LEARNER CHARACTERISTIC BASED LEARNING EFFORT CURVE MODE: THE CORE MECHANISM ON DEVELOPING PERSONALIZED ADAPTIVE E-LEARNING PLATFORM

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ABSTRACT
This study aims to develop the core mechanism for realizing the development of personalized adaptive e-learning platform, which is based on the previous learning effort curve research and takes into account the learner characteristics of learning style and self-efficacy. 125 university students from Taiwan are classified into 16 groups according to learning efficiency, learning style and self-efficacy. The learner characteristic based learning effort curve mode (LECM) is developed by conducting multi-factor regression on the corresponding learning effort curves generated by the specific group. The research findings conclude that the learner characteristic based LECM is able to represent the specific learning characteristics of the corresponding learning style and self-efficacy effectively. The core value of the learner characteristic based LECM is to realize the future development of personalized adaptive e-learning platform through taking it as the core mechanism.
Keywords: e-learning, learner characteristics, learning effort, learning style, self-efficacy

INTRODUCTION
Simonson et al. (2003) argued that most of e-learning platforms focused on ICT (Information and Communication Technology) operation instead of learner characteristics. However, Kumar (1999) recommended that the design of e-learning platforms should consider learner characteristics in order to promote learning efficacy. Because the future trend of services and products is towards personalization, there are some research confirm that multimedia teaching materials improve students' studies, for example, a experimental design prove multimedia teaching materials lead to significance difference in students' chemistry test grades (Lou, Lin, Shih & Tseng, 2012). How to set e-learning material, such as the design of an e-learning platform should consider personalization and adaptability as key criterions. Brusilovsky (2001) noted that the importance of e-learning was to develop the personalized adaptive e-learning mechanism which adapted to individual learner characteristic. Therefore, this study aims to develop the core mechanism which supports the development of personalized adaptive e-learning platform.

A good e-learning mechanism must be based on learner characteristics. The classification of learning style makes adaptive e-learning more sensible (Keh, 2004) and self-efficacy is the key factor of e-learning performance (Yu, 2007; Thompson & Lynch, 2003). However, most of e-learning platforms do not consider learner characteristics and even lack for dynamic real-time based mechanisms which promote effective learning. Hence, most of e-learning platforms are not able to achieve adaptive learning effectively.

This study takes learning style and self-efficacy as learner characteristics. And then utilize the dynamic real-time based learning effort quantification technique (Hsu et al, 2009, Hsu & Chang, 2011) to construct learner characteristic based LECM which is in line with the learning characteristic of corresponding learner characteristic. For the future research, the normalized learner characteristic based LECM is generated by enlarging the quantity and coverage areas of sampling. And then take the normalized learner characteristic based LECM as the core mechanism in developing learning progress diagnosis database. In the meantime the specific adaptive learning path and support is also developed based on the corresponding learning characteristics which are interpreted from the learner characteristic based LECM at modular base. Through embedding modulized adaptive learning path and support, dynamic real-time based learning effort quantification technique and learning progress diagnosis database into an e-learning platform, authors plan to realize the development of personalized adaptive e-learning platform.

LITERATURE REVIEW
In this study, learning style and self-efficacy are taken into consideration for the learner characteristics according to the findings of literature review.

Learning Style
The learning style is the preference of message acquisition approach in learning process and context (Kraus et al., 2001). People can promote learning through constructing the learning process and learning context which fit with the preference of specific learning style (Gau & Tzai, 1999; Reiff, 1992). Because of the technology

development, there are more and more digital devices using in the processing of learning, some research focus on Ubiquitous learning, which students can learn at every time and everywhere (Huang, Chen & Wang, 2012). Besides Ubiquitous learning, it is also important about the learning material and theory itself. The learning style theory (Kolb, 1985) has been cited widely in academic researches (Demirkan, & Demirbas, 2008; Wang et al., 2006). Kolb (1985) constructed the learning process into two perspectives and four directions. One is apprehension perspective which includes the directions of concrete experience (CE) and abstract conceptualization (AC) according to the consideration of experience acquisition. The other is transformation perspective which includes directions of reflective observation (RO) and active experimentation (AE) according to experience transformation (Kolb & Kolb, 2005a). In light of CE-AC and RO-AE, learning style is classified into four quadrants which are accommodator, assimilator, converger and diverger (Kolb, 1985). Please refer to Kolb's learning style quadrant shown in Figure 1.

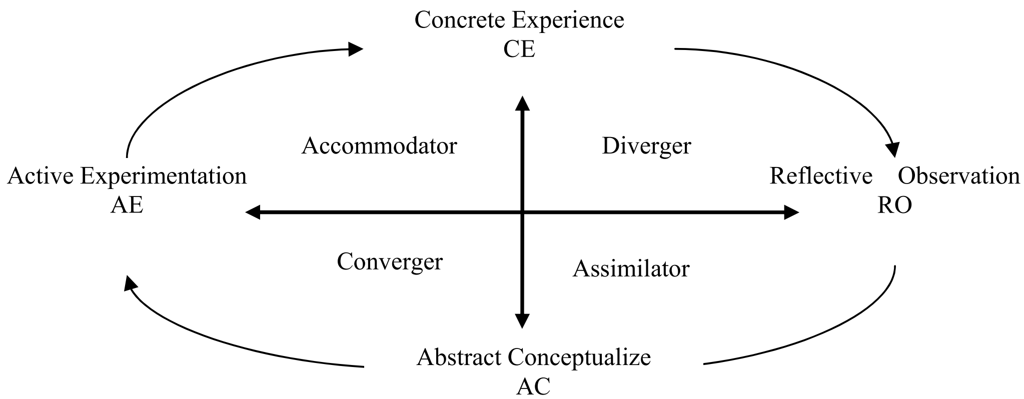

Figure 1. Kolb's learning style quadrant

Chou and Wong (2000) noted that there was significant interaction between e-learning approaches and learning styles. Federico (2000) found that there was significant correlation between learning style and e-learning performance. Kraus et al. (2001) also found that e-learning performance was enhanced once the curriculum of e-learning was suitable for the needs of specific learning style. Terrell (2002) and Meyer (2003) argued that learning style has decisive influence on e-learning performance. Papanikolaou et al. (2006) argued that learning style should be considered in the design of e-learning platform in order to promote learning motivation and performance. In summary, learning style is an important learner characteristic to be considered in e-learning. Akdemir & Koszalka (2008) stated learning styles play critical roles that influence student retention and success in web-based learning environment. Besides all, Ku & Chang (2011) discussed the recent studies about learning style, and support the view that learning style is an ongoing issue of great importance to educational research obviously.

Self-efficacy

Self-efficacy is the belief in success (Bandura, 1986). Such belief is generated by the self assessment on the ability to accomplish specific task. Therefore, self-efficacy represents the confidence level in accomplishing specific task successfully. People are more capable of achieving specific goal continuously while they have high self-efficacy. Jerusalem & Schwarzer (1992) argued that self-efficacy is the self-conscious control ability to adapt to pressure while face problems. Therefore, self-efficacy is a resource of pressure adaptation. People with high self-efficacy have better self-conscious control ability, which results in controlling challenging environment effectively (Gecas, 1989; Greenglass et al., 1999; Kear, 2000). Usually people with higher self-efficacy are more possible to carry out challenging tasks. Some research apply digital game to study, the motivational materials be proved enabling the application and maximize (Moon, Jahng & Kim, 2011). Furthermore, they are more capable of recovering from frustration in order to carry out tasks successfully instead of giving up at halfway (Bandura, 1992, 1997; Jerusalem & Schwarzer, 1992; Kear, 2000; Scholz et al., 2002).

Lent (1984) noted that students with high self-efficacy achieve better learning performance. Hutchins (2004) noted that self-efficacy is the key factor for learners to acquire and sustain skills continuously. In autonomic e-learning context, self-efficacy plays important role in learning performance promotion (Hsu, 2007; Thompson & Lynch, 2003). In summary, self-efficacy is an important learner characteristic to be considered in e-learning.

Learning Efficiency

The traditional assessment in education primarily deals with learning performance which presents a learner's achievement measured by the test score on task. Learning performance is one assessment dimension of cognitive load. Higher cognitive load often results in lower test score and less learning performance (Pass & van Merriëboer, 1994). For many practical cases, it is feasible for two people to achieve the same learning performance levels with devoting different effort levels. Hence, both people have identical learning performance but expertise might be higher for the person who performs the task with less effort than for the person who devotes substantial effort. Therefore, an appropriate diagnostic technique of expertise should include assessments of effort and performance. Kalyuga and Sweller (2005) developed a dynamic diagnostic technique named cognitive efficiency (E) which is defined as $E=P/R$, where R is the effort rating and P is the performance rating on the same task. But cognitive efficiency is not a real-time based technique because the effort is not able to be assessed at real-time base. Therefore, Hsu et al. (2009) developed learning efficiency which is a learning progress diagnosis technique. It is defined as learning performance divided by learning effort equals to learning efficiency. Consequently, the learning effort of a leaner is able to be assessed and quantitatively measured by self selecting learning pathes at dynamic real-time based approach.

In Hsu and Chang's research (2011), the learning effort is represented as a visualized learning effort curve. By comparing the learning effort curve modes generated by the high learning efficiency and low learning efficiency groups in e-learning process, the progress of learning effort tends to descend for the high learning efficiency group. In contrast, the progress of learning effort tends to ascend for the low learning efficiency group (Hsu & Chang, 2011). Such finding is in accordance with the arguments of cognition load theory that lower effort results in higher performance (Kalyuga et al., 2000; Mousavi et al., 1995; Sweller et al., 1998).

METHOD

Subjects

178 university students from Taiwan participated the e-learning activity on IC3 Mentor e-learning platform. 125 of 178 were qualified as the subjects based on the readiness of learning records and the assessment results of learning style inventory and self-efficacy scale.

Tool

The research tool includes learning style inventory, self-efficacy scale, IC3 Mentor e-learning platform, rapid assessment quantification technique and learning effort quantification technique. Subjects were classified according to learner characteristics by applying the assessments of learning style inventory and self-efficacy scale. The learning records of each individual subject generated in the e-learning process on IC3 Mentor were converted into learning effort and learning efficiency that were presented in numerical data format by applying rapid assessment quantification technique and learning effort quantification technique.

1. Learning Style Inventory (LSI)

The learning style inventory developed by Kolb (1984) had been examined by Cronbach α coefficient test with the results of .82, .71, .83 and .78 for accommodator, assimilator, converger and diverger accordingly (Kolb, 1985). Many scholars also claimed that LSI is an effective research tool with high reliability (Commings & Wirley, 2001; Demirbas & Demirkan, 2007; Wells et al., 1991). The validity of LSI is also very high (Sewall, 1986). It takes about 10 to 15 minutes to answer 12 questions in LSI; therefore, LSI does not cause too much loading on subjects. In this study, LSI is used to assess subjects' learning style and classify subjects into four learning styles which are accommodator, assimilator, converger and diverger accordingly.

2. Self-Efficacy Scale (SES)

The self-efficacy scale developed by Zhang and Schwarzer (1995) had been applied on 293 university students and the Cronbach α coefficient test with the result .91 indicated that SES is an effective research tool with high reliability. And there is only a single component to be extracted by principle component analysis, which represents high validity (Scholz et al., 2002). There are 10 questions in SES and every question is assessed by the 4-point scale which is incorrect for 1, fairly correct for 2, mostly correct for 3 and fully correct for 4. Total score points will be around 10 to 40 points. Subjects with higher SES scores represent better self-efficacy. In this study, SES is used to assess self-efficacy and classify subjects into high and low self-efficacy groups.

3. IC3 Mentor E-Learning Platform

IC3 Mentor is the e-learning platform of IC3 (Internet and Computing Core Certifications) which is a global ICT (Information and Communication Technology) certification applied over 128 countries worldwide (Certiport, 2008). IC3 Mentor is a learning/assessment blended learning system. Learners can self-determine the learning path in the multi-layer learning structure of IC3 Mentor.

4. Dynamic Real-Time based Learning Effort Quantification Technique

Learning effort (Hsu et al, 2009, Hsu & Chang, 2011) is developed based on cognition load theory (Sweller, 1990) and dynamic assessment theory (Allal & Ducrey, 2000). Learning effort with positive value represents ascending learning effort, and learning effort with negative value represents descending learning effort. Dynamic real-time based learning effort quantification technique (Hsu et al, 2009, Hsu & Chang, 2011) is developed as a dynamic real-time based quantification technique based on learning effort, RAT- Rapid Assessment Test (Kalyuga & Sweller, 2004) and cognition efficiency theory (Kalyuga & Sweller, 2005). It was utilized to convert learning records into learning effort numerical data in this study.

5. Learning Effort Curve

The learning effort numerical data, which is converted from learning records by the dynamic real-time based learning effort quantification technique, is a two dimensional numerical data that can be transformed to a visual graphic information called learning effort curve (Hsu et al, 2009, Hsu & Chang, 2011). Refer to Figure 2, learning effort is increasing from learning unit 1 to 4, which presents a learner tends towards learning effort growth. Learning effort is decreasing from learning unit 4 to 6, which presents a learner tends towards descending learning effort.

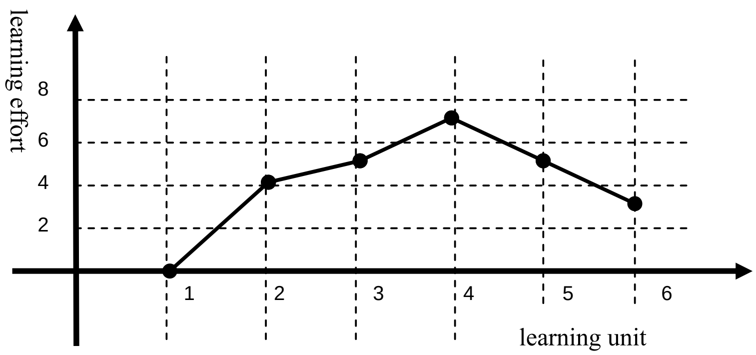

Figure 2. Learning effort curve

Procedure

The research structure is shown in Figure 3. The detail procedure is shown as following:

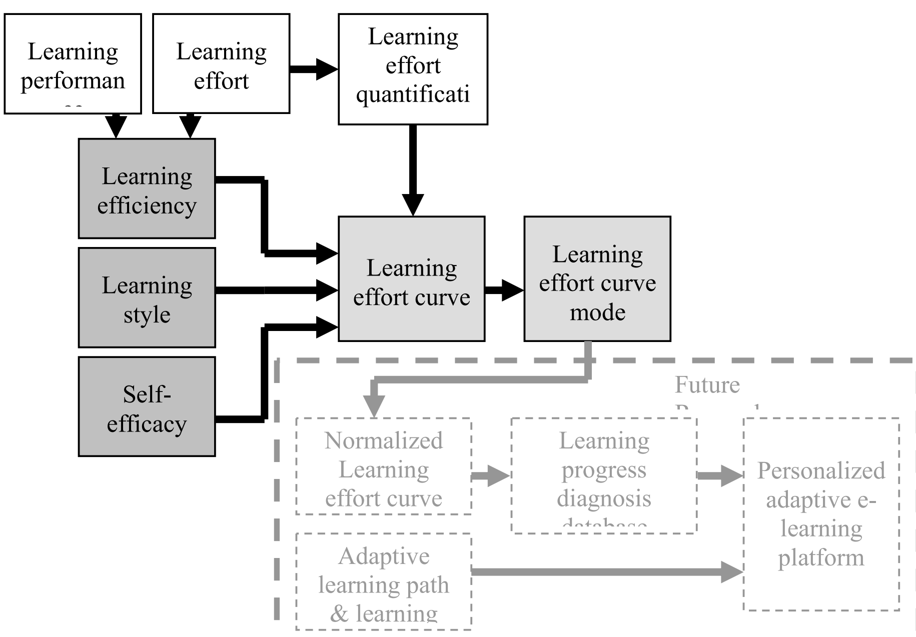

Figure 3. Research structure

1. Subjects are classified according to learner characteristics which include learning style and self-efficacy. For learning style, subjects are classified into accommodator, assimilator, converger and diverger by the assessment of LSI. For self-efficacy, subjects are classified into low and high self-efficacy groups by the assessment of SES.
2. All subjects conduct e-learning on IC^3 Mentor platform. Every subject was requested to accomplish the same 31 learning units with the same learning sequence. The learning records of each subject are recorded at real-time base in the learning process.
3. The learning records of each subject are converted into learning effort numerical data by the dynamic real-time based learning effort quantification technique. Then the learning effort numerical data is transformed into a two-dimensional curve called learning effort curve by the graphic processing. Every subject generates his/her own learning effort curve at dynamic real-time based approach in the learning process.
4. In the meantime, the learning records of each subject are also converted into learning performance numerical data by RAT (Kalyuga & Sweller, 2004; Hsu et al, 2009, Hsu & Chang, 2011). The learning efficiency is generated by the numerical calculation of learning performance and learning effort (Hsu et al, 2009, Hsu & Chang, 2011). For learning efficiency, subjects are classified into low and high learning efficiency groups.
5. Based on procedure 1 and 4, subjects are classified into 16 learner characteristic based groups according to learning style, self-efficacy and learning efficiency. In the meantime individuals' learning effort curves are also classified into 16 groups accordingly. The learner characteristic based LECM for each group is generated by conducting multi-factor regression on the learning effort curves classified in the specific group. Consequently, 16 learner characteristic based LECMs are generated for 16 groups accordingly.
6. For the future research, the normalized learner characteristic based LECM is generated by enlarging the quantity and coverage areas of sampling. And then take the normalized learner characteristic based LECM as the core mechanism in developing learning progress diagnosis database. In the meantime the specific adaptive learning path and support is also developed according to the corresponding learning characteristics which are interpreted from learner characteristic based LECM at modular base. Through embedding modulized adaptive learning path and support, dynamic real-time based learning effort quantification technique and learning progress diagnosis database into an e-learning platform, authors plan to achieve the development of personalized adaptive e-learning platform.

RESULTS

Learner Characteristic Based Learning Effort Curve Mode (LECM)

Subjects are classified into 16 groups according to learning style, self-efficacy and learning efficiency. The sample distribution chart is represented in Table 1.

Table 1. **Sample distribution chart – learning style vs. self-efficacy vs. learning efficiency**

Learning Style	Self-efficacy (SE)	Samples	Learning Efficiency (LE)	Samples	Group
Accommodator	High SE	9	High LE	3	1
			Low LE	6	2
	Low SE	9	High LE	4	3
			Low LE	5	4
Assimilator	High SE	28	High LE	14	5
			Low LE	14	6
	Low SE	14	High LE	6	7
			Low LE	8	8
Converger	High SE	34	High LE	17	9
			Low LE	17	10

	Low SE	14	High LE	7	11
			Low LE	7	12
Diverger	High SE	15	High LE	10	13
			Low LE	5	14
	Low SE	2	High LE	2	15
			Low LE	0	16

The learner characteristic based LECM is generated for each group by conducting multi-factor regression processing. But the sample quantity of group 15 and 16 is not sufficient (please refer to Table 1) for multi-factor regression processing. Hence, only 14 learner characteristic based LECMs are generated in this study, which represents the learning effort curve mode according to specific learner characteristic of each group. 14 learner characteristic based LECMs are shown in Figure 4.

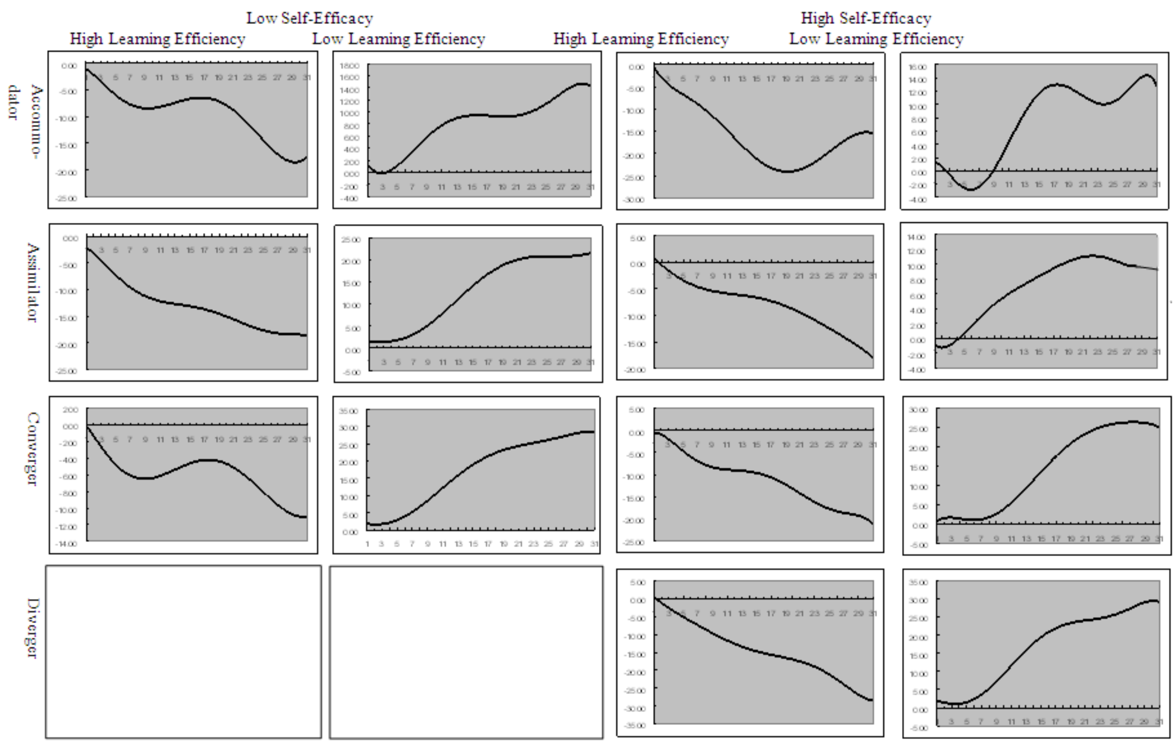

Figure 4. Learner characteristic based learning effort curve modes

The findings are shown as following according to the analysis on 14 learner characteristic based LECMs:

1. The overall characteristic of learner characteristic based LECMs

All learner characteristic based LECMs represent the consistent characteristic no matter what learning style or self-efficacy belongs to. For the high learning efficiency groups, the learning effort of all learner characteristic based LECMs tends to descend continuously and stays at negative learning effort value. In contrast, the learning effort of all learner characteristic based LECMs tends to ascend continuously and stays at positive learning effort value for the low learning efficiency groups. Such is in line with the learning effort curve studies (Hsu & Chang, 2011).

2. The influence of self-efficacy on learner characteristic based LECMs

For high learning efficiency, no matter what learning style belongs to, the learning effort in high self-efficacy groups indicates more variance range and more descending trend compared with the one in low self-efficacy groups. That is, subjects with high self-efficacy tend to promote learning efficiency through descending learning effort continuously. Furthermore, for low learning efficiency groups, no matter what learning style belongs to, the learning effort in high self-efficacy groups indicates less variance range and less ascending trend compared with the one in low self-efficacy groups. And it is easier to approach convergent mode. That is, subjects with high self-efficacy tend to achieve learning effort saturation through adapting to the impact caused by ascending learning effort. Such lowers the risk of discontinuous learning caused by divergent ascending learning effort. These findings are in line with self-efficacy studies (Bandura, 1997; Jerusalem & Schwarzer, 1992; Kear, 2000; Schwarzer & Scholz, 2002) that it is easier for people with high self-efficacy to adapt themselves to learning frustration and recover themselves for continuous learning.

3. The influence of learning style on learner characteristic based LECM

(1)Accommodator's Learner Characteristic Based LECM

Accommodator's learner characteristic based LECM represents non-linear inflection. Learner characteristic based LECM tends to descend and then ascend in the ascending range. Or in the other way, learner characteristic based LECM tends to ascend and then descend in the descending range. Such is in line with the study findings on accommodator characteristics that an accommodator is a risk-taking person who is more easily influenced by the learning context and other learners and tends to approach tasks by trials and errors (Diaz & Cartnal, 1999; Kolb & Kolb, 2005b; Reid, 1995; Smith & Kolb, 1996; Wu, 1997). Therefore, accommodator's learner characteristic based LECM represents tremble curve profile with several inflections of learning effort caused by the process of trials and errors.

(2)Assimilator's Learner Characteristic Based LECM

Assimilator's learner characteristic based LECM represents less learning effort variance range. Such is in line with the study findings on assimilator characteristics that an assimilator tends to establish institutionalization by integrating all the learning experiences and knowledge. An assimilator follows the model established in institutionalization in order to reduce trials and errors and risk-taking (Diaz & Cartnal, 1999; Kolb & Kolb, 2005b; Reid, 1995; Smith & Kolb, 1996; Wu, 1997). Therefore, an assimilator's learning effort variance stays relative low because of institutionalization.

(3)Converger's Learner Characteristic Based LECM

Converger's learner characteristic based LECM represents convergent mode. Such is in line with the study findings on converger characteristics that a converger tends to keep problems converge gradually in order to get resolution through practical practices (Diaz & Cartnal, 1999; Kolb & Kolb, 2005b; Reid, 1995; Smith & Kolb, 1996; Wu, 1997). In the problem convergence process, the learning effort variance is getting lower gradually along with the progress of problem resolution. Therefore, converger's learner characteristic based LECM tends to approach convergence.

(4)Diverger's Learner Characteristic Based LECM

Diverger's learner characteristic based LECM represents divergent mode. Such is in line with the study findings on diverger characteristics that a diverger tends to approach problem shooting by imagination and feeling with innovative explorartion (Diaz & Cartnal, 1999; Kolb & Kolb, 2005b; Reid, 1995; Smith & Kolb, 1996; Wu, 1997). A diverger's learning effort keeps descending while his/her feeling is in line with successful learning progress. In contrast, a diverger's learning effort keeps ascending while he/she experiences learning frustration. Therefore, diverger's learner characteristic based LECM tends to approach divergence.

DISCUSSIONS

For the future research, first of all, the normalized learner characteristic based LECM for every learner characteristic based group will be established by enlarging the quantity and coverage areas of sampling. Once the normalized learner characteristic based LECMs are established, the learning characteristics of each normalized learner characteristic based LECM can be extracted by analyzing the mathematical characteristics of the curve profile of learning sectors which include descending sector, ascending sector, convergent sector, divergent sector and inflection points. And then develop learning progress diagnosis database based on the learning characteristics extracted from normalized learner characteristic based LECMs, which contains the learning progress for each specific sector of normalized learner characteristic based LECM. That is, a learner's learning progress can be diagnosed by crossly comparing the numerical data converted from his/her learning effort curve with the corresponding learning characteristics in the learning progress diagnosis database at dynamic real-time based approach. As long as the specific learning characteristic is identified from the learning effort curve generated by the learner in the e-learning process, which is in line with the corresponding learning characteristic in the learner progress diagnosis database, then the learning progress of a specific learner can be anticipated since it tends to be similar to the corresponding learning progress in the learning progress diagnosis database. In the meantime, the modulized adaptive learning path and support is developed through interpreting the learning characteristics of the specific learning sector of the normalized learner characteristic based LECM. Therefore, once the learning progress can be diagnosed through e-learning process at dynamic real-time based approach, and then the e-learning platform can provide the suitable adaptive learning path and support for a specific learner at personally base according to the anticipation of future learning progress accordingly. Consequently, it's a feasible approach to achieve personalized adaptive e-learning by the core mechanism of learner characteristic based LECM. Hence, it's the core value of learner characteristic based LECM on this study.

The detailed future research is shown as following:

1. Normalized Learner Characteristic Based LECM

The learner characteristic based LECM can be normalized by enlarging the quantity and coverage areas of sampling. Then the variance between a specific learner's learning effort curve and the normalized learner characteristic based LECM is reduced. That is, the normalized learner characteristic based LECM becomes an effective tool in representing a learner's learning effort resume at learner characteristic base. Hence, specific normalized learner characteristic based LECMs are established for each learner characteristic based group.

2. Learning progress diagnosis Database

The learning characteristics of each normalized learner characteristic based LECM can be extracted by analyzing the mathematical characteristics of the curve profile of learning sectors which include descending sector, ascending sector, convergent sector, divergent sector and inflection points. And then the learning progress diagnosis database is developed by classifying those learning characteristics extracted from normalized learner characteristic based LECMs in the mathematical format for every learning characteristic based group.

3. Modulized Adaptive Learning Path and support

For a particular learner characteristic, the learning characteristics can be interpreted under specific learning sector of the normalized learner characteristic based LECM. And then the corresponding learning path and support is designed to suit with the specific requirements accordingly in order to enhance learning, which is an adaptive approach. Such is designed to adapt to the requirements of specific learning sector of the normalized learner characteristic based LECM accordingly; therefore, it is also a modulized approach to establish different modulized adaptive learning path and support for the corresponding requirements of specific learning sector.

4. The Personalized Adaptive e-Learning Platform

By crossly comparing a learner's learning effort curve with the learning progress diagnosis database at specific learning sector, the corresponding learning characteristics in the learning progress diagnosis database is identified. And then the future learning progress of the learner's learning effort curve can be anticipated. The suitable modulized adaptive learning path and support is provided according to the anticipation status in order to improve learning at dynamic real-time based approach. The learning sector is moving forward dynamically along the learning process in order to conduct learning progress diagnosis at real-time based approach. The modulized adaptive learning path and support will be replaced by a new module according to the learning progress diagnosis results. As long as the learning sector is moving forward continuously along the whole learning process, then the corresponding modulized adaptive learning path and support is provided according to learning progress diagnosis results at real-time based approach. Consequently, the personalized adaptive e-learning platform is constructed to promote learning by receiving suitable modulized adaptive learning path and support through the continuously feed-forward learning progress diagnosis at real-time based approach.

CONCLUSION

E-learning should consider learner characteristics in order to promote learning. Learning style and self-efficacy become the key factors in the development of adaptive e-learning, which are the key learner characteristics considered in this study. Subjects were classified into 16 learner characteristic based groups in light of learning style, self-efficacy and learning efficiency. The learning effort curves generated by the subjects in the specific group were transformed into the learning effort curve mode (LECM) at learner characteristic base, which represented the specific learning effort curve mode for the corresponding profile of learner characteristics based group. By the analysis of learner characteristic based LECMs for 16 groups, the findings indicate that the learning effort of learner characteristic based LECMs tends to descend continuously for the high learning efficiency groups; the learning effort of learner characteristic based LECMs tends to ascend continuously for the low learning efficiency groups. That is, no matter what learner characteristics belong to, descending learning effort results in high learning performance and ascending learning effort results in low learning efficiency, which is in accordance with the previous research findings on learning efficiency and learning effort curves (Hsu et al, 2009, Hsu & Chang, 2011). Furthermore, the particular learning characteristic of the person with specific learning style and self-efficacy is in line with the progress of learning effort represented by the corresponding learner characteristic based LECM. Therefore, for the specific learner characteristics, the learner characteristic based LECM is proved to be an effective core mechanism for the development of learning progress diagnosis.

The normalized learner characteristic based LECM is required to be established because there are missing learner characteristic based LECMs for two groups and the quantity and coverage areas of sampling is also relative smaller in this study. For the future research, the first step is to establish the normalized learner characteristic based LECM, and then take the normalized learner characteristic based LECMs as the core mechanism to develop the learning progress diagnosis database. In the meantime the adaptive learning path and support is designed at modular base for specific requirements at different learning progress status. The final target of the future research is to realize personalized adaptive e-learning by embedding the modulized adaptive learning path and support, the dynamic real-time based learning effort quantification technique and learning progress diagnosis database into an e-learning platform. By the personalized adaptive e-learning platform, learner's learning progress can be feed-forward diagnosed and anticipated continuously by the learning progress diagnosis database. And then the corresponding modulized adaptive learning path and support is provided according to learning progress diagnosis results at real-time based approach.

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