Analysis on the Adaptive Scaffolding Learning Path and the Learning Performance of e-Learning

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Abstract: - Existing instruction websites record learners' portfolios, they only collect the browsing time and homepage information, without directly provide teachers with more data for further analyzing learner behaviors. Consequently, this investigation uses the learners' portfolio left in the e-learning environment, and adopts "data mining" techniques to establish for each cluster of learners the most adaptive learning path pattern, which can provide a "scaffolding" to guide each cluster of learners. Using statistical methods, this investigation analyzes whether the navigational learning map of "scaffolding learning path (SLP)" can improve learning performance.

This investigation discovers that among the three clusters of learners, the learners in the experimental group under the two clusters other than high-score cluster, after taking the "scaffolding learning path" as their navigational learning map, achieve more significant progress than the learners of comparative group. This implies that through the "scaffolding learning path," the learning performance of most learners can be improved.

Key-Words: - E-learning, Learning path, Scaffolding theory, Learning portfolio, Data mining

1 Introduction

In a non-synchronous e-learning environment, owing to the lack of instruction and guidance by a real teacher, learners must take the initiative to learn. However, if the teaching materials are poor, learners face the three problems of : control of learners, disorientation, and cognitive overload in the e-learning environment. This research issue is important in the current e-learning environment. Furthermore, traditional teaching resources, such as textbooks, typically guide the learners to follow fixed sequences to other subject-related sections related to the current one during learning processes. Web-based instruction researchers have given considerable attention to flexible curriculum sequencing control to provide adaptable personalized learning programs. Curriculum sequencing aims to provide an optimal learning path to individual learners as every learner has different prior background knowledge, preferences, and often various learning goals [4].

Hypermedia teaching applications may use additional learning procedures as guided navigation, hierarchical contents presentation, sequenced deterministic presentations, and other deterministic procedures. On the other hand, different students have different presentation preferences. Some papers present an adaptive environment application for Web-based learning [6].

Therefore, general web-based teaching materials cannot consider the differences among individual learners, leading to problems such as disorientation, cognitive overload, and so on. Some scholars have found that navigational learning map can help reduce learner disorientation. Chen and Chuang [3] indicated that knowledge map construction can integrate and organize the problems of fragmentary knowledge created after browsing in an e-learning environment. To improve learning performance, learners can use the knowledge map constructed by professionals since it can provide scaffolding for learning activities, to construct knowledge and achieve the goal of organization of the learning knowledge. Therefore, this investigation proposes "scaffolding learning paths," which provide different learning patterns based on the learning abilities of different learners, and give learners an adaptive navigational learning map.

Based on the above phenomena, this investigation has the following objectives:

1. Use the "learning portfolio tracker of the intelligent e-learning system" to record the learning paths of learners of different clusters that have achieved excellent results.
2. Use "portfolio mining" to establish adaptive "scaffolding learning paths".
3. Use "statistical method" to analyze whether the navigational learning map of the "scaffolding learning path" can improve learning performance.
4. Use the analyzed results as a reference for teachers in designing the teaching materials and instruction strategies.

2 Literature Review

This investigation discusses the three problems of learner control, disorientation and cognitive overload that learners confront in e-learning environments. Regarding the problem of learner control, many studies indicate that the hyperlink characteristic of networks enables learners to freely select the linking points and sequence. However, to learners with no cognitive strategy or ability, excessive control may reduce learning performance [1].Regarding the problem of "learner disorientation," In an open network environment, learners can randomly browse a website through the hyperlink function, and can even link to other websites. Regarding the problem of "cognitive overload," many studies indicate that when facing the control-free information, learners must make continuous decisions and judgments. If learners are unsure about their needs, they may devote too much unnecessary attention to some areas, causing cognitive overload and anxiety regarding information [1]. Consequently, from the viewpoints of constructivism and adopting the knowledge map scaffolding learning strategy, this study provides learners with the integrated knowledge regarding e-learning to reduce the problem of fragmentary knowledge in e-learning [3]. Regarding scaffolding theory, this is an instruction theory proposed by Vygotsky, a psychologist who believed that "cognitive" development can be divided into two levels: real and potential. The former is the level at which learners can solve their problems independently, while the latter is the level at which whenever learners encounter problems in the process of initiative construction of knowledge, they can only solve problems under the guidance of or through cooperation with others (teachers, outstanding classmates, etc). Vygotsky terms the distance between these two levels the zone of proximal development (ZPD). Therefore, if instruction can be close to learner ZPD, it can help learners improve from the original development level to a higher development level. It also implies that teachers have adopted a temporary supportive structure to assist learners in developing their learning ability. Such guidance is called "scaffolding" [9].

Scaffolding learning theory proposes that teachers should construct different learning scaffolding stands according to level of ability development and learning progress of different learners [10]. Therefore, this investigation employs the learning paths of different learners left in an e-learning environment to establish adaptive learning paths. Learning path describe the connected paths of time sequence of a learner's visit of the lessons of the teaching materials. , as shown in Fig. 1.

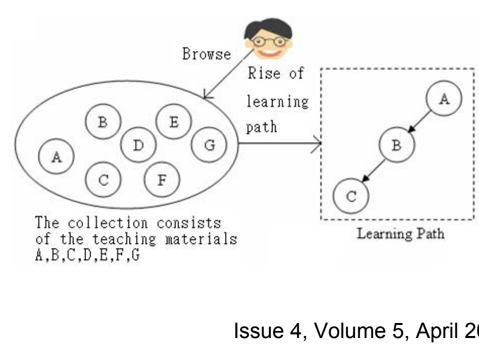

Fig. 1 Learning Paths

To conduct the scaffolding learning path, the portfolios record of learner's reading materials has to be collected. The portfolios record is also known as log files. Relevant research suggested that Analog software could be applied to achieve the goal.

Analog is the log file analysis software written in C. Analog mainly analyzes the log in the website which currently may process the administrator's self-defined pattern from the log; and the load balanced system interaction log. Which analysis, including in the browsing peak time, the daily capacity over a week which filters which page the robots browse over the most; and what browser and operation system the visitor uses and so on. [12].

Therefore, many scholars indicate studies that most of the learners' common learning paths are found in their learning portfolios. These paths provide teachers with the most important reference for understanding the learner behavior model. Since learning portfolios record the learning sequence of individual learners or the order of the teaching materials, the investigation adopts sequential pattern mining (AprioriAll algorithm) to find out which significant and useful learning path is most appropriate. Generally, AprioriAll algorithm can find out all the large sequences that meet the least support standard. Nevertheless, learning portfolio analysis and mining application indicate that the maximal sequential pattern, which is not contained in other "large sequences", should be identified if it can assist learners. Thus, for portfolio mining, suitable adjustments should be made to the AprioriAll algorithm. For example, if the sequential pattern identified using the original AprioriAll algorithm is A→D→G, A→D, A→G, D→G, then through "portfolio mining," the sequential pattern A→D→G becomes the output [8].

Besides the abovementioned theoretical foundation, some scholars [5] suggest that if teachers provide learners with suitable knowledge map scaffolding during unit learning, they can turn scattered knowledge and concepts into meaningful knowledge structures through knowledge construction and organization. Thus, this study thus employs "portfolio mining" to establish the most adaptive learning paths for different clusters of learners, known as "scaffolding learning paths." These paths are designed to verify whether "scaffolding learning path" can improve the learning performance of different clusters of learners.

3 Experimental Design

Many studies have demonstrated that the records of student learning paths and learning performance in the e-instruction system can be provided as a reference for teachers to evaluate the learning accomplishments of students and diagnose their learning difficulties. The records represent useful and authentic evaluation data. Hence, through "learning portfolio monitoring" in the "intelligent e-learning system," the investigation records the learning path data of learners. However, a complete experimental design process must formulate as follows:

3.1 Research targets

The study subjects were 44 Grade-12 students who learned "Visual Basic program language" using the "e-learning" model. The learning period was from Feb. 15 to Jun, 15, 2006, lasting four months.

3.2 Research tools

This study employs the following tools:

(1) Teaching materials structure: Use the spiral curriculum structure to present the teaching materials.

(2) Use of intelligent e-learning system: Record the learning path data of learners.

(3) Arranging real mid-term and end-term examinations.

3.3 Implementation

From early-term to mid-term examinations, the learners read the "basic concepts" covered in each chapter of the teaching materials via the intelligent e-learning system. This comprised the Step 1 Learning which automatically recorded the learning paths of learners. Via "portfolio mining" , the learning paths of students from different clusters who achieved excellent results were found out to establish an adaptive "scaffolding learning path" to guide learner learning. Moreover, based on the mid-term and end-term examinations, and through the adaptive scaffolding learning path, the learners were guided to further read the advanced concepts covered in each chapter of the teaching materials. This was the Step 2 Learning which allowed learners to jump from concrete to abstract materials, and from simple to the complicated sequential contents of the learning curriculum. The learning of each step formed a circumference. Subsequently, the difficulty was increased, and the scope was gradually expanded. Finally, complete knowledge was learned. This approach was labeled the spiral curriculum, as shown in Fig. 2.

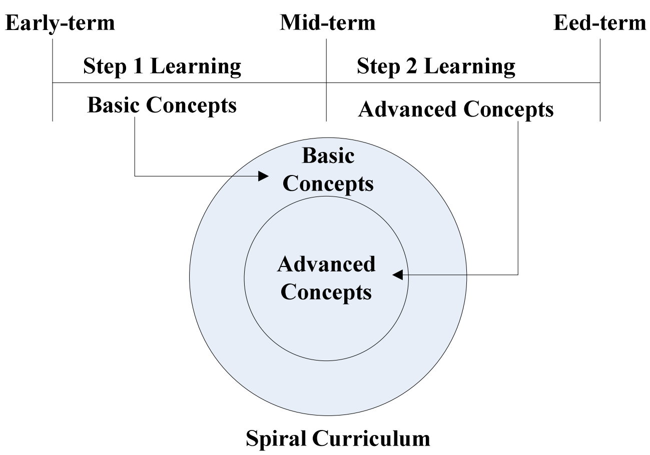

Fig. 2 Sketch map of spiral curriculum of e-learning

3.4 Data accumulation

To record the portfolios of learning activities of learners in the e-Learning system, as well as the subsequent accumulation and analysis of data, this study adopts the portfolios collection process as shown in Fig. 3.

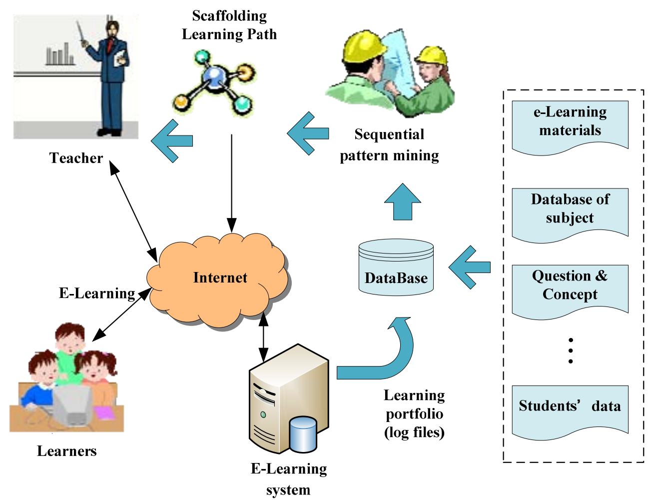

Fig. 3 learning portfolio collection processes

To collect learner learning portfolios, this study uses an intelligent e-learning system as shown in Fig. 3. This system records the time that a learner spends browsing a section of a chapter. The learning portfolios are stored in a learning database. Programs are then written in ASP.NET to analyze the learning portfolios. To ensure integrity, the following data filtering strategies are used on the collected portfolios:

(1) In the e-learning system, a learner simultaneously performs multiple learning activities. For example, learners may browse the learning materials, while simultaneously joining in interactive discussion groups with other learners. To correctly calculate the reading time, the system subtracts the time that a learner spends in interactive discussion from the total time spent in the system.

(2) While a learner is browsing a learning material, he may leave his browser on the same section and attend other non-learning-related activities. Such behavior tends to be associated with a very long reading time. Similarly, learners may browse a section find that they are not interested and skip to other sections. In this case the reading time is very short. To prevent the reading times from being recorded in the above cases, this study sets lower and upper bounds on the reading time. Restated, if a reading time is less than the lower bound or exceeds the upper bound, it is not recorded in the system. In this study, we set the lower bound at 60 seconds and the upper bound at 300 seconds [11].

4 Data Analysis

This investigation first entered the original data on the learner reading portfolio formation in the e-learning system into the Excel statistical software, and then transferred the data to statistical analysis software, SPSS for Windows 10.0, for processing and analysis. To verify and analyze the research objectives, the four procedures below were conducted. The structural flow chart is shown in Fig. 4.

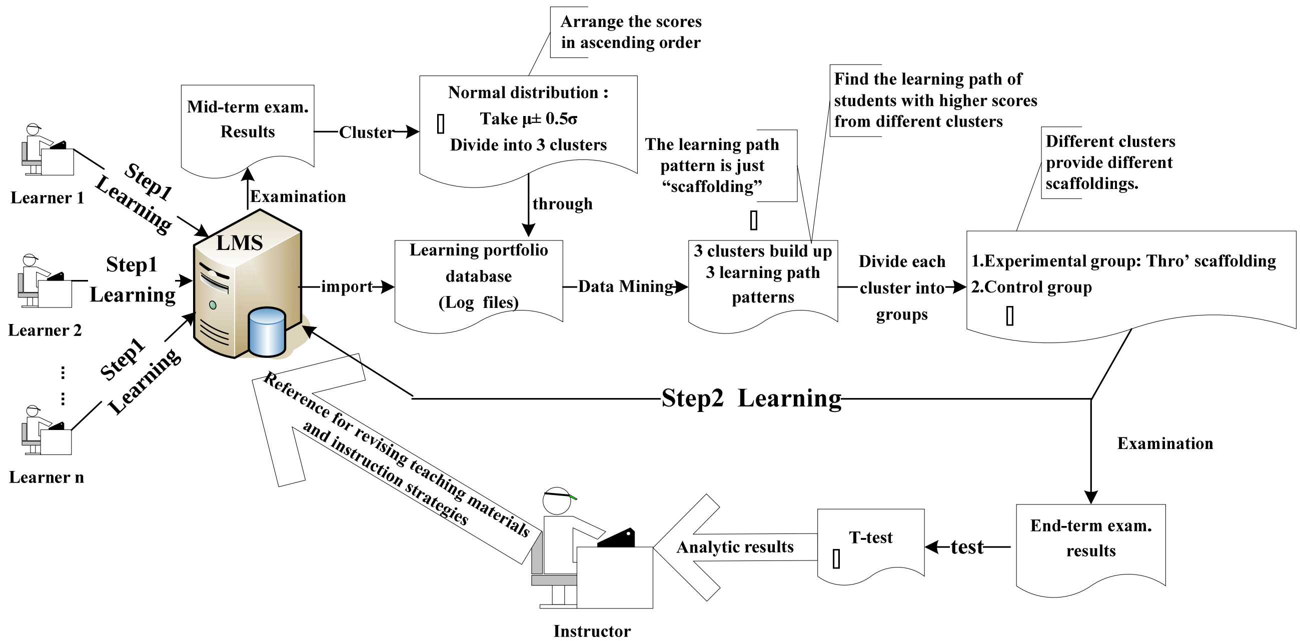

Fig. 4 Structural flow chart of Study

4.1 Analysis of cluster

(1)Learner scores obtained in the "mid-term examination" were arranged in ascending order.

(2)The academic results of all the learners were supposed to have a normal distribution [2], with mean μ and variance σ^2. This study thus attempted to use the nature of normal distribution for clustering of learners. Moreover, μ is corresponds to the probability density function of the normal distribution. Thus, $P(|X-\mu|) < 1\sigma \approx 68\%$. This implies that in the normal distribution, the students with the probabilities of below 1 standard deviation comprise approximately 68% of the students of the class, and thus comprise the majority of the learners. To consider the size difference of the clusters of students and avoid excessive cluster variation, 0.5σ was taken as the size unit. As a percentage of total number of learners, the percentages of the numbers of learners in each group are as follows:

$P(X > \mu + 0.5\sigma) \approx 30.85\%$
(Group 1: High-score cluster)

$P(|X - \mu| < 0.5\sigma) \approx 38.3\%$
(Group 2: Medium-score cluster)

$P(X < \mu - 0.5\sigma) \approx 30.85\%$
(Group 3: Low-score cluster)

Therefore, the numbers of the various clusters are showed in Table 1.

Table 1. Group differences in mid-term examination results among the various clusters

Results and No. of Students \ Clustering	Cluster 1 (High-score cluster)	Cluster 2 (Medium-score cluster)	Cluster 3 (Low-score cluster)
Mid-term examination results (X)	100~55	54~29	28~0
No. of Students	14	16	14

Remarks: μ = 42, 0.5σ = 11, the unit of X is scores.

(3)Use "ANOVA" to test the differences among the three clusters. ANOVA was employed to judge whether the "variation among groups" was significantly greater than "in-group variation," so as to test whether the "factor (referring to learning performance)" for clustering was the significant "factor" affecting the "mother body." Therefore, This study thus employed ANOVA to test whether the average figures of the learning performance of the three normal mother bodies (i.e. "high-score cluster," "medium-score cluster," "low-score cluster") were the same or not.

(a) Test:
Ho: $\mu 1 = \mu 2 = \mu 3$
H1: $\mu i \neq \mu j$ For some $i \neq j$

(b) Result of Analysis: As showed in Table 2 Table of Analysis of Variables.

Table 2. Table of Analysis of Variables

Source of Variation	Sum of Square	Degree of Freedom	Mean Square	F	P-Value
Variation among groups	17922.032	2	8961.016	93.539	.000*
In-group variation	3927.790	41	95.800		
Total variation	21849.822	43			

Note: * P-value < 0.05

Since P-value < 0.05 (significant standard), Ho is rejected. This indicates that the means of the learning performance among different clusters of students are significantly different.

4.2 Establishment of the most adaptive learning paths

The records of learner learning portfolio, from the beginning of the term to mid-term examination, left in the e-learning environment were analyzed. This study employed AprioriAll algorithm of the sequential pattern mining in the data mining technique to find out the learning paths of learners that achieved better results from different clusters. As argued by Kelley [7], under a normal distribution, the most suitable proportion is that the high-score and the low-score clusters occupy 27% respectively. Therefore, 27% of the top students of each cluster were combined to establish a learning pattern for each cluster of learners, and provide a reference for various clusters of learners.

The methods and procedures used in portfolio mining are as follows:

Input: The learning paths and the minimum support of the top 27% of learners, who refer to those learners of "low-score cluster," "medium-score cluster" and "high-score cluster" having achieved excellent results.

Output: The maximal sequential learning patterns of the three clusters are acquired.

Procedure 1: The AprioriAll algorithm is used to identify all the large sequences that meet the minimum degree.

Procedure 2: Find out the maximal sequential pattern which is not contained in other large sequences, and adopt it as the output.

Real example:

Suppose the learning path data is obtained for the learners in a class. The learning records include the student number of the learner, the browsing date, and the homepage of the teaching materials being read. A real case is examined here as an example: Suppose the number of the 27% top learners of the “medium-score cluster” with excellent results is 5. Their learning paths of the homepage are listed in Table 3, where the learning portfolio data of these five learners is indicated. In the table, I = {A,B,C,D,E} is the set of all the homepage items, and T = {T1,T2,T3,T4,T5} denotes the set of all the learners. Suppose the minimum support = 40%, and the minimum reliability = 50%. Using AprioriAll algorithm, all the useful related rules are calculated. Basically, the method of sequential pattern mining contains the following five procedures:

Procedure 1: Sequential arrangement stage

First the sequence of the learner student numbers is arranged in ascending order and the browsing dates are arranged in chronological order. During the sequential arrangement, the student number of learners is taken as the primary key, while the browsing date is taken as the secondary key. The sequential database of learners can be obtained based on sequentially arranged results, as displayed in Tables 3 and 4.

Table 3. Data of learners’ student number and browsing date following sequential arrangement

Student No.	Browsing Date	Homepage Item
T1	2005/02/15	A,B
T1	2005/02/25	C
T1	2005/03/2	D,E
T2	2005/02/14	A,B
T2	2005/02/27	C
T2	2005/03/10	E,F
T3	2005/02/16	C
T3	2005/03/25	E,F
T4	2005/02/15	A,B,C
T5	2005/02/20	C
T5	2005/06/25	E,F

Table 4. Learner homepage browsing sequence

Student No.	Homepage Browsing Sequence
T1	<(A,B)(C)(D,E)>
T2	<(A,B)(C)(E,F)>
T3	<(C)(E,F)>
T4	<(A,B,C)>
T5	<(C)(E,F)>

Procedure 2: Creation of large itemsets.

During this stage large itemsets are identified. Each large itemset comprises a large 1-sequence. Supposing the number of least support is 3, and then an AprioriAll algorithm can be used to find all the large itemsets, and correspond all the itemsets to the respective codes. For example, the itemsets (A, B) (i.e. 1-sequence <(A,B)>) is contained in the sequence of the learners “T1,” “T2” and T4,” and the number of its support is 3. Therefore, it is a large itemset. And the itemset (C,F) (i.e. 1-sequence <(C,F)>) is not contained in any learner’s sequence. Therefore, it is not a large itemset, as shown in Table 5.

Table 5. Large itemsets and the corresponding codes

Large Itemset	No. of Support	Corresponding Code
(A)	3	1
(B)	3	2
(C)	5	3
(A,B)	3	4
(E,F)	3	5

Procedure 3: Transformation stage

The process of sequential pattern mining requires determining whether a certain sequence is contained in the learner sequence. To accelerate the calculation, the learner sequence is transformed according to the following principles:

(1)If the browsed homepage does not contain any large itemset, it is removed from the learner sequence.

(2) If the learner sequence does not contain any large itemset, it will be removed from the transformed database. However, during the related calculation, the total number of learners remains unchanged.

(3) If every browsed homepage in the learner sequence is contained in the set formed by large itemsets, and is replaced. The indication is $\{I_1,I_2,\ldots,I_n\}$, where $I_j(1 \leqq j \leqq n)$ denotes the

large itemset. For example, suppose there are large itemsets (A), (B) and (A,B), then if the learner sequence is (A,B), it will be replaced by the set of large itemsets {(A)(B)(A,B)}. For example, the homepage browsing sequence of learner "T1" is (D,E), which does not contain any large itemset, and thus is canceled from the learner sequence. Furthermore, if the homepage browsing sequence of learner "T4" is (A,B,C), which contains the large itemsets (A), (B), (C) and (A,B), so the browsed homepage (A,B,C) is transformed to be {(A),(B),(C),(A,B)}, as shown in Table 6.

Table 6. Data of transformed data

Student No.	Learners' Sequence after Transformation	Indicated by the Corresponding Code
T1	<{(A),(B),(A,B)}{(C)}>	<{1,2,4}{3}>
T2	<{(A),(B),(A,B)}{(C)}{(E,F)}>	<{1,2,4}{3}{5}>
T3	<{(C)}{(E,F)}>	<{3}{5}>
T4	<{(A),(B),(C),(A,B)}>	<{1,2,3,4}>
T5	<{(C)}{(E,F)}>	<{3}{5}>

Procedure 4: Stage of creation of large sequence

Use the transformed database to create all the large sequences. The candidate 2-sequence and the corresponding number of supports are listed in Table 7.

Table 7. Candidate 2-sequences and the corresponding number of supports

Candidate 2-Sequence	No. of Support	Candidate 2-Sequence	No. of Support
<1,1>	0	<3,4>	0
<1,2>	0	<3,5>	3
<1,3>	2	<4,1>	0
<1,4>	0	<4,2>	0
<1,5>	1	<4,3>	2
<2,1>	0	<4,4>	0
<2,2>	0	<4,5>	1
<2,3>	2	<5,1>	0
<2,4>	0	<5,2>	0
<2,5>	1	<5,3>	0
<3,1>	0	<5,4>	0
<3,2>	0	<5,5>	0
<3,3>	0		

Procedure 5: Creation of maximal sequence

Find out the maximal sequence based on all the large sequences.The large 2-sequence and the corresponding number of supports are shown in Table 8.

Table 8. Large 2-sequence and the corresponding number of support

Large 2-Sequence	number of support
<3,5 >	3

The acquired large 2-sequence is <3,5>, which satisfies the minimum support. The code is transformed to be the original name <C,E,F>. The most adaptive learning path of the homepage for teaching materials is shown in Fig. 5.

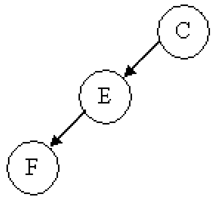

Fig. 5 Most adaptive learning path of the homepage of teaching materials

4.3 Sub cluster

In most studies, although "data mining" can be employed to find out the most adaptive learning path of a learner, no studies have conducted further investigations and studied whether the most adaptive learning path can significantly improve the learning performance of learners. Yang [10] indicated that the scaffolding learning theory suggests that different learning support stands should be constructed based on differences among learners in terms of ability development and learning progress. Therefore, it is extremely important to provide different learning paths for learners under different clusters. Consequently, the study proposes adaptive "scaffolding learning paths" to verify whether the learning performance of different clusters of learners can be improved. Before verification, the different clusters of learners are further subclustered into the "experimental group" and "comparative group," as listed in Table 9. The sub clustering way is performed as follows:

By using random selection method, each cluster is divided into "experimental group" and "comparative group."

(1)Experimental group: Provides "scaffolding learning paths" as navigational learning aids.

(2)Comparative group: Adopts traditional and non-navigational e-learning methods.

Table 9.Experimental groups of each cluster and the control of the number of students of each group

Various clusters / Various groups	Cluster 1 (High-Score Cluster)	Cluster 2 (Medium-Score Cluster)	Cluster 3 (Low-Score Cluster)
Experimental Group	7	8	7
Comparative Group	7	8	7
Number of Students	14	16	14

4.4 t-Test

To understand the learning performance of the learners of the experimental group in each cluster after being guided by "scaffolding learning path," learners were required to start Step 2 Learning after mid-term examination, and attend end-term examination at the end of the term. Since this study intended to investigate whether the learning performance of the learners of each cluster, after being guided by "scaffolding learning path," could be significantly improved, each cluster was subclustered into two groups, i.e. "experimental group" and "comparative group." As the two groups belonged to the test of the average of two mother bodies, the samples they used were independent samples. Thus, the t-test of the average of independent samples was employed. And t-test is to compare the difference of average between two mother bodies. Therefore, this study used t-test to analyze whether the establishment of an adaptive "scaffolding learning path" could significantly improve the learning performance of learners.

Suppose the significant standard is α. If P-Value<α, then H0 is rejected. It implies that there exists a significant difference between the average of experimental group and the average of comparative group. If P-Value≧α, then H0 is not rejected. It implies that there exists no significant difference between the average of experimental group and the average of comparative group. The t-test results of the study are shown in Table 10, tests of independent samples of the experimental groups and comparative groups of the three clusters of learners.

Table 10. Tests of independent samples of the experimental and comparative groups of the three clusters of learners

Clustering and Subclustering / Item		Average	Standard Deviation	t-Value	Significance
High-Score Cluster	Experimental Group	70.86	16.65	.636	.537
	Comparative Group	65.71	13.45		
Medium-Score Cluster	Experimental Group	52.00	10.30	2.657	.019
	Comparative Group	38.91	9.39		
Low--Score Cluster	Experimental Group	37.14	9.58	4.253	.001
	Comparative Group	17.71	7.36		

Note: **P-value < 0.01

As demonstrated by the t-test of the independent samples, after the learners under the medium-score cluster and the low-score cluster followed the "scaffolding learning path," they both have significant difference (the p values of both are less than .05), but there is no significant difference found in the high-score cluster.

5 Discussion

This investigation finds that among the three clusters of learners, the learners belonging to the "experimental groups" and from the medium-score and low-score clusters, other than the learners of the high-score cluster, have significant improvement after taking "scaffolding learning path" as the navigational aid to their learning. Although the statistically analyzed results of the medium-score cluster and the low-score cluster show that the "experimental group" has more significant difference than the "comparative group," the p-value of the "low-score cluster" is 0.01, which is less than the p-value 0.019 of "medium-score cluster." It also implies that the learners of "low-score cluster" are in greater need of navigational aid on their learning when comparing with the learners of "medium-score cluster." Therefore, a majority of the learners must encounter problems in the process of initiative construction of knowledge, but the learning performance of the learners taking an adaptive "scaffolding learning path" as a navigational aid in their learning is significantly different from the learning performance of the learners without any adaptive "scaffolding learning path" as a navigational aid in their learning.

In addition, this study also discovers that the learning performance of the learners of "experimental groups" under the high-score cluster and the learning performance of the learners of "comparative groups" under the same cluster do not achieve significant difference. Therefore, the researcher has to go deep into the analysis on the learning paths of the learners of the high-score cluster listed after the 27% top students. The analysis shows that the learning paths of the learners under the high-score cluster are quite similar. In this way, among the factors affecting the learning performance of the learners of the high-score cluster, "scaffolding learning path" is not a main factor. Therefore, applying "scaffolding learning path" as a navigational aid to the instruction cannot effectively improve the learning performance of the learners of "experimental groups" under the high-score cluster.

Hence, in a non-synchronous e-learning environment, teachers not only should provide adaptive teaching materials, but more importantly, should collect the personal learning paths of learners left in the e-learning system to establish adaptive "scaffolding learning paths" so as to offer different navigational learning aids to the learners of different clusters. Moreover, "scaffolding learning paths" can also guide learners to enter the zone of proximal development of learners, thus effectively helping learners have progress from the original development level (real level of development) to a higher development level (potential level of development).

6 Suggestions

As found in this study, the learning performance of the learners of "experimental groups" under the high-score cluster and the learning performance of the learners of "comparative groups" under the same cluster do not achieve significant difference. Thus, it is suggested that the researcher not only should take "scaffolding learning paths" as the navigational learning aids for learners, but also has to make in-depth analysis and investigation of the factors affecting the learning effects of learners. For example, the researcher should also consider the factors of interaction among learners in the e-learning environment, the number of times of their being online, the reading time of the teaching materials, the submission situation of the online homework, and so on, and import them to the instruction activities and strategies at the right timing. Then the learners of the high-score cluster can get better learning performance; otherwise, the learning performance of many learners of the medium-score cluster, as being guided by "scaffolding learning path," shall very soon surpass the learning performance of the learners of the high-score cluster.

Meanwhile, there is one noteworthy thing that after the learners of the low-score cluster are guided by "scaffolding learning path," if the learning performance is significantly improved, the instructor can suggest that the 27% top learners under the "low-score cluster" try to refer to the "scaffolding learning path" of the learners of "medium-score cluster." But they are not suggested to use the "scaffolding learning path" of the learners of the "high-score cluster".

The effect of the scaffolding learning path in this study is not significant to the "high-score cluster". Therefore, it is suggested that the factors affecting "high-score cluster" learning effects can be further explored in future research. It will contribute to providing different learning strategies to "high-score cluster" besides "low and medium-score cluster" learners from teachers and consequently different students' needs will be looked after.

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