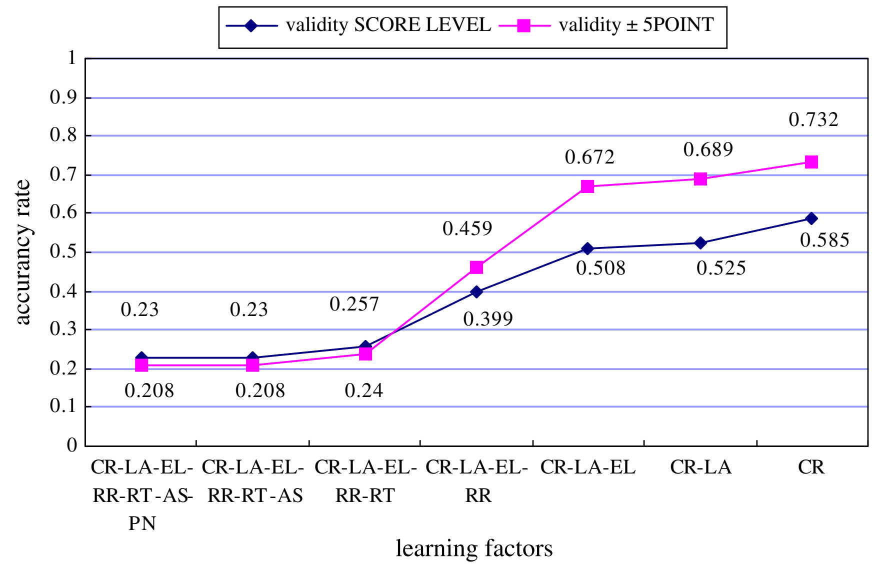


Fig. 5. The predicted accuracy rates of 183 testing data under considering various combinations of learning factors for the two proposed accuracy evaluation methods.

more sets of dependent learning factors, such as {CR, LA}, {RR, RT} and {PN, EL}, are included, the lower accuracy rate is displayed in Fig. 5. For example, when the dependent learning factor set {CR, LA} is considered to perform the learning performance assessment, the predicted accuracy rate is lower than those of only considering the learning factor {CR}. According to the results, the independent learning factors to each other facilitate the learning performance assessment. In addition, Fig. 5 shows that the proposed grey relational analysis scheme can help the proposed learning performance assessment scheme to identify the significant learning factors. When the learning factors with low grey relational grades, such as PN, AS and RT, were considered to perform the learning performance assessment, the predicted accuracy rate will descend. Conversely, if only the learning factor with the largest grey relational grad, i.e. CR, was considered, then the proposed method obtains the highest prediction accuracy rate.

Based on the above experimental results, the study infers that there are two main reasons determining the effectiveness of the considered learning factors, thus leading to obtaining the highest prediction accuracy rate when only the learning factor CR was considered. First of all, some considered learning factors may be irrelevant or lowly relevant with the learning performance, such as the learning factors PN and AS. Moreover, capturing the valid data of some considered learning factors, such as the valid reading time (RT) and the valid amount of reading courseware (RR), to discovery learning performance assessment fuzzy rules is a highly challenging task. Particularly, capturing the valid reading time (RT) is a difficult task while a learner has idle reading behavior. Moreover, accurately identifying the valid amount of reading courseware (RR) is also a difficult task while a learner clicks fast the courseware or skips the reading courseware.

3.2. The discovered learning performance assessment rules in the actual teaching scene

To verify how the feedback of learning performance assessment outcomes affects the learning performance in the actual teaching activity, 69 third-grade students of Taipei County Jee-May Elementary School, who had majored in the "Fractions" course unit in elementary school mathematics, were invited to test this system. To discover learning performance assessment rules associated with the final test grade (GRADE), the learning portfolios with 9 considered learning factors mentioned in Sections 2.2.1 and 2.2.2 were used to mine the learning performance assessment rules. After performing factor analysis, the four learning factors {CR}, {RT}, {AR} and {CD} were identified as key learning factors influencing learning performance. Similarly, the proposed scheme of mining learning performance rules was employed to discover 40 fuzzy rules like the type listed in Table 5 based on the four key learning factors in the actual teaching experiment.

3.3. The implemented learning performance assessment tools

3.3.1. The teacher side formative assessment tool

Fig. 6a–k displays the proposed teacher formative assessment tool implemented on the PDA to support teachers to perform formative assessment in a computer classroom with the Internet for supporting web-based learning. Before using the formative assessment tool, teachers have to register their user accounts and passwords in advance. Fig. 6a shows the user login interface. After a teacher logins the mobile assessment tool by legal accounts, the user menu with two functions is displayed as Fig. 6b for teachers. The first function is to view the detailed learning statuses of individual learners on the PELS, and the second function is to perform the formative assessment in the classroom with computer-assisted learning.

In Fig. 6b, if the second function is selected, then teachers can assess learning statuses of individual learners including attendance statuses, concentration degree, question and answer responses, and learning comments. Fig. 6c shows the interface for assessing the attendance statuses of learners. Fig. 6d displays the interface for recording learners' question and answer responses during learning processes. Fig. 6e shows the interface that can assist teachers to evaluate the concentration degrees of individual learners. In Fig. 6f, several default comments about learners' learning performances can be selected for assessing the learning statuses of individual learners. In addition, these default comments can also be edited by teachers. Fig. 6g illustrates the interface for editing learning comments as positive or negative. In other words, each teacher is free to create his/her comments that characterize his/her learners.

If the first function (Fig. 6b) is selected, teachers can view the comprehensive degrees of individual learners relative to courseware through the interface (Fig. 6h). Fig. 6i displays the interface for viewing the variances of learners' learning abilities during learning processes. Furthermore, each learner has to take a test after finishing the learning process on the PELS, and then the tests results are stored in the user profile database. Fig. 6j displays the interface for viewing learners' test scores. The interface makes teachers understand learners' learning effects on the PELS and this function is also helpful to judge whether performing remedy learning is needed. Finally, the learning portfolios based on the considered learning factors gathered by PELS system and PDA-based teacher assessment tool were utilized to mine learner's learning performance assessment rules. Fig. 6k shows the discovered learning rules influencing learners' learning performances. In conclusion, the proposed teacher side formative assessment tool offers assessing information related to learners' learning statuses on the PELS as well as provides a friendly user interface for assessing learners' learning processes by PDA. Using the tool, teachers not only can monitor learners' learning statuses, but also know how to guide more effectively learning.

3.3.2. The learner side formative assessment tool

Fig. 7a and b presents the feedback interface of learning performance assessment for individual learners on the PELS. In Fig. 7a, the learning feedback assessed by the teacher side formative assessment tool can help each learner to adjust his/her learning strategy during learning processes. During teaching, learning feedback information was first explained to students by the teacher. That each learner understood the meaning of feedback information was then confirmed. After that, the system inferred the final learning score according to the discovered formative assessment fuzzy rules automatically. The inferred score was conveyed to individual learner, thus reminding the learner with low learning score to learn more hard in the next learning stage. Next, the learning behavior in the classroom with

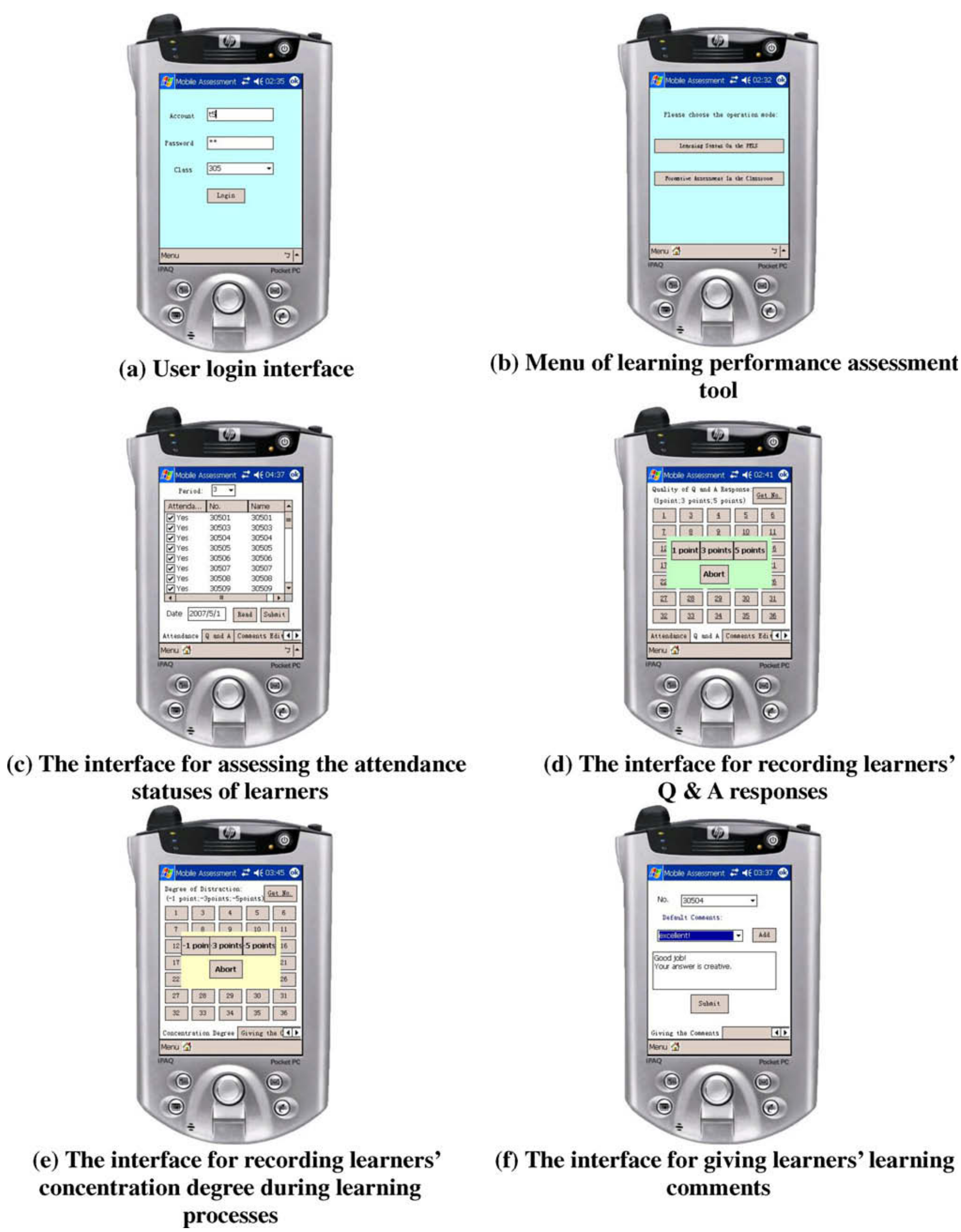


Fig. 6. The implemented mobile formative assessment tool for teachers.

(g) The interface for editing learning comments as positive or negative

(h) The interface for viewing the difficulty levels of courseware from learners' feedback responses

(i) The interface for viewing the variances of learners' learning abilities assessed by the proposed PELS during learning processes

(j) The interface for viewing learners' test scores

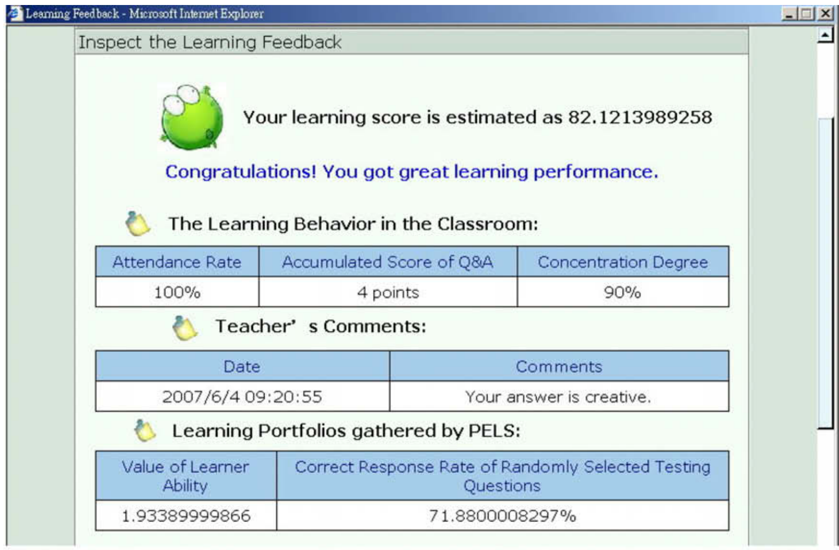
(k) The interface for viewing the discovered learning performance assessment rules

Fig. 6 (*continued*)

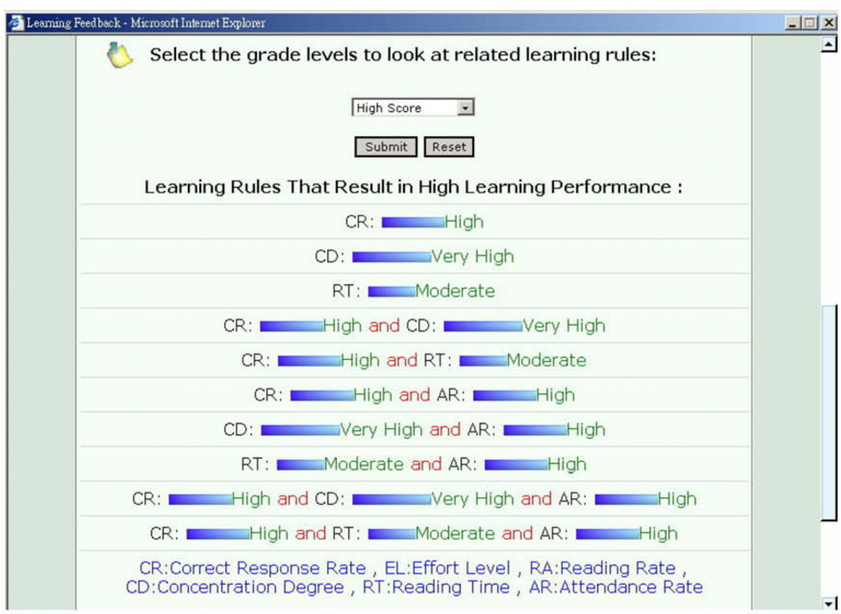
computer-assisted learning including the attendance rate, accumulated score of question and answer responses, accumulated score of teacher's comments were displayed to individual learners through the feedback interface on PELS. In this work, these learning portfolios recorded by teacher through PDA are integrated with learning portfolios gathered by PELS to progress the formative assessment. These formative assessment outcomes are helpful to illustrate the learning pictures of the learning process. In addition, learner ability and correct response rate of randomly selected testing questions were also important messages for each learner. Each learner can use the information to view his/her final learning states and make his/her learning better. Finally, Fig. 7b displays the learning rules associated with five grade levels involving "very high score", "high score", "moderate score", "low score" and "very low score". Learners could select different grade levels to look at related learning rules and find out key learning factors influencing the learning performance.

3.4. Experimental design

The participants of this study were recruited from two intact three-grade classes of Taipei County Jee-May Elementary School. The pre-test–post-test nonequivalent group design of quasi-experimental method was adopted for investigating the promotion of learning performance in the study. Its purpose was to assess whether learning feedback of formative assessment contributes a significant positive effect on the promotion of learners' learning performances and learning attitude. In the experiment, the teacher first explained the system operation procedures for all participators in the first hour, and then all participators logged in the system to perform the learning process. There



(a) Learning feedback about learning behavior of individual learners from teacher formative assessment



(b) The discovered learning performance rules

Fig. 7. The implemented feedback interface for the discovered learning performance assessment rules on PELS.

are 35 learners in the experimental group and 34 learners in the control group, ranging in age from 9 to 11 years old. The experimental group received a two-week mathematical courseware learning in a computer classroom using PELS with learning feedback of formative assessment during learning processes. In contrast with the experimental group, the control group received the same mathematical courseware by PELS without learning feedback of formative assessment during learning processes. Both the learning modes perform the pre-test and post-test for comparing the difference of learning performance before and after learning.

3.5. Learning evaluation

Three evaluating procedures including a pre-test, post-test and questionnaire were performed to assess the learning outcomes for the proposed system. That is, the learning evaluation in the study includes two parts which, respectively, are the learning performance promotion of learners and questionnaire results from learner's feedback responses.

3.5.1. Learning performance evaluation

Table 6 displays the comparison result of learning performance for both the learning modes. The results reveal that 54.29% learners who learnt by the PELS with formative assessment feedback have progressive score, but only 52.94% learners who learnt by the PELS without formative assessment feedback have progressive score. Additionally, the information is beneficial to further analyzing the learning performance by statistics analysis method. In the work, the independent-samples *t*-test and matched-pairs *t*-tests were used to analyze

Table 6
Comparison result of learning performance for both the participating groups conducting different learning modes

Comparison item vs. learning mode	The experimental group performing learning with formative assessment feedback	The control group performing learning without formative assessment feedback
Number of learners	35	34
Mean score of pre-test	86.86	86.03
Standard deviation of pre-test	9.858	13.969
Mean score of post-test	91.86	87.94
Standard deviation of post-test	6.869	14.622
Number of learners with progress score	19 (54.29%)	18 (52.94%)
Number of learners with retrogression score	6 (17.14%)	8 (23.53%)
Number of learners with constant score	10 (28.57%)	8 (23.53%)

whether the experimental group with formative assessment feedback or the control group without formative assessment feedback provides benefits in terms of learning performance promotion based on pre-test and post-test scores. The results listed in Table 6 indicate that the mean and standard deviation of the experimental group on the pre-test score is 86.86 and 9.858 points, respectively. The mean and standard deviation of the control group on the pre-test score is 86.03 and 13.969 points, respectively. Since these two participating groups do not reach significant difference on the pre-test score ($t = -.285$, $p = .776 > 0.05$), the mathematics abilities of two participating groups in the "Fraction" unit can be viewed as equivalent before performing the experiment process.

Next, the post-test of two participating groups were also analyzed using independent-samples t-test and the mean scores of the experimental and control groups on the post-test score are 91.86 and 87.94, respectively. The t-test result ($t = 1.417$, $p = .163 > 0.05$) shows that two participating groups do not reach significant difference on the post-test score. Thus, this study further compared the pre-test and post-test for each group using the paired-samples t-test. The experimental result shows that the difference of the mean scores of pre-test and post-test is -5 and the results of paired-samples t-test reach the significant level ($t = -3.3$, $p = .002 < 0.05$). In other words, the promotion of learning performance in the experimental group is significant and the mean score increases 5 points.

Next, the pre-test and post-test scores of the control group are also assessed using the paired-samples t-test. In the experimental result, the difference of the mean scores between pre-test and post-test is -1.91 and the result of paired-samples t-test ($t = -1.169$, $p = .251 > 0.05$) shows that the control group does not achieve significant difference after performing learning mode without formative assessment feedback. In addition, the post-test score in the experimental group is 3.92 points higher than that in the control group. This result can prove that the learning performance of the learning mode with formative assessment feedback is superior to the learning mode without formative assessment feedback.

Moreover, to investigate whether the proposed learning modes with and without formative assessment feedback provide different learning performances for learners with various mathematics abilities, the learners of each class in both the participating groups were divided into three groups based on their pre-test scores. The learners whose pre-test scores are above 27% in each class are viewed as high score group, and the learners whose pre-test scores are below 27% are viewed as low score group. The remaining learners are viewed as moderate score group. Similarly, the paired-samples t-test was employed to analyze these three groups with different learning abilities in both the experimental and control groups, respectively. Table 7 shows the result of the paired-samples t-test. In the experimental group, the progress scores of the learners with high, moderate and low score are -2.00, 5.00 and 12.778, respectively. Besides, the t-test results of the three different score groups of the experimental group (i.e. the high score group: $t = -1.309$, $p = .223 > 0.05$; the moderate score group: $t = -3.464$, $p = .003 < 0.05$; the low score group: $t = -3.507$, $p = .008 < 0.05$) show that the score progress of the moderate and low score groups reaches significant level after performing the learning mode with formative assessment feedback, but the high score group does not reach significant level. Nevertheless, all the t-test results of the three different score groups in the control group do not reach significant level. In conclusion, the proposed learning mode with formative assessment feedback indeed surpasses the learning mode without formative assessment feedback because it can direct learners to adjust their learning states based on immediate learning performance result during learning processes.

Table 7
The paired-samples t-test result of three groups with various learning abilities for both the experimental and control groups

Learning abilities	Class vs. statistics	Pre-test		Post-test		Paired difference		t	Sig.
		Mean	Standard deviation	Mean	Standard deviation	Mean (pre-test–post-test)	Standard deviation		
High score group	306(Exp.)	96.50	2.415	94.50	4.972	2.000	4.830	1.309	.223
	305 (Ctrl.)	97.27	2.611	93.64	6.360	3.636	5.954	2.025	.070
Moderate score group	306(Exp.)	88.13	2.500	93.13	5.439	−5.000	5.774	−3.464	.003*
	305 (Ctrl.)	90.00	.000	94.17	5.845	−4.167	5.845	−1.746	.141
Low score group	306(Exp.)	73.89	9.280	86.67	8.660	−12.778	10.929	−3.507	.008*
	305 (Ctrl.)	77.35	15.012	82.06	18.205	−4.706	11.106	−1.747	.100

Table 8
The descriptions of question types

Question type	The number of questions	Description
Personal information	3	To get the personal information about learners who attend the learning activity
System operation	5	Questions related to the user interface and the content of learning materials
Learning attitude	6	To investigate whether the system can enhance learners' learning motivation or interests or not
Learning mode	6	Questions related to the proposed PELS system with formative assessment feedback responses for individual learners
Learning performance	4	To explore whether the learning mode can promote their learning achievements and confidence or not

Table 9
The satisfaction evaluation results of questionnaire

Question type	Question	The number of learners			
		The experiment group		The control group	
		Yes	No	Yes	No
(a) The investigation results of the personal information					
Personal Information	Do you have any computer at your home?	33 94.29%	2 5.71%	32 94.12%	2 5.88%
	Do you like to use the computer?	34 97.14%	1 2.86%	32 94.12%	2 5.88%
	Have you ever used any web site for learning?	15 42.86%	20 57.14%	17 50%	17 50%

Question type	Question	Satisfaction degree									
		The experimental group					The control group				
		Strongly agreed	Agreed	No opinion	Disagreed	Strongly disagreed	Strongly agreed	Agreed	No opinion	Disagreed	Strongly disagreed
(b) The investigation results of the system operation											
	I think that the PELS learning system provides a friendly user interface	21 60%	8 22.86%	6 17.14%	0 0%	0 0%	23 67.65%	5 14.71%	5 14.71%	1 2.94%	0 0%
	The flash learning materials make me understand the fraction unit of mathematics course more easily	21 60%	10 28.57%	3 8.57%	0 0%	1 2.86%	23 67.65%	6 17.65%	4 11.76%	1 2.94%	0 0%
	It is interesting to me to operate and learn mathematics actively on the PELS learning system	20 57.14%	5 14.29%	9 25.71%	0 0%	1 2.86%	23 67.65%	4 11.76%	3 8.82%	0 0%	4 11.76%
	I think the PELS system is an excellent learning tool to assist mathematics learning	23 65.71%	10 28.57%	2 5.71%	0 0%	0 0%	22 64.71%	3 8.82%	7 20.59%	0 0%	2 5.89%
	I agree that learning through the Internet is very convenient because I can perform mathematics learning at any time and place	18 51.43%	11 31.43%	5 14.29%	0 0%	1 2.86%	20 58.82%	3 8.82%	5 14.71%	3 8.82%	3 8.82%
	Average	84%		14.28%	1.72%		77.65%		14.12%	8.23%	
(c) The investigation results of the learning attitude											
Learning Attitude	Learning by the PELS learning system can promote my learning interest	18 51.43%	11 31.43%	5 14.29%	0 0%	1 2.86%	20 58.82%	6 17.65%	4 11.76%	1 2.94%	3 8.82%
	I agree that using the PELS system to learn mathematics is a very interesting learning mode	21 60%	8 22.86%	5 14.29%	0 0%	1 2.86%	23 67.65%	5 14.71%	3 8.82%	1 2.94%	2 5.88%
	I feel happy when I learn mathematics by the PELS learning system	19 54.29%	10 28.57%	5 14.29%	0 0%	1 2.86%	19 55.88%	7 20.59%	3 8.82%	2 5.88%	3 8.82%
	I think that using the PELS learning system to perform mathematics learning can attract me to concentrate on the mathematics course	18 51.43%	9 25.71%	5 14.29%	0 0%	3 8.57%	23 67.65%	2 5.88%	5 14.71%	2 5.88%	2 5.88%
	To learn mathematics by the PELS learning system is a cheerful learning experience to me	20 57.14%	13 37.14%	2 5.71%	0 0%	0 0%	24 70.59%	2 5.88%	5 14.71%	0 0%	3 8.82%
	I feel it is easy to learn mathematics after using the PELS system	18 51.43%	12 34.29%	4 11.43%	0 0%	1 2.86%	23 67.65%	2 5.88%	7 20.59%	0 0%	2 5.88%
	Average	84.29%		12.38%	3.34%		76.47%		13.24%	10.29%	
(d) The investigation results of learning mode											
Learning Mode	I agree that my teacher record my learning process including the frequency of proposing questions, the concentration degree, etc.	20 57.14%	11 31.43%	4 11.43%	0 0%	0 0%	20 58.82%	4 11.76%	5 14.71%	3 8.82%	2 5.88%
	The records of learning behaviors in the classroom can represent a part of my learning performance	19 54.29%	13 37.14%	2 5.71%	0 0%	1 2.86%	16 47.06%	4 11.76%	10 29.41%	2 5.88%	2 5.88%
	The PELS learning system with formative assessment feedback is very helpful to my mathematics learning	16 45.71%	13 37.14%	6 17.14%	0 0%	0 0%	–	–	–	–	–

Table 9 (*continued*)

Question type	Question	Satisfaction degree									
		The experimental group					The control group				
		Strongly agreed	Agreed	No opinion	Disagreed	Strongly disagreed	Strongly agreed	Agreed	No opinion	Disagreed	Strongly disagreed
	The PELS learning system with formative assessment feedback can enhance my learning motivation, thus let me learn better	21 60%	7 20%	6 17.14%	0 0%	1 2.86%	–	–	–	–	–
	I expect that my teacher can often interact with me during my mathematics learning process	–	–	–	–	–	21 61.76%	4 11.76%	7 20.59%	0 0%	2 5.88%
	I think I can learn better if my teacher gives some suggestions related to my learning statuses during the learning process	–	–	–	–	–	19 55.88%	8 23.53%	4 11.76%	2 5.88%	1 2.94%
(e) The investigation results of learning performance											
Learning Performance	The PELS learning system can promote the learning effect and my learning achievement.	19 54.29%	10 28.57%	6 17.14%	0 0%	0 0%	20 58.82%	6 17.65%	4 11.76%	3 8.82%	1 2.94%
	I think that using the PELS learning system can effectively promote my mathematics ability in a short time.	18 51.43%	11 31.43%	4 11.43%	1 2.86%	1 2.86%	21 61.76%	3 8.82%	8 23.53%	1 2.94%	1 2.94%
	The PELS learning system increases my confidence of learning mathematics.	19 54.29%	12 34.29%	4 11.43%	0 0%	0 0%	21 61.76%	1 2.94%	9 26.47%	1 2.94%	2 5.88%
	I satisfied my learning performance on the PELS learning system.	22 62.86%	9 25.71%	2 5.71%	1 2.86%	1 2.86%	23 67.65%	3 8.82%	6 17.65%	0 0%	2 5.88%
	Average	84.97%		11.43%	2.86%		72.06%		19.85%	8.09%	

3.5.2. Questionnaire analysis

To evaluate learners' satisfaction degree for the learning mode and learning system, a questionnaire which involves 24 questions distinguished five various question types was designed to measure whether the provided services in the PELS with formative assessment feedback satisfy the real requirements of most learners. The five question types contain the personal information about learner's learning experience using the computer, the convenience of the system operation, the learners' learning attitude towards using the proposed learning system, the benefits related to the proposed learning mode with formative learning feedback, and the improvement of learner's mathematics abilities and confidence after using the proposed learning mode. Table 8 gives a summarization of the descriptions of question types. Totally, there are 35 learners in the experimental group and 34 learners in the control group to participate in the experiment and they were invited to fill out this questionnaire after attending the two weeks' learning activity. The evaluation results of satisfaction degree are listed in Table 9. To conveniently observe the evaluating results, the investigation results of "strongly agreed" and "agreed" are merged as "approved", and the investigation results of "strongly disagreed" and "disagreed" are merged as "disapproved".

The investigation results of the personal information are listed in Table 9(a) and it indicates 94.29% learners of the experimental group and 94.12% learners of the control group have computers at home. Additionally, 97.14% learners of the experimental group and 94.12% learners of the control group like to use computers, but only about a half of learners of both the groups, respectively, used the learning system through the Internet. From Table 9(b), the satisfaction degrees of "approved" of system operation of the experimental group are 84% and that of the control group are 77.65%. Moreover, Table 9(c) specifies the 84.29% learners of the experimental group and 76.47% learners of the control group agreed that the proposed learning system can promote their learning motivation. Finally, in terms of the learning mode and learning performance, the results are summarized in Tables 9(d) and (e). Most learners in two participating groups agreed that the learning records and learning feedback provide benefit in terms of the promotion of the learning performance. 84.97% learners of the experimental group and 72.06% learners of the control group believed that the proposed learning system can improve their confidence in learning and get good grades in the learning.

3.6. Discussion

The experimental results show that the mathematics abilities of most participators are promoted after performing learning assisted by the proposed learning mode with immediate learning feedback of formative assessment during learning processes. In addition, the result of questionnaires indicates that they agreed that their mathematics abilities were promoted and they like to learn mathematics using the proposed learning mode. Moreover, most learners satisfied the designed user interfaces and system functions. Furthermore, the proposed formative assessment scheme has some disadvantages that need to be further improved. One problem is how to promote the correct rate of the gathered learning portfolios, especially for effective reading time. The correct rate of learning portfolios influences the results of the proposed formative assessment rule mining scheme and noisy data of learning portfolios have to be filtered out before conducting learning performance assessment fuzzy rule mining. Another topic is that the clustering method of key learning factors affects the fuzzy membership functions used in the employed fuzzy association rules mining. In this work, the K-means clustering algorithm was used in this study and it is especially sensitive to initial clustering centers. Therefore, the other more excellent cluster methods can be considered to determine the fuzzy membership functions for the employed fuzzy association rule mining scheme in the future. The other issue is that how to validate the discovered learning performance assessment fuzzy rules. The learning rules obtained from the formative assessment scheme are helpful to learners and teachers, but proposing an effective mechanism to validate the quality of the learning performance assessment rules is urgently needed. Finally, some disadvantages of the proposed system with regard to system functions from the learners' feedbacks can be improved in our future work.

4. Conclusion and future work

This study presents formative assessment tools that contain the proposed key learning factor analysis and learning performance assessment rule mining scheme for discovering simplified and key fuzzy learning rules for evaluating the learning performance of learners. The proposed scheme can help teachers to perform precise formative assessment according to the learning portfolios of individual learners in a computer classroom with Internet-assisted web-based learning environment. The inferred learning performance assessment rules can be adopted as a teaching reference guide for teachers and as learning outcome feedback for learners. The feedback mechanism allows learners to understand their current learning statuses and make appropriate learning strategy adjustments during learning processes. Therefore, this mechanism enables learners to become active learners while self-examining their own learning behavior or outcomes. Additionally, teachers can determine the main factors influencing learning performance in a web-based learning environment based on the interpretable learning performance assessment rules. Hence, teachers can alter their teaching strategies according to these main factors affecting learning performance. Meanwhile, because teachers save much time in evaluating learning, they can devote extra time to teaching and designing courseware. Experimental results reveal that the evaluation results of the proposed formative assessment scheme are very close to those of summative assessment results, and that the proposed factor analysis scheme can simplify the learning performance assessment rules. Furthermore, most learners agree that the learning feedback of formative assessment can significantly assist mathematics learning, enhance the learners' mathematics abilities and promote their learning interests.

Although the proposed formative assessment tool has been successfully implemented on the PELS and PDA, several issues are worth further investigation. First, future research will explore more reliable learning factors affecting learning performance. This study adopts nine learning factors to model learners' learning performance during learning processes. However, the PELS cannot currently capture the valid reading time while a learner has idle reading behavior. This problem leads to unreliable learning factor RT. Moreover, the PELS cannot accurately identify the amount of courseware that needs to be read when a learner rapidly clicks or skips part of it. Therefore, the PELS needs to be enhanced to identify the most accurate learning portfolios available in order to obtain reliable learning factors in the future. Moreover, the e-learning system should support a friendly web interface to enable professional educators to define the adaptive learning factors conveniently according to their instruction needs. Second, applying the proposed learning performance assessment scheme to support other novel learning scenarios is also an essential research issue. Mobile learning and context-aware ubiquitous learning have both recently become popular research issues in the e-learning field. Hence, applying the proposed learning performance assessment scheme according to the learning portfolios in a learning recorder that can record detailed learning processes relating to context information for mobile or context-aware ubiquitous learning is a valuable research issue in the future. Finally, in addition to the formative assessment presented herein, many researchers have studied other learning performance schemes to replace summative assessment. Game-based learning performance assessment is a novel and potential idea to measure learners' various abilities, such as creative abilities. Such learning assessment is more interesting than traditional paper and pencil assessment methods.

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