A study of learning time patterns in asynchronous learning environments

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Abstract
This research makes use of learning time intensity, burst evaluating equations, and state denotation approaches to evaluate the learning time characteristics of students. Through comparing learning time intensity, six burst styles and three diligence styles are categorized. From the statistical results and interaction content analysis, some pedagogical phenomena were found. The first finding is that the more diligent learners were, the higher the quality and quantity of their interaction. The second is that learners whose learning time intensity was mainly located in the early period of the course and whose interaction content included many complaints were suspected to be possible dropouts. The third finding is that learners whose learning time intensity was mainly located in the later period had achievements that were significantly different from those of the regular periodical reading learners whose learning time intensity was distributed in all periods of the course. The above findings raise some issues and suggestions for those concerned with proposing asynchronous courses. As students can pace their own learning in an asynchronous learning environment, it is hard to avoid getting used to intermittent intensive reading. Instructors should consider seriously how to guide students to learn in a proper sequence through a well-scheduled instructional programme. It is necessary to encourage students to exercise self-discipline in regular on-line reading for better learning outcomes.

Keywords
learning time intensity, learning time pattern, learning time distribution, learning activity, interaction

Introduction
Based on the theory of constructivism, humans ‘construct’ their own knowledge instead of simply receiving information. As a result, the learner-centred model has been frequently proposed as a trend in contemporary education (Menges 1994; Felder & Brent 1996; Locatis & Weisberg 1997; Sandholtz et al. 1997; Wolfe et al. 1998).

Meanwhile, with the tremendous developments of information technologies, on-line learning has become a significant education model. Today, with the use of the Internet, both students and teachers can actually break the bounds of time and space. Students are particularly able to flexibly control their own learning paces in an asynchronous learning scenario. In such a situation, learning characteristics are a serious concern.

A number of personality characteristics related to learning were probed, including ambiguity tolerance, anxiety, field dependence/independence, active/passive learning, locus of control, and self-efficacy. Other learner characteristics, such as learning style, metacognition, self-regulated learning, motivation, were also explored. These characteristics form various learning modes, causing various attitudes and behaviours towards learning, and greatly influencing the performance of on-line learning as well as face-to-face
learning. One of the important variables that are associated with learning achievements is known as learning time (Carroll 1963; Bloom 1968; Harnischfeger & Wiley 1976; Fredrick Wayne & Walberg Herbert 1980; Johnston & Aldridge 1985; Hwang et al. 2002). Learning time means the amount of time students were actually engaged in learning. Provided with variables based on the aforementioned attributes, a formative approach can be utilized to assess performance of learners.

The invisibility of the on-line learning process makes it difficult to assess learner performance in a web-based learning environment. Some measurements, such as ‘the frequency of accessing on-line materials’ and ‘the frequency of learning management system (LMS) login’, have been proposed as diagnostic tools for instructors to understand students’ on-line learning behaviour, but these measurements provide little insight into pedagogical meaning. Accordingly, this research focused on the different learning patterns that students used and explored the various learning attitudes in the Internet learning environment, so that some suggestions can be generated from a pedagogical perspective.

**Literature review**

Many research studies have found that length of learning is closely and positively associated with learning results (Carroll 1963; Bloom 1968; Harnischfeger & Wiley 1976; Fredrick Wayne & Walberg Herbert 1980; Johnston & Aldridge 1985). The relationship between time spent studying and achievement was first examined by Carroll (1963). Further investigations to enhance the relationship were done by Bloom (1968), Carroll (1973), Fredrick and Walberg (1980), Johnston and Aldridge (1985) and Carroll (1989). Besides spent time affecting achievement, the motivation factor represented by learning interest and attitude has also been examined and identified as significant (Uguroglu 1979). Ability is another factor identified as significant (Leinhart 1977).

In 1963, Carroll proposed the theory of ‘the model of school learning’, which indicates that the degree of learning is a function of the time spent on learning and the time needed, that is, \( f = \frac{\text{time spent}}{\text{time needed}} \). Time needed means the time needed for each student to learn and understand the learning material; it varies depending on many factors such as the quality of instruction, the opportunity and learning ability of each student. Carroll believed that students could be proficient in a subject when a certain ratio of the amount of time students were actually engaged in learning the subject to the amount of time needed to learn the subject existed.

Impressed with Carroll’s ideas, in 1968, Bloom took the Model of School Learning further by concluding that if, (1) aptitude could predict a learner’s learning rate, then it should be possible to set the degree of learning expected of a student to a certain level of performance. Then, (2) if the instructional variables, such as the opportunity to learn and the quality of the instruction, are under the instructors’ control. Then, (3) instructors should be able to ensure that each learner attains the specified objective. Bloom concluded that given sufficient time and quality instruction, nearly all students could learn.

Johnston and Aldridge proposed an exponential learning model in 1985, which included learner characteristics, specifically, aptitude and motive, as conditions related to the learning achievement. Therefore, learning achievement can be predicted by a function of student characteristics and the time spent in learning.

The above research on how learning time affects the learning characteristics and effect indicated that learning time correlates highly with learning achievement. Learning time is not only related to learning effect, it can also reflect the learning attitude of the learner. The more time the learner spends on reading, the stronger his motivation, and the more positive his learning attitude.

The purpose of this research is to explore the features of each different asynchronous learning time pattern. To make the learning time patterns much more useful in learning, some pragmatic implications in pedagogy could be investigated. Thus, from the features of learning time patterns and its pedagogical meaning, some diagnoses of learning status of learners could be obtained and delivered to teachers in real time. They could then give adaptive remedial learning to learners.

**Learning time distribution**

Learning time distribution consists of the distribution of individuals’ web-based course inter-arrival time.
and the distribution of their on-line duration. The inter-arrival time means the length of time between two successive logins to the teaching website of web-based course. An example of this is given below. An LMS was designed to automatically record students’ learning processes in a web-based learning environment. Through employing data transformation technologies, data of inter-arrival time and duration were extracted to construct the learning time distribution on a 12-week web-based course.

Figure 1 depicts a learning time distribution of student A in a specific web-based course. The first time student A studied on-line material was at $T_0$, and its duration was $D_{20} = T_{20} - T_0$. The next time student A accessed the course was at $T_{2050}$, and its duration was $D_{40} = T_{2090} - T_{2050}$. The inter-arrival time between the two login times was $D_{2050} = T_{2050} - T_0$, and so on. Eventually, the learning time distribution of student A, which represented learning characteristics, was constructed.

In order to calculate ‘time actually spent’ (Carroll 1963) precisely, a monitoring mechanism called ‘mouse tracking’ was utilized. The mechanism was programmed in Java script, and was embedded in Active Server Pages (ASPs). It captured some events triggered by input devices (e.g., mouse and keyboard), preventing the system from recording when learners stopped reading but did not log off the teaching website. Time recording was stopped, the current page was redirected to the homepage of the teaching website and the learner was required to login again if the learner’s mouse has not moved during a fixed length of time such as 5 minutes, it would be considered that learners had continued reading learning materials and a confirming message sent to the database. Although the above two mechanisms were not enough to exactly record engaged time, they really helped to reduce the inaccuracy of recording engaged time.

**Research design**

Three-hundred and forty students participated in the web-based courses including Basic Computer Concept (BCC), Multimedia and Database, etc. Each course took twelve weeks (all from Nov 17, 2001 to Feb 10, 2002) and was divided into 12 subtopics. So there was one subtopic per week. Office hours were arranged on-line every Wednesday night. In the office hour, instructors and assistants joined the chat room to discuss learning and questions of the course with learners. Besides this synchronous interactive learning, students also could leave their questions on the asynchronous discussion forum for their classes to seek answers.

Moreover, all students were asked to finish some assignments before being allowed to read the material for next week. Therefore, they were under a certain pressure to pace their study to meet the course schedule, otherwise some passive learners would have given up due to falling to far behind. Assignments were corrected and marked by instructors, and final examinations were held in the end of courses. At the end of this course, homework (55%), group assignments (15%), and final test (30%) were aggregated and regarded as student’s final score.

![Fig. 1 Learning time distribution in the asynchronous course.](image-url)
The variables in this research are defined as follows:

1. Asynchronous learning time patterns: this includes two variables, students’ Burst State and Diligence State. The two variables are employed to investigate how diligent and how intensive students’ learning time is and will be described in detail by using inter-arrival time and duration in the next section.

2. Asynchronous learning achievements: The final score of the students.

3. Degree of interaction: The results from content analysis of students’ interactive activities. We will investigate the influence of asynchronous learning time patterns on learning achievements and degree of interaction.

**Evaluation of learning time patterns**

In the realm of digital communication, the concept of ‘Burst’ is typically utilized to explain the phenomenon of sudden data-transmission (Daniel & Virgilio 1998). This research makes use of ‘Burst’ concept to investigate a student’s learning time pattern within the web-based course.

**Burst evaluating equations**

Two states, Burst State and Diligence State, were employed to describe the learning time patterns in the section. By using inter-arrival time and duration in the learning time portfolio, the two states could be investigated and obtained. Diligence State was employed to measure how diligent students spent time reading learning materials and Burst State was employed to evaluate how intensive students spend time reading learning materials. Before the above two states are formally defined, the following equations were first derived and defined as below.

**Average duration (or inter-arrival) of the ith learner: \( \lambda_i \)**

Suppose that the Web course took \( \tau \) days (\( \tau > 0 \)), and a total of \( N \) learners participated in it. Let \( L_i \) represent the aggregated duration (or inter-arrival) of \( i \)th learner during these \( \tau \) days, \( \lambda_i \) represent the average duration (or inter-arrival) of \( i \)th learner during the same periods, that is,

\[
\lambda_i = \frac{L_i}{\tau} \tag{1}
\]

**Average duration (or inter-arrival) of the \( k \)th learner within the \( l \)th phase: \( \lambda_{il(k)} \)**

Now we divide these \( \tau \) days into \( n \) phases, so that each phase has \( \tau/n \) days (denoted as \( \tau' \)). Let \( L_{il(k)} \) represent the aggregated duration (or inter-arrival) of the \( i \)th learner within the \( k \)th phase; Let \( \lambda_{il(k)} \) represent the average duration (or inter-arrival) of the \( i \)th learner within the \( k \)th phase, that is,

\[
\lambda_{il(k)} = \frac{L_{il(k)}}{\tau'} = \frac{n \times L_{il(k)}}{\tau} \tag{2}
\]

**Average duration (or inter-arrival) of all learners within the \( k \)th phase: \( \overline{\lambda_{(k)}} \)**

Let \( \overline{\lambda_{(k)}} \) represent the average duration (or inter-arrival) of all learners within the \( k \)th phase, that is,

\[
\overline{\lambda_{(k)}} = \frac{\sum_{i=1}^{N} L_{il(k)}}{N \times \tau'} \tag{3}
\]

**Burst State, Burst Rate and Diligence State**

The preceding equations were utilized to investigate students’ learning time pattern during the Web course. The above two states, Burst State and Diligence State, were formally defined with the preceding equations in the section. Combining the two states, some learning implications and their relationships were investigated. To simplify this example, we divide the Web course into three phases (i.e., \( \tau \) was divided into three parts): prior, middle, and posterior phase.

**Burst State: comparing \( \lambda_{il(k)} \) with \( \lambda_i \)**

For each student, Burst State of the \( i \)th student within each phase is defined as a binary digit \( X \) (with the value of 0 or 1). For the \( i \)th student within the \( k \)th phase, \( X_k \) is assigned to 0 if \( \lambda_{il(k)} \) is smaller than \( \lambda_i \), otherwise \( X_k \) is assigned to 1 (\( \forall k \in \{1, 2, 3\} \)). Thus, Burst State of each student can be represented as such a burst denotation: \( X_1X_2X_3 \). Totalled \( 2^n \) (in this case, \( n = 3 \)) combinations will be generated, but since \( 111 \) and \( 000 \) are not available, \( 2^n - 2 \) combinations are reasonable. Moreover, since we are investigating the ‘Burst’ State, in \( X_1X_2X_3 \)\textsubscript{Inter–Arrival}, each \( X \) with the value of 0 represents a burst phase.

The combinations of Burst-State denotation are shown as Table 1(a) (from ‘duration’ point of view)
and Table 1(b) (from ‘inter-arrival’ point of view). Six $(2^3 - 2 = 6)$ reasonable combinations are generated. Based on the presentation of each combination, we categorize these six denotations into six burst styles: the Posterior, the Midterm, the Posterior+, the Prior, the Prior-Posterior, and the Prior+ burst. The following descriptions and figures were given to explain each Burst State in details.

**Prior Burst**
Students in this category spent more time (from duration point of view) or logon frequently (from inter-arrival point of view) in the early phase of the Web course. Fig. 2 provides a typical pattern of this style. As the time distribution diagram shows in Fig. 2, students were relatively active in the first four weeks, but after that, students rarely participated in the course.

**Prior+ Burst**
Similar to the Prior Burst, students in this group show their learning intensity in the early phase. We can treat this style as a stronger pattern of the Prior style.

**Midterm Burst**
Students in this category show their learning intensity in the middle phase. Figure 3 provides a typical pattern of this style.

**Prior-Posterior Burst**
Students in this category show their learning intensity in the early and the later phases. Figure 4 provides a typical pattern of this style. As the time distribution diagram shows in Fig. 4, the students studied for about three weeks at the beginning of the Web course, then were negligent for about five weeks, and at the end again participated for about two weeks.

**Posterior Burst**
As contrasted with Prior burst, students in this category show their learning intensity in the later phase. Figure 5 provides a typical pattern of this style. As the time distribution diagram shows in Fig. 5, the students started to participate actively in the later phase of the course.

**Posterior+ Burst**
Similar to the Posterior Burst, students in this category show their learning intensity in the later phase. We can treat this style as a stronger pattern of the Posterior style.

**Burst Rate:** $\overline{B}_{(k)}$
This research defined ‘burst rate’ as ‘the percentage of Burst students in all students within a particular
Let $B(k)$ represent burst rate within the $k$th phase, that is,

$$B(k) = \frac{\text{number of Burst students within the $k$-th phase}}{\text{number of all students}} \quad (4)$$

**Diligence State: comparing $\lambda_{i(k)}$ with $\bar{\lambda}_{(k)}$**

Instructors could determine the relative Diligence State of each student by the use of this comparison. Similar to the approach of Burst-State denotation, for the $i$th student and the $k$th phase, $X_k$ is assigned to 0 if $\lambda_{i(k)}$ is smaller than $\bar{\lambda}_{(k)}$, otherwise $X_k$ is assigned to 1. Totted $2^3 \, (= 8)$ combinations will be generated, and all combinations are reasonable.

With the Diligent-State denotation, the instructor could make an inference to say ‘the $i$th student was relatively diligent at the first phase because $\lambda_{i(1)}$ is smaller than $\bar{\lambda}_{(1)}$’. However, in such a self-paced learning environment, comparisons of diligence among students show less meaning in a single phase than in the whole period that the Web course was held. From comparisons made over the whole period, three categories with significant differences emerged: the Negligent, the Diligent, and the Normal.
**The Negligent**

Students in this category took the Web course negligently. That is, the denotation of this style was 000. Figure 6 illustrates a typical pattern of this style. As the pattern shown in Fig. 6, this type of student seldom participated in the Web course.

**The Diligent**

Students in this category took the Web course diligently. That is, the denotation of this style was 111. Figure 7 illustrates a typical pattern of this style. As the pattern shown in Fig. 7, this type of student made lots of effort on this course.

**The Normal**

All students except the Diligent and the Negligent are the Normal. That is, the denotation of this style would be 001, 010, 011, 100, 101, and 110.

**Data analysis and results**

In order to verify whether the preceding approach can effectively distinguish students into different styles of learning time patterns, both descriptive statistics and inferential statistics were utilized.

**Achievements in Burst States and Diligent States**

**Descriptive statistics**

Table 2 shows the number of students and their achievements at different Burst States, whereas Table 3 indicates the data at different Diligent States.

**Correlation between Burst States and achievements**

Table 4 shows a significant difference in achievement between Posterior Burst groups (the Posterior and the Posterior+) and the prior ones (the Prior and the Prior+) or the Midterm one. Especially, a significant difference at the 0.01 level exists between the Posterior+ and the Prior ones or the Midterm one.

However, with respect to the students in the Diligent category, no matter what kind of Burst State the students were, there was no significant difference in their achievements.

**Correlation between the Diligent States and achievements**

Employing the data shown in Table 3, each pairs of three Diligence States were compared with investigate

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**Fig. 6**  A typical pattern of the Negligent.

**Fig. 7**  A typical pattern of the Diligent.
achievement difference with $T$-test statistics. The results show that a significant difference at the 0.01 level exists between all pairs of three Diligence States (Diligent and Normal, Diligent and Negligent, Normal and Negligent). These meanings show that the more diligent the students were, the higher achievements they received.

### Learning status and learning activities with Burst States and Diligent States

#### Pragmatic pedagogical implication of learning time patterns

As instructors of asynchronous courses, we are very interested in students learning behaviour. Once an instructor notices abnormality of students’ behaviour, the instructor would like to give them proper help or stimulus in real time. Also, co-students in the same group of collaborative learning could prompt those members who stop working at a certain moment.

### Dropouts

Students whose learning intensity was categorized in prior period (i.e., Prior Burst) and had Diligence State in Negligent were suspected to be possible dropouts.

In this research, about 39% of Prior Burst students, 36% of Negligent students, and 58% of the students with Prior Burst and Negligence finally dropped out.

#### Crammers

Students whose learning intensity was categorized in posterior period (i.e., the Posterior Burst) and had Diligent State in Normal were called crammers. Crammers spent less time in prior period.

As the results shown in Table 2, the percentage of the Posterior Burst students was about 26.2%. As shown in Table 5, there was a significant difference between crammers and the Diligent students, and the standard deviation value of the Diligent students was smaller than crammers. Therefore, when students

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**Table 2. Achievements of Burst States**

<table>
<thead>
<tr>
<th>Burst State</th>
<th>Student number</th>
<th>%</th>
<th>Achievement mean</th>
<th>Achievement SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Posterior</td>
<td>89</td>
<td>26.2</td>
<td>75.33</td>
<td>16.13</td>
</tr>
<tr>
<td>Midterm</td>
<td>40</td>
<td>11.8</td>
<td>63.44</td>
<td>28.56</td>
</tr>
<tr>
<td>Posterior+</td>
<td>21</td>
<td>6.2</td>
<td>78.14</td>
<td>9.90</td>
</tr>
<tr>
<td>Prior</td>
<td>92</td>
<td>27.1</td>
<td>55.76</td>
<td>30.74</td>
</tr>
<tr>
<td>Prior-Posterior</td>
<td>49</td>
<td>14.4</td>
<td>67.62</td>
<td>27.12</td>
</tr>
<tr>
<td>Prior+</td>
<td>49</td>
<td>14.4</td>
<td>63.09</td>
<td>27.90</td>
</tr>
<tr>
<td>Total</td>
<td>340</td>
<td>100.0</td>
<td>65.93</td>
<td>26.42</td>
</tr>
</tbody>
</table>

**Table 3. Achievements of Diligence States**

<table>
<thead>
<tr>
<th>Diligence State</th>
<th>Student number</th>
<th>%</th>
<th>Achievement mean</th>
<th>Achievement SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diligent</td>
<td>58</td>
<td>17.1</td>
<td>82.78</td>
<td>5.09</td>
</tr>
<tr>
<td>Normal</td>
<td>161</td>
<td>47.4</td>
<td>68.57</td>
<td>23.21</td>
</tr>
<tr>
<td>Negligent</td>
<td>121</td>
<td>35.6</td>
<td>54.35</td>
<td>30.97</td>
</tr>
<tr>
<td>Total</td>
<td>340</td>
<td>100.0</td>
<td>65.93</td>
<td>26.42</td>
</tr>
</tbody>
</table>

**Table 4. The results performing independent samples $T$-test of achievements and Burst States**

<table>
<thead>
<tr>
<th>Burst State</th>
<th>$N$</th>
<th>Mean</th>
<th>SD</th>
<th>$T$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prior</td>
<td>92</td>
<td>55.76</td>
<td>30.74</td>
<td></td>
</tr>
<tr>
<td>Midterm</td>
<td>40</td>
<td>63.44</td>
<td>28.56</td>
<td>-1.386</td>
</tr>
<tr>
<td>Posterior</td>
<td>89</td>
<td>75.33</td>
<td>16.13</td>
<td>-5.387**</td>
</tr>
<tr>
<td>Posterior-posterior</td>
<td>49</td>
<td>67.62</td>
<td>27.12</td>
<td>-2.360*</td>
</tr>
<tr>
<td>Prior</td>
<td>92</td>
<td>55.76</td>
<td>30.74</td>
<td></td>
</tr>
<tr>
<td>Posterior+</td>
<td>21</td>
<td>78.14</td>
<td>9.90</td>
<td>-5.791**</td>
</tr>
<tr>
<td>Prior</td>
<td>92</td>
<td>55.76</td>
<td>30.74</td>
<td></td>
</tr>
<tr>
<td>Posterior+</td>
<td>21</td>
<td>78.14</td>
<td>9.90</td>
<td>-2.936**</td>
</tr>
<tr>
<td>Prior</td>
<td>92</td>
<td>55.76</td>
<td>30.74</td>
<td></td>
</tr>
<tr>
<td>Posterior+</td>
<td>21</td>
<td>78.14</td>
<td>9.90</td>
<td>-2.370*</td>
</tr>
<tr>
<td>Prior</td>
<td>92</td>
<td>55.76</td>
<td>30.74</td>
<td></td>
</tr>
<tr>
<td>Posterior+</td>
<td>21</td>
<td>78.14</td>
<td>9.90</td>
<td>-3.319**</td>
</tr>
</tbody>
</table>

* $P<0.05$ ** $P<0.01$
spend less time at the beginning of the course, instructors have to find some ways to encourage the students in learning early.

**Regular periodic reading learners**

By the definition, Diligent learners studied the learning materials regularly because they spent much time on reading in all phases of the course. As the results shown in Table 3, learners who were Diligent not only had higher achievements, but also their achievements standard deviation values were small. Although asynchronous courses can provide a self-learning paced environment for learners, students should be encouraged by instructors to keep regularity in learning anyway.

**Stimulus by learning/teaching activity**

In traditional classroom environments, teachers are used to utilizing learning activities to stimulate students’ learning motivation. Likewise, some learning activities were arranged in the asynchronous courses, such as face-to-face teaching, on-line office hours, and final exam, to re-shape learning time patterns and stimulate learning motivation. The schedule of learning activities in the asynchronous courses was described as follows: There were two face-to-face teaching sessions scheduled at the beginning and the midterm of the course, 11 on-line office hours scheduled on each Wednesday of the first eleven weeks, and one final exam given in the last week.

The researchers employed the above-proposed method to analyse the motivation stimulus of the learning activities in the asynchronous course. The time of the course was divided into 86 phases. Each phase occupied one day. Then the burst rates of reading learning materials in Equation (4) were obtained and shown in Fig. 8.

**Face-to-face teaching**

There were two face-to-face teaching sessions in the course. The first one was held at the beginning of the course and the second one in the midterm of the course shown in Fig. 8. The burst rates of the previous day and the day of face-to-face teaching were 18.53% and 15.59%. It showed that the burst rate of the day before face-to-face teaching was slightly increased. So the motivation to study learning materials was not effec-

![Fig. 8 Burst rate curve of learning activities.](image-url)
tively stimulated by the learning activity. By investigating the content of face-to-face teaching, it was found that unidirectional lecturing about general academic researching was conducted in the face-to-face teaching; thereby students have no pressure to read web-based learning materials.

**On-line office hours**

There are 11 on-line office hours in the course shown in Fig. 8. It was shown that the burst rate was largely increased on the day of every on-line office hours. This is because students spent time studying learning materials in addition to attending the interaction of the virtual office hours with teachers. Note that the time spent in the interaction of the on-line office hours are not counted in calculating the time studying web-based learning materials.

**Final exam**

As shown in Fig. 8, the burst rate of reading learning materials was increased from one week before the final exam (burst rate 17.06% increase to 38.24% from Jan 26, 2002 to Feb 1, 2002). It means that learning time intensity was effectively enhanced due to the final exam. That is, burst reading could be obtained by giving exams to students.

In Fig. 8, another interesting phenomenon was found that each Monday the burst rate of students increased. When interviewing the students, the reason given was that students who are teachers in elementary or high schools were used to studying web-based learning materials on the first day that they were made available to students, which is usually Monday.

**Interaction differences in Burst States and Diligence States**

To further explore the differences in interaction performed by Burst States and Diligence States, the content of the on-line communication was analysed. This study categorized the interactive activities as follows (Hwang & Wang 2002)

**Searching for answers**

Due to lack of face-to-face instruction in asynchronous learning environment, on-line interaction became the main channel to search for answers. The following dialogue is an example of students utilizing on-line interaction to search for answers.

S1: Can anyone tell me why the computer keep showing the message ‘memory is not enough’ when I am using the spread sheet?
TA: What's the spec. of your computer?
S1: I don’t know how to get the info? Could you show me how?
TA: Just right click mouse on ‘My computer’, and you'll find it.

**Helping others**

Some students would help others to find the solution to their questions/problems, as shown in the following dialogue.

S2: S1, what size is your RAM?
S1: 128MB. Does it make any differences?
S2: Try to use Windows 2000.
S2: I suggest trying windows 2000 to see if it gets better.

**Discussion among students**

Students spent time discussing course-related issues when the instructor was not on-line. The following dialogue is a discussion of their Multimedia project.

S3: It sounds also good if we do research on excavation for this homework.
S4: ‘Excavation research’. Good!
S4: But maybe it needs many pictures.
S3: Just download from the Internet.
S5: We also can take pictures by digital camera.

**Complaint**

Sometimes interaction was for complaints, such as complaining that some learning materials are very difficult.

**Proposing suggestions**

Students sometimes gave suggestions on-line, as shown in the following dialogue.

S6: Could we have our own course’s discussion board? That may help our discussion more convenient.

**Looking for partners**

Since one of the projects was group project, the students were required to find partners.
Free chatting

Free chatting was the most common social activity in synchronous interaction. It occurred more frequently near the beginning or the end of a certain period of synchronous interaction.

This research utilized test–retest method to verify the reliability of the categorization of interactive activities (Budd et al. 1967). Three persons participated in a same coding procedure and were grouped as pairs. The following equations are utilized.

The agreement of one pair \( S = \frac{2M}{N_1 + N_2} \)

\( M \): the number of interaction records coded as the same categorization by one pair of people

\( N_1 \): total number of records coded by the first person of the pair

\( N_2 \): total number of records coded by the second person of the pair

Reliability = \( \frac{N \times \bar{S}}{1 + [(N - 1) \times \bar{S}]} \)

\( N \): the number of people participated in coding

\( \bar{S} \): the average value of the agreement of each pair

The results show that the reliability is 0.8780, which fulfills the requirement of exceeding 0.85 (Kassarjian & Kassarjian 1988). It indicates that the categorization is objectively acceptable.

In this research, a total of 4001 interactive records were analysed. The results show that free chatting was the main interactive activities (68.91%). However, the second, third and fourth interactive activities were learning related and they were, respectively, discussion among students (17.35%), searching for answers (7.87%) and looking for partners (2.05%). It shows that although on-line interaction was considered a formal part of the web-based course, free chatting was still a basic way to socialize with others – even most of them had never met – in an asynchronous web-based learning environment. Table 6 shows the distribution of interactive activities among different Burst States, several points are found as follows:

1. In the four types of course-related interactive activities (‘searching for answers’, ‘helping others’, ‘discussion’, ‘suggestion’), it was found out that the students in Posterior + Burst and Prior-Posterior Burst interacted more than others. Besides, students at Prior Burst State were also aggressive in interacting with others, which demonstrated that they showed high motivation in learning in the early phrase of the course. On the other hand, students at Posterior Burst States showed the least interest in these interactive activities; however, their achievements were not bad (Table 2).

2. In the area of ‘Complaint’, a higher percentage of complaints was found among the students at Midterm, Posterior + and Prior Burst States.

3. In the area of social interactive activities (‘Looking for partners’ and ‘Free Chatting’), the Posterior Burst students were the most passive. Since students in this category are ‘crammers’, the time they spent on courses was small in the early and the middle phrases. They seldom involved themselves in interacting with peers, so it was difficult for them to look for learning partners, and they had fewer people to chat with.

To investigate the distribution of interactive activities among different Diligence States shown in Table 7, it was found that students in the Diligent category showed a much more active attitude. This was relatively, less frequent in the Negligent State, that is, the more diligent the students are, the more active they are in interaction.

### Conclusion and suggestions

The methods examined in this research can be utilized as diagnostic tools to assess students’ learning beha-

<table>
<thead>
<tr>
<th>Interactive Activities</th>
<th>Prior</th>
<th>Prior+</th>
<th>Midterm</th>
<th>Prior-posterior</th>
<th>Posterior</th>
<th>Posterior+</th>
</tr>
</thead>
<tbody>
<tr>
<td>Searching for answers</td>
<td>2.24</td>
<td>3.20</td>
<td>3.60</td>
<td>3.92</td>
<td>4.00</td>
<td>7.13</td>
</tr>
<tr>
<td>Helping Others</td>
<td>0.81</td>
<td>1.87</td>
<td>0.50</td>
<td>0.75</td>
<td>0.15</td>
<td>2.50</td>
</tr>
<tr>
<td>Discussion among students</td>
<td>9.86</td>
<td>3.00</td>
<td>4.40</td>
<td>15.33</td>
<td>3.15</td>
<td>18.88</td>
</tr>
<tr>
<td>Complaint</td>
<td>1.00</td>
<td>0.40</td>
<td>1.60</td>
<td>0.83</td>
<td>0.45</td>
<td>1.38</td>
</tr>
<tr>
<td>Proposing Suggestions</td>
<td>0.19</td>
<td>0.20</td>
<td>0</td>
<td>0.25</td>
<td>0.15</td>
<td>0.13</td>
</tr>
<tr>
<td>Looking for partners</td>
<td>0.57</td>
<td>0.87</td>
<td>1.40</td>
<td>1.25</td>
<td>0.25</td>
<td>0.88</td>
</tr>
<tr>
<td>Free chatting</td>
<td>44.57</td>
<td>14.33</td>
<td>22.00</td>
<td>58.08</td>
<td>11.65</td>
<td>57.00</td>
</tr>
</tbody>
</table>

viour, and then some complementary instructional programmes can be conducted in time. This research found that:

1. The more the students – especially the Posterior + burst and the Posterior burst – intensify their reading, the higher their achievements are.
2. The students who were more diligent had higher achievements in learning. Furthermore, no matter what kind of Burst State they were, it made no difference to their learning achievements.
3. The more diligent the students, the higher was the quality and quantity of interaction.

From the above findings, two conclusions can be generated as follows:

1. From the analysis of Burst States and Diligence States addressed, students’ learning characteristics on Burst dimension and on Diligence dimension can be distinguished and explained. Through the methods examined in this research, learning achievement and interaction level can be predicted and thus some complementary instructional programmes can be conducted in time.
2. Students who are more diligent get higher achievement as well as interact more actively. Thus this verifies the proposition addressed by Carroll et al. (Carroll 1963; Bloom 1968; Harnischfeger & Wiley 1976; Fredrick Wayne & Walberg Herbert 1980; Johnston & Aldridge 1985), that is, students achieve more when they invest more time in learning, and which also fits perfectly into an asynchronous web-based learning environment.

Based on the results of the study, some suggestions can be made. First, as students can pace their own learning in an asynchronous learning environment, it’s hard to avoid getting used to intermittent intensive reading. Instructors should consider seriously how to guide students to learn in a proper sequence through a well-scheduled instructional programme. It is necessary to encourage students to exercise self-disciplined regular on-line reading for better learning effects. Moreover, solutions could include setting rules and system design; for example, a progress control with the rule that ‘Move to next advanced level only after submitting homework’, and a system design that displays the amount of on-line reading time of each student so as to motivate individuals to cultivate regular on-line learning habits through comparing themselves with other peers. Second, provided with the results of Burst State and Diligence State analysis, instructors can observe the time distribution directly from their pedagogical perspectives, thus generating more pedagogical meanings.

Acknowledgements

We would like to acknowledge the previous and current editors, Professor Bob Lewis and Professor Charles Crook, and the anonymous reviewers whose suggestions and comments are helpful in the improvements of this paper.

References


Table 7. Average interaction frequency versus Diligence States

<table>
<thead>
<tr>
<th>Interactive activities</th>
<th>Diligent</th>
<th>Normal</th>
<th>Negligent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Searching for answers</td>
<td>9.57</td>
<td>3.05</td>
<td>1.91</td>
</tr>
<tr>
<td>Helping others</td>
<td>2.14</td>
<td>0.79</td>
<td>0.65</td>
</tr>
<tr>
<td>Discussion among students</td>
<td>21.71</td>
<td>8.29</td>
<td>2.21</td>
</tr>
<tr>
<td>Complaint</td>
<td>2.07</td>
<td>0.84</td>
<td>0.35</td>
</tr>
<tr>
<td>Proposing suggestions</td>
<td>0.21</td>
<td>0.21</td>
<td>0.09</td>
</tr>
<tr>
<td>Looking for partners</td>
<td>1.79</td>
<td>0.68</td>
<td>0.44</td>
</tr>
<tr>
<td>Free chatting</td>
<td>74.64</td>
<td>35.32</td>
<td>10.88</td>
</tr>
</tbody>
</table>


