COMPUTERS & EDUCATION

Computers & Education 42 (2004) 267–287

www.elsevier.com/locate/compedu

The relationship of learning traits, motivation and performance-learning response dynamics

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Received 23 March 2003; accepted 4 August 2003

Abstract

This paper proposes a model of learning dynamics and learning energy, one that analyzes learning systems scientifically. This model makes response to the learner action by means of some equations relating to learning dynamics, learning energy, learning speed, learning force, and learning acceleration, which is analogous to the notion of Newtonian mechanics in some way; therefore, this model is named Learning Response Dynamics. First, in this paper, the relationship between learning dynamics and learning speed has been investigated in a learning system, and then the changes of learning energy are inferred from the relationships obtained. The learning effect is estimated according to the changes of the learning energy. Based on the learning portfolios of the learners, the model is designed to investigate the changes of learning speed over time. Various dynamics will influence the learning speed. These dynamics include the traits of the learners, the traits of the learning materials, and the stimulation of the learning activities. How to use different dynamics to motivate the learners is crucial to the success of learning. This model converts the factors in a learning system to quantified and comprehensible data, deducing the relationships between those factors. It makes the study of the learning system more efficient and scientific. With the experience of the two-year ongoing experiments on distance learning, and with the learning information discovered from the web-based-distance-class learners' learning portfolios by means of data mining techniques, the learning model mentioned above is inferred, tested and verified.

Keywords: Data mining; Learning portfolios; Learning dynamics; Newton's mechanics; Learning curve

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0360-1315/$ - see front matter
doi:10.1016/j.compedu.2003.08.004

1. Preface

The greatest difference between asynchronous learning and traditional face-to-face learning in the classroom is in its independence from time and space. However, the independence from time and space is undoubtedly an obstacle to the learners when we give consideration to the contents and design of learning materials and individuated learning strategy. For one thing, it separates learners from teachers and other learners in time and space so that learners cannot ask questions and get the answers from teachers timely; for another thing, teachers cannot precisely sense and know the learners' learning situation to adapt their teaching rate of progress and materials dynamically. This is quite true especially when the computerized video is not used. Therefore, asynchronous learning strategy has been seriously questioned to be effective.

Traditional approaches to teaching-learning problems are mostly based on the personal opinions of the experts interviewed or the results of the questionnaires issued. However, such approaches are prone to errors (Moore & Kearsley, 1996). Consequently, teachers may as well adapt their teaching rate of progress and materials by observing the response of their students in class, as is in effect a remedial measure but not the best solution. But now, thanks to the advent of the computer and Internet, educators can collect and precisely record learners' learning portfolios that were difficult to be quantified and recorded before. This new technical aid integrates technology into education still further.

Thanks to information technology, the learning portfolios can be objectively recorded and established to serve as a basis for putting adaptive learning mechanism into practice efficiently. And this is one of the important advantages of asynchronous learning. The implementation of the adaptive learning system is based on the learning portfolios, the ones that will gradually grow to be a huge learning data warehouse. Then we can discover useful learning information from the learning data warehouse by data mining. The learning information can be divided into two categories: the learning traits and the traits of a curriculum. The learning traits include learning ability, learning aptitude, learning style and cognitive style; while the properties of a curriculum include the level of difficulty of the learning materials, learning activities, and assessment.

Based on this realization, an adaptive learning website must not only choose and offer suitable learning materials to each student in accordance with his/her individual differences at the beginning of learning, but also should be aware of the learning situation and response of the student any time in the process of learning in order to provide him/her with various teaching strategies and suitable learning activities at the right time. It is very difficult to provide individuals with an adaptive anytime-anywhere learning environment in the traditional way to teach; however, by using the database and data mining, teachers adopting asynchronous learning strategy can analyze and understand the distinguishing traits of the learners and the traits of the learning materials so that they can go further to provide the learners with adaptive learning contents and learning activities. Information technology makes asynchronous learning much better and more efficient.

2. Reference literature

First, this paper is intended to probe into the mathematical function of and the relationships between the traits of the learners, learning time, and the learning effects. Then we will use these relationships and the mathematical function to scientifically construct the asynchronous learning theory step by step.

2.1. Function of learning time

Actually, a number of researchers have proposed various opinions on the study of functions of learning time (Bloom, 1968, 1976; Carroll, 1963; Johnston & Aldridge, 1985; Karweit, 1986). Carroll (1963), who proposed the model of school learning, believed that students could be proficient in the subjects they were learning when there existed a certain ratio of the amount of time students were actually engaged in learning the subjects to the amount of time needed to learn those subjects. The equation he proposed to define the model of school learning is:

$$\text{Learning} = \text{F}[\text{time actually spent}/\text{time needed}] \tag{1}$$

By time needed, it means that the time needed for each student to learn and understand the academic material varies depending on the quality of instruction, the opportunity and learning ability of each student. By time actually spent, it means the time students have and are willing to spend learning. Theoretically, the performance of learning of students is a function of aptitude, ability, quality of instruction, perseverance and opportunity.

Johnston and Aldridge (1985) proposed the exponential learning model and brought into the model the internal characteristics of individual learners such as individual ability and motivation for learning. With this model, learning effects can be indicated and predicted by the function of students' traits and the amount of time spent. The following equation defines the exponential learning model:

$$L = 100\left[1 - \mathrm{e}^{-k(t+t_0)}\right] \tag{2}$$

L = learning effects; t = time; t_0 = time spent on the subject before beginning to learn it; $k = cm$ where c stands for ability and m stands for motivation; and e = logarithm.

The concept of exponential growth has been introduced here; that is, learning effect is expressed in a form of continuously changing amount that will grow exponentially as the amount of the learning time increases. This exactly means that the learning effect is the function of time, ability, and motivation. This exponential function implies that the more learning time the students have spent, the better the learning effects will be. One thing needs to be mentioned here is that the various factors such as self-realization, interest, and the needs for work affect the motivation variable.

The implication of this exponential function is that the more engaged time students have, the better the learning effects will be. Still one more thing needs to be mentioned here is that various factors affecting the motivation variable 'm' include qualitative factors such as self-realization, interest, and the needs for work.

Karweit (1985) believed that learning effects were closely related to learning time and that a learning system itself was a matter of relationships between various dynamics. Regarding common views on the relationships between learning time and learning effects, Karweit pointed out that most researches hypothesized that the learning effects would be the same for each additional unit of time added to the learning time; that is, learning speed was constant during the learning process. Karweit did not agree with that hypothesis and asserted that learning effect varied depending on different students and situations even if the learning time spent was equal. Karweit proposed the following equation to describe the relationship of learning effect and learning speed.

$$L(t) = L_0 + \int_0^t R(t)dt \tag{3}$$

L_0 = the prior learning effect; $R(t)$ = the learning rate at time t; $L(t)$ = the accumulated learning effect after leaning for the time length t.

The equation above indicates that the students' learning effects from time 0 to time t should be equal to the sum of all the individual learning effects produced, with learning speed at different time, in each smaller unit of this leaning time. Therefore, the relationship of the learning speed and learning effect is not in a linear form, and much attention should be paid to the change of learning speed during the learning process. For this reason, Karweit claimed that teachers should adaptively change their teaching progress rate and provide students with adaptive learning materials and activities timely in order to gain the best learning effects.

Learning effects are influenced not only by learning speed, but also by characteristics of the learning materials, for example, the level of difficulty. We will continue to investigate the influences of the learning speed and the traits of the learning materials on the learning effects and to modify Karweit's model of learning power in order to deduce a more precise learning-effect equation.

2.2. Factors that affect learning

Based on the results mentioned above, the following factors that influence distance learning are listed and their effects on the learning time is briefly explained:

- *Levels of difficulty of the learning materials*: Israel scholar Salomon (1984) asserts that the easier the information a person perceives, the less he/she will exert himself/herself to comprehend its contents or look into its source. Such inference has been confirmed by a number of researches and experiments.
- *Losing interest*: Students will not keep their learning enthusiasm and interest at a high level forever. To the contrary, they are likely to lose interest in subjects they are learning especially when they have to spend long period of time learning. It was found that the longer the learning term is, the relatively shorter time they spend on the learning materials, and even spend no more time on them to the end.
- *Attitude*: The more positive attitude learners have, the longer time they are willing to spend studying the learning materials and engage in learning more enthusiastically (McMillan, 1977; Sanderson, 1976). Learners with positive learning attitude also have better learning persistence; that is, they can better resist learning fatigue. Therefore, increasing the amount of learning time is positive to the learning effects of students with positive learning attitude.
- *Ability*: Learning ability makes the outcome of the learning time greatly different. Generally speaking, students who have better ability spend relatively shorter time studying same learning materials than other students. That is to say, learning ability should have a reverse effect on learning time (Wiley & Harnischfeger, 1974; Fredrick, Walberg, & Rasher, 1979; Carroll, 1989).

3. Theoretical framework and research motivation

According to the documents being reviewed above, the traits of the learners and the traits of the learning materials are two important factors that influence the learning process (Carroll, 1989; Fredrick, Walberg, & Rasher, 1979; Johnston & Aldridge, 1985; McMillan, 1977; Salomon, 1984; Salomon & Leigh, 1984; Sanderson, 1976; Wiley & Harnischfeger, 1974). In addition, the amount of time the learners spend on the learning materials can also affect the learning effects (Karweit, 1985). As shown in Fig. 1, the vertical line in the middle of the picture represents the time a learner spends in learning, with the points on it meaning the achievements the learner can have at different time T when the rectangle to the left of the time line interacts with the other one to the right of the time line, the rectangles representing the traits of the learners and the traits of the learning content respectively. As to the traits of the learners mentioned in the document above, the aptitude, ability, and the amount of time being spent on the learning materials greatly affect the learning effects. The following three traits of the learners will be discussed in this paper:

1. The learners' learning ability: Even learning the same contents, learners of different learning abilities have different learning effects.
2. The learners' learning attitudes: Learners who have a positive learning attitude can usually easily meet the requirements of the lessons they are learning and learn better.
3. The learners' interest in the learning materials: The greater the interest in the learning materials the learners display, the better the learning effects can be expected.

As to the learning materials, two things can affect the learning effects: the level of difficulty, the layout and the structure of the contents. Learners may get frustrated and give up learning if the learning materials are too difficult to understand; while learners may learn little or just waste their time if the learning materials are too easy for them. Other related things like the arrangement of

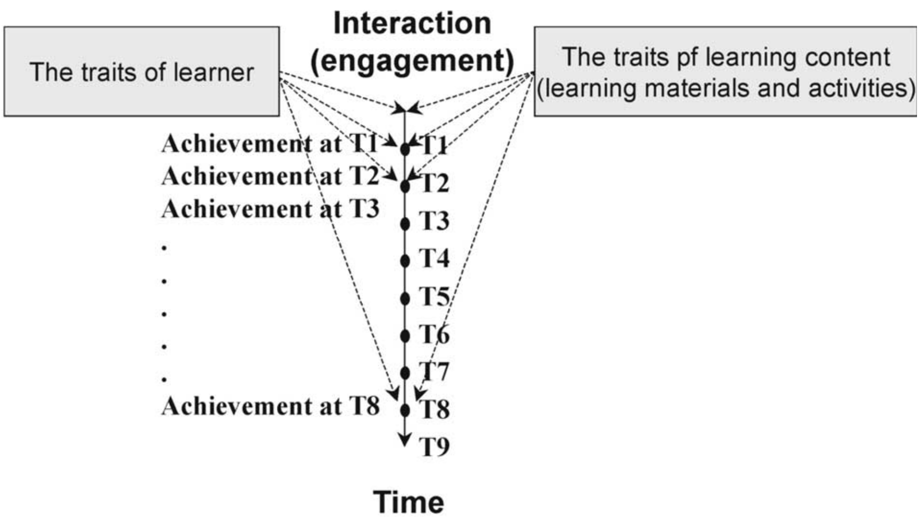

Fig. 1. Interaction between the traits of the learners and the traits of the learning materials, and its effects on the learning achievement over time.

the words, graphics, and charts or the contents well organized or not all contribute to the learning effects in some ways.

Converting the affecting-learning factors mentioned above into information that was quantified and comprehensible, and deducing the relationships between these factors further, we integrated these learning factors to propose a new learning theory. It was a theory to which a similar notion of Newton's mechanism had been applied. This new learning theory would make the study of learning systems more efficient and scientific. Furthermore, we used data mining to dig out precious learning information from learning portfolios accumulated from distance courses in the past 2 years, and then used the information to infer and verify the learning theory we had proposed.

4. Research method—learning dynamics

Referring to Carroll's and Johnston and Aldridge's learning equations and taking various factors that influence learning into consideration, the equation describing the traits of asynchronous learning materials was proposed (Hwang, Shiu, Wu, & Li, 2002). The equation was employed to estimate the learning effect. In other words, the traits of the learning materials and of the learners were investigated in an asynchronous learning environment, and then learning time per day (learning speed) and learning effects were estimated on the basis of the trait evaluation.

Provided that a distance course offers only learning materials on the web without offering other accompanied teaching activities such as online discussion, teacher-student online activities; so to speak, only the presentation of the learning materials, then the learning-material–trait equation is to be the learning speed, which is the theory this research is based on. The learning-speed equation is as follows:

$$Q_{ijk}(T_j) = \frac{A_{ik}}{1 + \mathrm{e}^{\theta_{ik} B_k \left[Tj - \alpha_{ik} \left(\frac{1}{B_k} - \theta_{ik} \right) \right]}} \tag{4}$$

Q_{ijk} = the learning speed of the student i learning the material k at the jth time unit; α_{ik} = the level of diligent in studying material k of student I; Tj = the jth time unit; A_{ik} = learning interest to material k for student I; θ_{ik} = the student's i abilities to learn material k. The greater its value is, the less the time needed to finish the material will be; and $B_{k=}$ the level of difficulty of the material k. The smaller the value is, the harder the material is.

The learning-speed equation mentioned above deduces learning speed on the basis of the traits of the learning materials and of the learners. The unit of learning speed is the amount of time spent reading the learning materials per unit of time. The notion of learning speed is analogous to that of velocity in Newton's mechanics. As in Newton's mechanics, velocity is expressed in the form of distance/per unit of time (e.g. 40 km/h); while the learning speed refers to the amount of time spent reading the learning materials per day (e.g. 50 min/day). Learning speed is in relation to individual differences and the traits of the learning materials. Fig. 2 shows the curve of the learning-speed function.

The value of the initial learning speed at the beginning of learning a new material is expressed by the following equation (See Fig. 2).

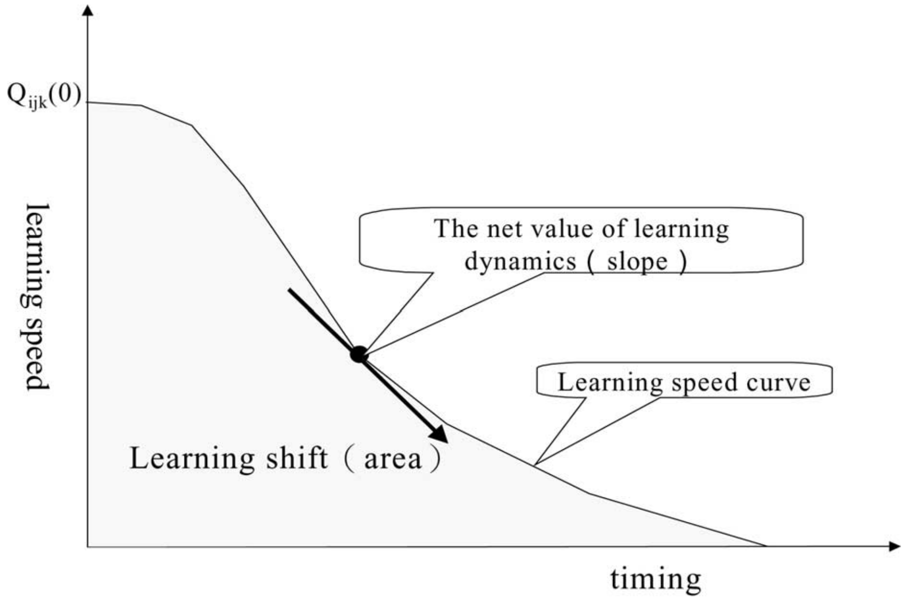

Fig. 2. The learning-speed curve.

$$Q_{ijk}(0) = \frac{A_{ik}}{1 + e^{-\theta_{ik} B_k \alpha_{ik} \left(\frac{1}{B_k} - \theta_{ik} \right)}} \tag{5}$$

Yet the learning speed is changing over time during the learning process owing to the influence of various learning dynamics. There are two kinds of learning dynamics: positive dynamics and negative dynamics. Positive dynamics includes tests, assignments, competitions and cooperative learning. Negative dynamics includes learning fatigue, learning inertia, burdens of family and burdens of work. The sum of positive dynamics and negative dynamics is the net value of the learning dynamics. When the net value is greater than zero, the learning speed will be accelerated; yet when its value is negative, the learning speed will be decelerated.

To stop the decline in learning speed over time, it is necessary to involve other positive dynamics into the learning process. How can we involve other positive dynamics into the learning process? A possible way to reach this effect is to timely add in awarding or inspiring activities such as assessments or competitions to increase the positive learning dynamics. Fig. 3 shows that the learning speed was raised after a competition was implemented.

Next, the first assertion of the learning dynamics is going to be introduced. Before we get into this session, the term *learning shift* is defined so that we can easily go further. The area generated by the learning speed on the time axis is equal to the total time the learners have spent, the area being defined as the *learning shift*. The following equation indicates that the learning shift π equals to the integral of the learning speed.

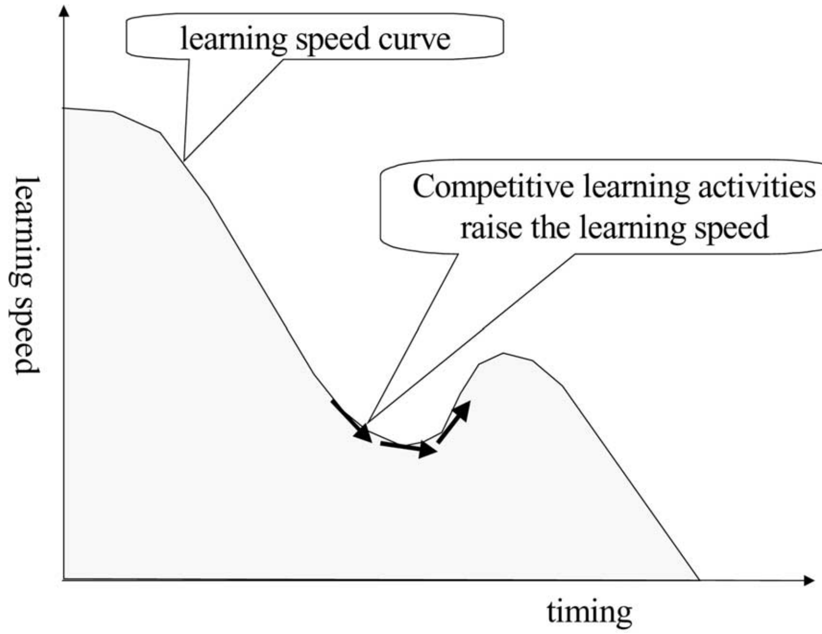

Fig. 3. Competitive learning activities raise the learning speed.

$$\pi = \int_0^\infty QijkdT = \int_0^\infty \frac{Aik}{1 + \mathrm{e}^{\theta_{ik}B_k\left[T - \alpha_{ik}\left(\frac{1}{B_k} - \theta_{ik}\right)\right]}}\mathrm{d}T$$
$$= \frac{Aik}{\theta_{ik}B_k}\left[-\left(-\theta_{ik}B_k\alpha_{ik}\left(\frac{1}{B_k} - \theta_{ik}\right)\right) + \ln\left(1 + \mathrm{e}^{-\theta_{ik}B_k\alpha_{ik}\left(\frac{1}{B_k} - \theta_{ik}\right)}\right)\right] \quad (6)$$

Learning shift times the net value of the learning force is to obtain the net value of the learning energy promoted, namely, the work done by the learning materials or by the learning activities acting upon the learners.

*4.1. The first assertion of the Learning dynamics: learning shift * the net value of the learning force = the net value of the learning energy*

What on earth is the learning force anyway? It was found that Newton's mechanism could be modified to apply to our new learning theory. Being analogous to the notion of Newton's mechanism in some way, our theory revealed that learning force was the multiplication products of the learning acceleration and the learning mass (M) of learners. Take reading for example, the greater the learning force is, the more likely the learners exert themselves to the utmost to study. It is the learning force that plays a significant role in making learners to learn enthusiastically.

The learning force can be produced by the external or internal factors. The external factors include learning materials or activities. The internal factors include interest.

If the net value of the learning force F_{ik} is constant, the net value of the learning energy is equal to learning shift times the net value of the learning force. The equation is as follows:

$$E_{ik} = \delta\pi \; F_{ik} \tag{7}$$

(note: δ is constant, varying depending on other traits of the learners or groups)

The change of the learning-speed curve indicates that learning deceleration is varied over time. Therefore, the net value of the learning force F_{ik} is variable in time. Based on the notion of our learning mechanism, the learning force (F) can be obtained from the following equation:

$$F_{ik} = Q_{ijk}^{'} M_i \tag{8}$$

Please note that $Q_{ijk}^{'}$ is the differential of the learning speed and M_i.is the learning mass of learner i. The learning mass in the equation we mentioned above is the data relating to the traits of the learners and can be obtained by tracing and analyzing the learners' learning portfolios over a long period of time.

Since the learning force is variable in time, the promoted net value of the learning energy E_{ik} is equal to the integral of the learning speed times the net value of the learning force. The equation is as follows:

$$\begin{aligned}
E_{ik} &= \left|\delta\int_0^{\infty} Q_{ijk}F_{ik}dT\right| = \left|\delta\int_0^{\infty} Q_{ijk}Q_{ijk}^{'}M_i dT\right| \\
&= \left|\delta M_i\int_0^{\infty} Q_{ijk}Q_{ijk}^{'}dT\right| = \left|\delta M_i\int^{\infty} Q_{ijk}dQ_{ijk}\right| \qquad \left(Let\frac{\mathrm{d}Q_{ijk}}{\mathrm{d}T} = Q_{ijk}^{'}\right) \\
&= \left|\frac{1}{2}\delta\Big[M_i Q_{ijk}^2(T) + c\Big]_{T=0}^{\infty}\right| \\
&= \left|-\frac{1}{2}\delta M_i\left(\frac{A_{ik}}{1+\mathrm{e}^{\theta_{ik}B_k\left[-\alpha_{ik}\left(\frac{1}{B_k}-\theta_{ik}\right)\right]}}\right)^2\right| \\
&= \frac{1}{2}\delta M_i\left(\frac{A_{ik}}{1+\mathrm{e}^{\theta_{ik}B_k\left[-\alpha_{ik}\left(\frac{1}{B_k}-\theta_{ik}\right)\right]}}\right)^2
\end{aligned} \tag{9}$$

(note: δ is constant, varying depending on other traits of the learners or groups)

The equation above reveals that the promoted net value of the learning energy E_{ik} may be obtained from the multiplication of the learning mass M_i by the square of the learning speed Q_{ijk} as well.

4.2. The derivative of the first assertion of the Learning dynamics: The net value of the promoted learning energy = learning mass * the square of learning speed*

The net value of the increased learning energy (E_{ik}) is the increment of the ability of the student i after finishing learning the material k. By summing up E_{ik} and the student's ability (obtained by conducting a prior test) prior to learning the material k, the after-learning ability can be evaluated after the student i has studied the material k. If the evaluated ability can truly (100%) is equal to the student's after-learning ability, there is no need to conduct an after-learning test. While if it reflects 80% or higher than 80% of the student's after-learning ability, the evaluated ability can be used as a basis to choose questions for the after-learning tests, making the tests more efficient.

Furthermore, the adaptive learning can be smoothly proceeding on the basis of the evaluated after-learning ability without tests, avoiding the disadvantage of constantly conducting tests to examine the learners' learning effects as in other studies of adaptive learning. The second assertion of the learning dynamics then can be deduced as follows:

4.3. The second assertion of the learning dynamics: The prior ability + the net learning energy = the after-learning ability

The ability-changing equation is as follows:

$$E_i^T = E_{\mathrm{i}}^0 + E_{ik} \tag{10}$$

E_i^T = the learning ability of the student i at the time T; E_i^0 = the learning ability of the student i at the time 0; E_{ik} = the increment of the ability of the student i after finishing learning the material k.

Fig. 4 shows the relationship between the change of the learning ability and the learning speed.

The ability-changing equation as you see above has made a modification to the Eq. (3) proposed by Karweit (1985). The increment of the learning ability is related to both learning speed and learning force. Therefore, if the integral of the product of the learning speed times the learning dynamics is calculated, a more precise increment of the learning ability is obtained. As to the reason why the ability increment has relation to both the learning speed and the learning force, the reason is that learning is actually a process with two dimensions: learners and learning materials/learning activities. In other words, the learning process implies the interactive relationships between the learners and the learning materials or activities.

5. Relationships between learning activities and learning speed

As was mentioned previously, learning dynamics can be categorized into two groups: the positive dynamics including examinations, assignments, competitive activities, and cooperative learning, and the negative dynamics including learning fatigue, learning inertia, family burden, and work burden.

Suppose that a distance course offers only learning materials on the web without offering other accompanied teaching activities, the learning curve is sure to be similar to the one shown in Fig. 2.

The initial learning speed at the beginning of the learning process goes down precipitately over time, which is not what instructors expect to see. Therefore, asynchronous learning should arrange a variety of learning activities to motivate the learners as well as to give them the learning materials. However, how various kinds of learning activities would influence the learning curve is worth of further investigation.

In fact, various learning activities will influence the learning speed just like the way the learning materials do. They would produce positive learning dynamics. In our study, for example, a learning competition was employed on the fourth day the course had started, announcing that the first three learners who found the three mistakes purposely arranged in the materials would be awarded prizes. The result did indicate that such kind of competitive learning activities would motivate students to learn positively and add positive dynamics to the learning curve as shown in Fig. 5. Of course, the situation the learning curve represents is more likely to conform to teachers' expectation. As to the comparison of quantified data of the influence that various kinds of learning activities have on the learning curve, an activity–trait model will be required. An activity–trait model will be used for the simulation and comparison of the learning activities, as is similar to the material–trait model used for the simulation of learning materials. We will further investigate the characteristics of various kinds of learning activities and try to propose a model to simulate learning activities in the future.

In addition, when a chapter of a course is accompanied with learning activities, combination of the activity–trait-model equation and the material–trait-model equation can be used to produce the equation of the curve of the learning speed. Therefore, no matter how varied the learning activities employed in a course may be, the influence on the learning speed can be evaluated by combining those trait equations.

All the data used in this study was from the distance courses, dated July 2000 to June 2001. The detailed information of the schedule and the contents of "Package Software" are shown as in Tables 1 and 2. There were totally four 3-month sessions. The three courses selected for our study

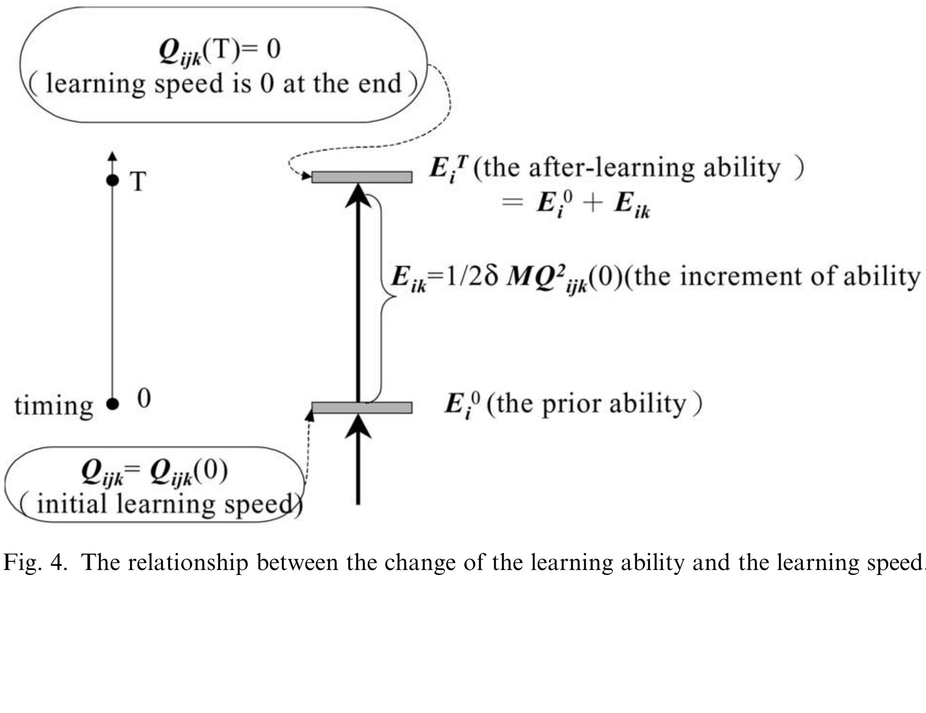

Fig. 4. The relationship between the change of the learning ability and the learning speed.

for each session were "Package Software", "Computer Network and Communication", and "Database", one chapter per week according to the schedule. Assignments were assigned to each chapter of each course and presented with the contents to learn at the same time to the learners. The learners were expected to complete their assignments within one week. Learners failing to hand in the assignments would not be allowed to study succeeded chapters.

From almost every place in Taiwan, the learners taking these courses were all junior high school and elementary school teachers on service. They usually learned the online materials with the computers at their own schools.

6. Experiment design and system architecture

6.1. Experiment design

The experiment design was employed in this paper. An asynchronous learning server recorded learners' portfolios when they read on-line materials. The Data Transformation Service (DTS) of an SQL Server 2000 was employed to translate the recorded portfolios into meaningful data (i.e., learning time) then the collected data was analyzed. The flow of data processing is shown in Fig. 6. Analyzed data is each learner's reading history (learning time) of each chapter. In order to obtain the total learning time of each chapter of each session we added up all the learners' learning time of the first 2 weeks (1st–14th day) spent reading each chapter.

By plugging the total learning time into the equation for learning speed curves, the learning speed curve of each chapter was obtained.

To guarantee the accuracy of the recorded learning time, the monitoring mechanism called "mouse tracking" was employed. This mechanism prevents further recording after learners stop reading but fail to logout. The monitoring mechanism using JavaScript is run at the client's end

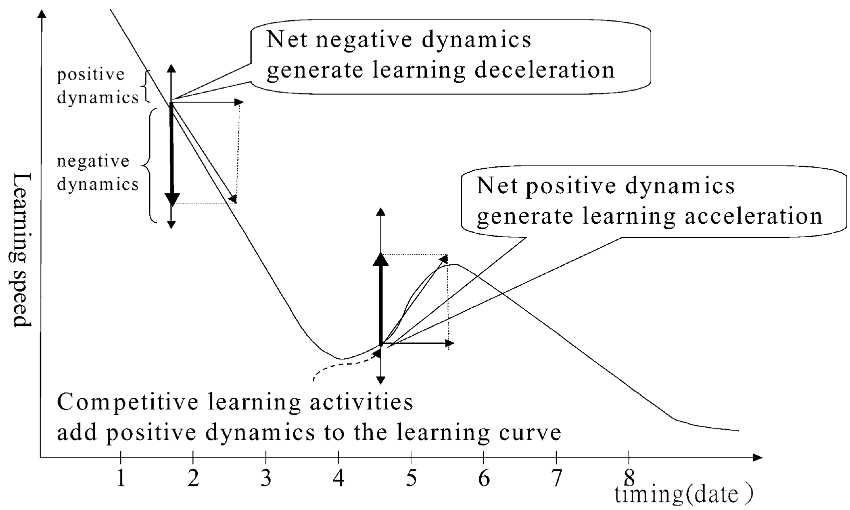

Fig. 5. Competitive learning activity generates positive learning dynamics.

Table 1
All sessions schedule and student number

Session	Time	Student number
1	2000/7 – 2000/9	94
2	2000/7 – 2000/9	54
3	2000/10 – 2001/1	63
4	2001/3 – 2001/6	77

Table 2
"Package software" curriculum schedule

Week	Subject	Annotation	Week	Subject	Annotation
1	Word processing 1	Face-to-face teach	7	Image process 1	
2	Word processing 2		8	Image process 2	
3	Excel		9	Animation	
4	PowerPoint		10	FrontPage	
5	Brower		11	Compression tool	
6	Email	Face-to-face teach	12	Internet tool	Examination

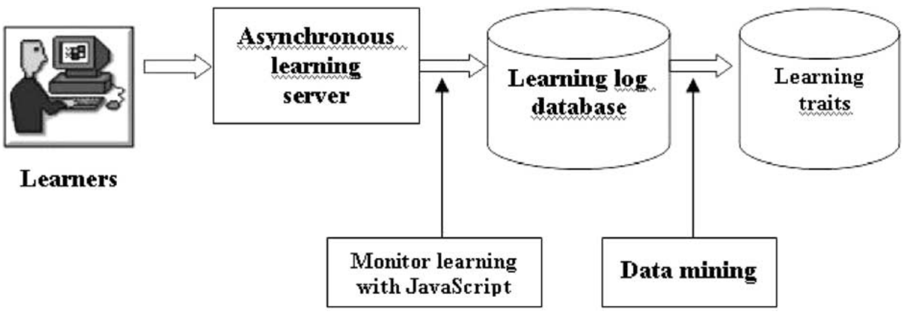

Fig. 6. The flow of learning portfolio processing.

such that, if the learner's mouse doesn't move for hundreds of seconds, the connection between the server and client is terminated.

6.2. System construction

The first thing to be done to analyze a learner's learning situation is gathering each learner's on-line learning data. Then analyze the collected data at the back-end and then use the results of the analysis to serve as a response model to verify the learning situation. To complete this, the system consists of an asynchronous learning server, an analysis model for learning portfolios, and a model for learning dynamics.

(1) Asynchronous learning server
Each learner can read on-line materials any time in any place by a logon asynchronous learning server. After the learner logs in, the asynchronous learning server records all the on-line behaviors of that learner until the connection between learner and server is terminated. Then important data can be gained from the analysis model for learning portfolios.
(2) Analysis model for learning portfolios
This model is mainly to discover the distribution of learners' reading time by implementing on-line analysis in real time. Then these data can be applied to follow-up research. To accurately gain the data needed for our research, we must first consider what data is meaningful and required by our research.
This model consists of five dimension data tables, shown in Fig. 7. The main use of the dimension data tables is to collect and analyze the learners' on-line reading situation. The function of each data table is as follows:

Stu: To record learner's data, such as level, name, gender, id and so on.
Time: A mapping table of date and weekday.
ReadIndx: To create index according to each day's login times. (This means that the index will show the number of times each learner logs in per day.)
Reading: To record learner's detail information during he (or she) is online. (Ex. which web pages being read and the amount of time being spent)
Webpages: To create index of each web page, which is the on-line learning material. Based on the value of the index, the learner's learning history can be recorded.
Part 1: To eliminate unwanted data in log files
Part 2: To search all learners' data from log files.
Part 3: According to data gained in Part 2, to find out all learners' reading time.
Part 4: To collect data on all learners' on-line learning situations.
Part 5: According to data gained in Part 3, to find out all learners' reading time for each chapter
Part 6: Collecting and analyzing learners' on-line learning situations and then responding immediately in real time.

(3) Model of learning dynamics
A learner's learning situation is judged not only by the results themselves but also by their response to the learning process. The purpose of the model of learning dynamics is to enable teachers to realize the traits of the learning materials and the students' response to the learning materials and learning activities. Once the data collected from the learners' on-line behavior are processed by the analysis model for learning portfolios, a set of analyzed data can be computed and then processed by the model of learning dynamics to complete the analysis of learning portfolios. With the help of the model of learning dynamics, teachers can analyze a learner's learning speed, learning acceleration, change of learning energy and visualize the result of the analysis by interpreting the result produced. In addition, the result produced can serve as a basis for improving adaptive learning in the future.
The results gained from this model are not only the learners' learning time. They also reveal more important information to us: Is the learner working hard or not? Is the material too

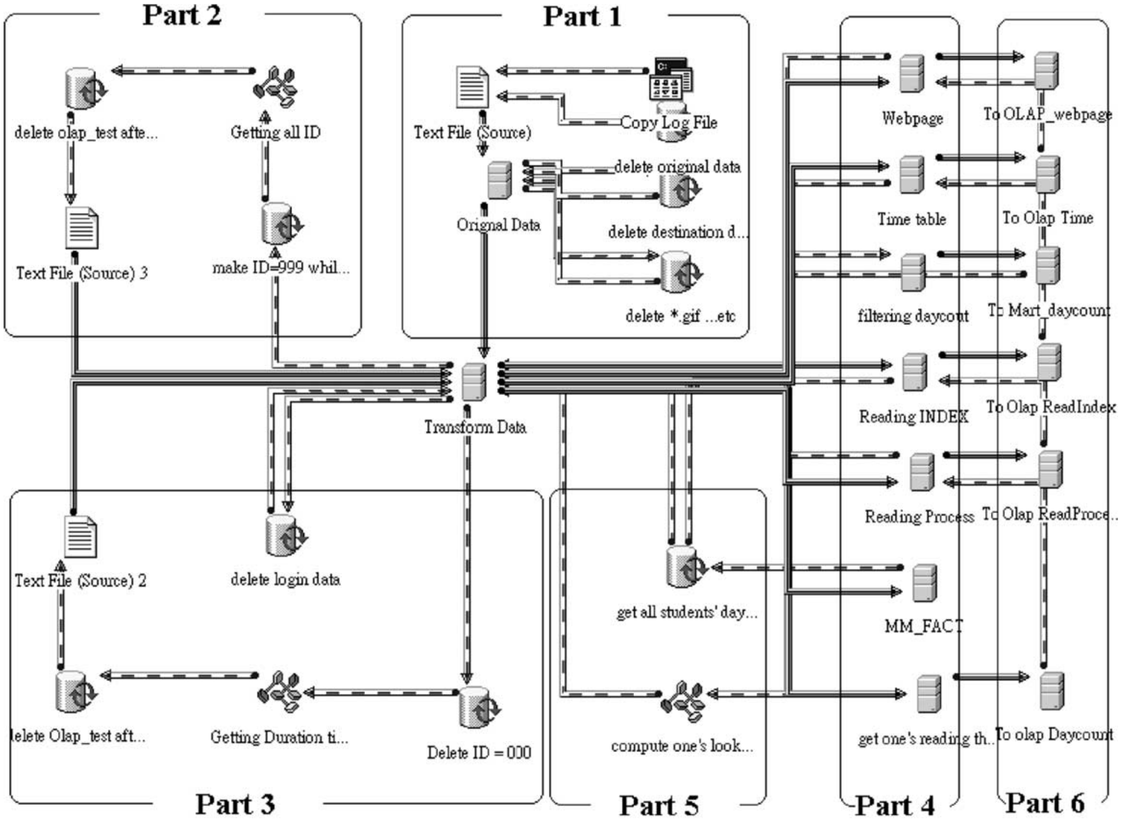

Fig. 7. The analysis modules of learning portfolio.

difficult? And furthermore, a real-time-on-line-monitored adaptive learning can be implemented if teachers can analyze a learner's portfolio in real time and give a real-time response to the learner by dynamically giving a stimulating or awarding learning activity timely such as giving real-time information, reminding to study lessons by e-mail, and delivering adaptive learning materials dynamically.

7. Results and analysis

7.1. Learning speed and acceleration

After collecting and processing the portfolios of the chapters at each session, the formula for learning speed and acceleration are employed to deduce the corresponding learning parameters, thereby gaining the curves of the learning speed and acceleration. The curves of some chapters are to be investigated as follows:

(1) Curve of learning speed: The curve of the learning speed and relative parameters such as B_k, θ_{ik} and α_{ik} was shown in Fig. 8: the vertical axis represents the learning speed, which measures the total time being spent reading the material each day; the horizontal axis represents the *n*th day; the little circle in this figure represents samples. This curve is a curve of learning speed obtained by performing non-linear regression, with a given convergence criteria $\leqslant$1.0e-04. The curves gained for some chapters of each session are shown in Appendix 1, the shapes of which are found to be quite similar after compared with Fig. 8, meaning that the equation for learning speed could basically work well. The curves indicate that learner motivation is high at the beginning of the learning session; however, the learning acceleration is negative, which means the learning speed is gradually decreasing unless learning activities are offered to the learners.
(2) Curve of learning acceleration: Four chapters are randomly selected and analyzed in Fig. 9, each chapter containing a pair of curves: the upper one is the curve of learning speed and the lower one is the curve of learning acceleration. These two curves together can more precisely reflect the changes and the trends of any chapters in any courses. For example, the learning speed in Fig. 9 was found to decrease rapidly between the first day and the fourth day, and the curve of learning acceleration reflected the same phenomenon. This means that a negative force caused the speed decrease during this period. On the fifth and sixth day the learning speed increased because learning acceleration increased. This is because the pressure of the exercise deadline caused learners to study the material more actively, which was genuinely reflected by the curve of learning speed. After this period, learning speed decreased to zero little by little.

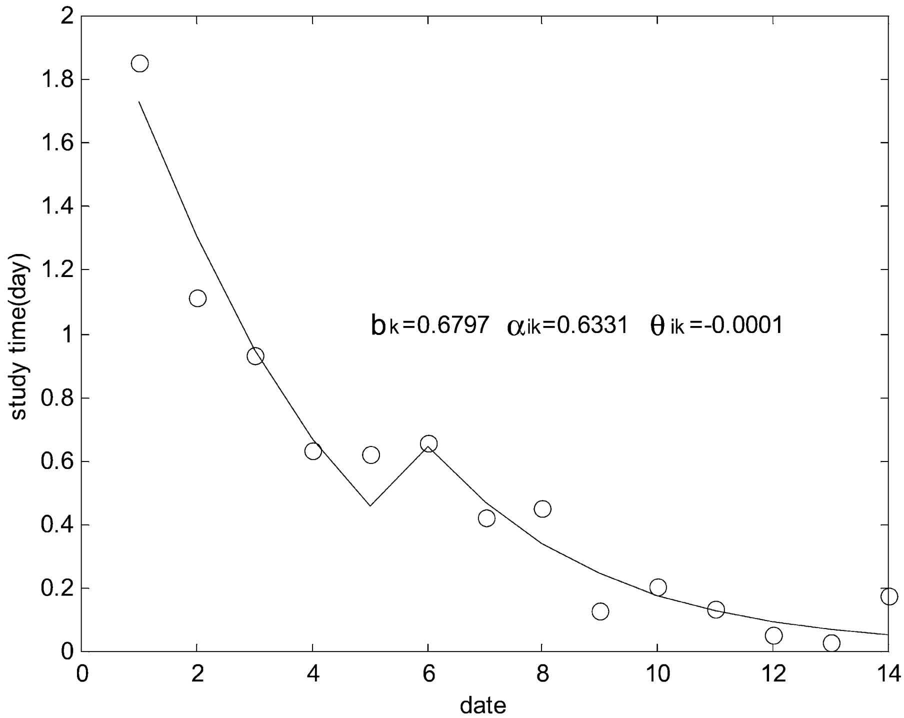

Fig. 8. The curve of learning speed.

With the curve of learning speed and the curve of acceleration, the change in learner's motivation can be more precisely predicted. For example, the curve of learning speed of Chapter 8 in the course of "Package Software" increases slowly between the fifth day and the sixth day in Fig. 9. This might give the mistaken impression that learning activity has not affected learners. The fact that the degree of increase in learning speed is low is just because the decrease in speed was low originally. Therefore, learner motivation caused by learning activities seemed not to be raised very much when the learners did not loose too much motivation.

In Fig. 9, it was found that even for different courses the shapes of the curves closely resembled each other. If teachers find learners' learning speeds decrease too much (in other words, the negative force is larger than ever), they should investigate what has caused this and arrange suitable learning strategies to increase the positive force.

8. The effects of learning activities on the learning speed

Generally speaking, school assignments, tests, and cooperative learning are commonly used in learning activities. The effects of some learning activities on the learning speed would be investigated as follows:

(1) *Assignments*: The most used learning activity is school assignments (including assessments). Teachers assign the subject of the assignment and learners hand it in before the deadline. How

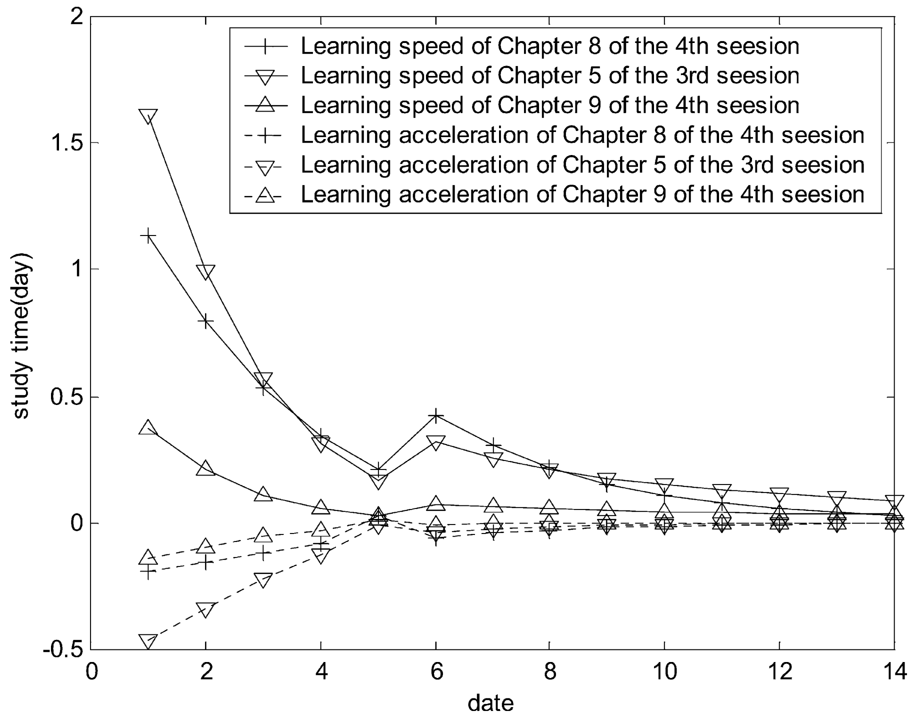

Fig. 9. The curves of learning acceleration and learning speed.

does this kind of learning activity affect learning speed? Fig. 10 presents the effects of the assignments of Chapter 5 and Chapter 6 for the same learners on the curves of learning speed, respectively. It shows that the learning speed of Chapter 5 decreased little by little between the first day and the fourth day. However, it began rising on the fifth day and the sixth day because of the stimulation of the deadline. This positive force raised learner motivation. Another similar case can be found in Chapter 6. But there are some differences between Chapter 5 and Chapter 6. The measurement of the decrease in learning speed of Chapter 5 is slower than that of Chapter 6, which means the material (as well as the assignments) of Chapter 5 effectively prompted learners to continue studying, hence a learning speed kept within a reasonable range. To the contrary, the learning speed of Chapter 6 decreased rapidly and the accompanied assignment did not effectively stimulate learner motivation so that the learning speed was pretty low after the fourth day. Obviously, Chapter 6 requires some necessary modifications to raise its learning dynamics, resulting in better learning effects.

The curves in Fig. 10 are actually the results of the combination of two equations: the material–trait equation and the assignment–trait equation; both curves were generated with non-linear regression. The material–trait equation and the assignment–trait equation have some elements in common: difficulty of the material or assignment and learner ability. Subject to the difficulties of the assignments and the learner ability as is the material–trait equation, the assignment-trait equation requires the following parameters: the difficulty of the assignment and learner ability. The imminent deadline of the assignment affects the learning speed of most learners so learning speed will rise conspicuously just before the deadline of the assignment.

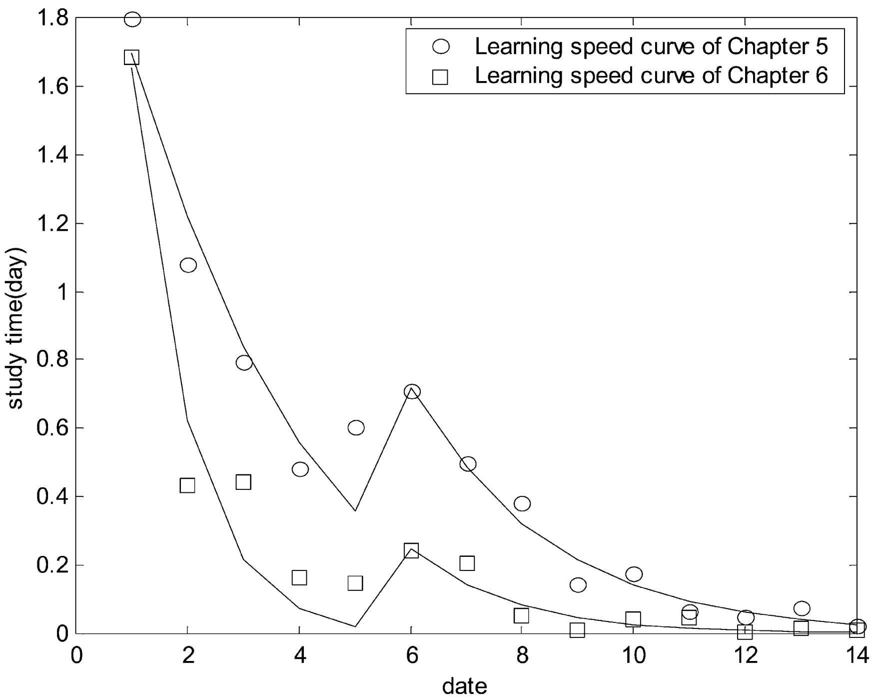

Fig. 10. The effects of assignment of Chapter 5 and Chapter 6 on learning speed curve.

(2) *On-line quiz*: The learning activity of Chapter 7 and Chapter 8 for the Database course at the fourth session was the on-line quiz (for other chapters it was assignments). Fig. 11 shows the curve of learning speed for the Database course in the fourth session: in view of the rise in learning speed, the on-line quiz seemed to be more efficient than assignments. It would not be difficult to figure out the reason why the learning speed raised so much. The reason is that learners more actively read the material to prepare for an on-line quiz, so learning motivation became maximal. Furthermore, the reading time of Chapter 7 and Chapter 8 is higher than that for other chapters. Does this mean the on-line quiz better than assignments? Not exactly, even though learning motivation does become maximal before an on-line quiz. After the quiz, the goal of learning (the on-line quiz) disappears, causing learners to stop reading the material.
(3) *Cooperative learning*: Fig. 12 shows the curve of learning speed of Chapter 9 of the Computer Communication course for the fourth session. The trend of this graph is different from others. This is because this chapter included two learning activities: assignments and cooperative learning, which made the data that we gained different from others. Too much learner behavior cannot be recorded in a cooperative learning environment (For example, learners establish contact using email, the telephone, and small group meeting etc.), which makes the model of learning response dynamics fail to interpret the curve of learning speed of this chapter.

8.1. Learning energy to predict the post-learning ability

From the schedule of the on-line course we know that the topic of Chapter 6 of the "Package Software" course is The Introduction to Email Tools.

Before learners read the contents of Chapter 6 they had to complete a pre-test. From the results of the pre-test, we calculated that the average pre-learning ability for all learners with respect to

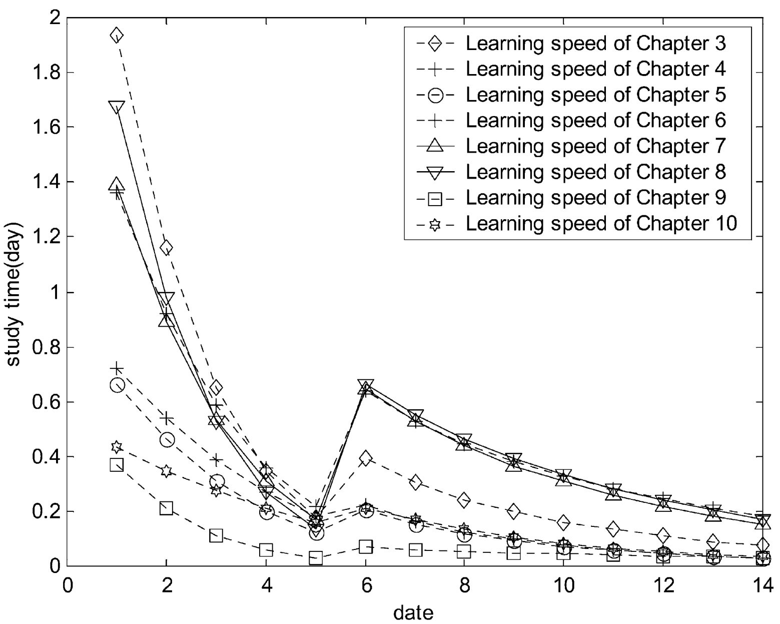

Fig. 11. The learning speed curves for each chapters of "Database" course for the fourth session.

Chapter 6 was 0.6330. Then we used a formula derived from the second equation of the learning dynamics model to compute the increment ($E_{ik} = 0.0648$) in learners' average post-learning ability, which was 0.6978 (0.6330 + 0.0648). We also held a post-test to measure learners' average post-learning ability, which was 0.6981. This value is very close to the value, 0.6978.

The learners' average post-learning ability for the leading group of Chapter 6 (19 learners) was 0.6677, the increment in learners' average post-learning ability being $E_{ik} = 0.1286$, so post-ability was 0.7963. According to the results of the post-test, we measured learners' average post-learning ability as 0.794791, which is similar to the value, 0.7963. These examples preliminary examine the assertions and make an important contribution to the assessment system in that they estimate post-learning ability by the assertions. The estimated results can apply to the single/multi choice assessment system, providing an important basis.

9. Conclusion and suggestion

Proposed in this paper, the theory of learning response dynamics is intended to make the educational research more efficient and scientific, the one systematically and scientifically predicting the learning result as well as analyzing the learning process by investigating factors such as learning speed, learning dynamics (learning acceleration) and learning energy (learning effect). Based on the notion analogous to Newton's mechanics, a number of assertions of learning response dynamics have been established and verified by conducting a series of experiments. As we expected, the result of our experiments basically supported the theory of learning response

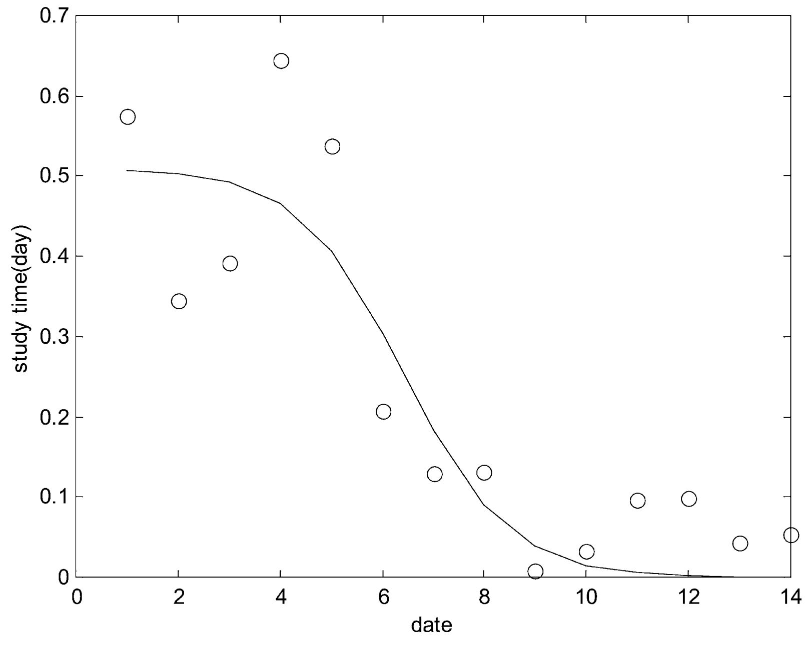

Fig. 12. The learning speed curve of Chapter 9 of "Computer Communication" for the fourth session.

dynamics we proposed. However, this is only a beginning of a new idea. A lot should be done to improve its weak points and make it mature.

Various kinds of learning activities or learning materials have influence on the curve of learning speed, which play an important role in the theory of learning response dynamics. Therefore, it is really necessary to have an activity–trait equation or a material–trait equation established. Some simple learning activities were investigated in our experiment, including school assignments and on-line quiz etc. Yet other learning activities which have a great deal of variety or which are more complicated in nature would be involved in our research in the future, the ones such as cooperative learning and the homework assignments for which bonus points would be awarded if it is submitted earlier before others before/on the due date. All the learning activities mentioned above are worth of investigating. The learning–activity–trait equation then could be deduced if the essential factors relating to learning speed were discovered and verified. If so, teachers can make the best arrangements for learning activities with the help of this equation and finally reach their teaching goal successfully.

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