The Influence Factors of Inherent Structure in e-Learning Process

Sfenrianto, Zainal A. Hasibuan, and Heru Suhartanto

***Abstract*—e-Learning involves very complicated processes. All processes in learning activities are designed to facilitate students to achieve the goals. Many factors influence the success of achieving those goals, such as learning style, motivation, knowledge ability, etc. In the conventional learning process, it's assumed that all factors are the same among students. However, this is not the case in the reality. Previous studies showed that the denial of those factors cause the unoptimal student's ability to learn. Hence, in order to improve the effectiveness of their learning process, those factors have to be facilitated. The result of our preliminary study indicates that the existence factors of inherent structure that reflect relationship among learning style, motivation and knowledge ability. In this paper, we propose an e-learning framework based on those factors.**

***Index Terms*—e-Learning, inherent structure, knowledge, ability, learning style, motivation, personalization**

I. Introduction

With the advance of information and communication technology, e-Learning becomes an integration parts in educational processes. E-Learning system has been developed by many education institutions to support the learning process. Most of e-Learning systems are still applied as a media to enrich traditional learning system and do not really address the influences of inherent factors such as learning style, motivation, knowledge ability, etc. Very often the students do not receive learning materials that suit those factors. Thus, the learning effectiveness becomes less optimal.

Considering those factors in the e-Learning system is studied by some previous researches who argue the importance of those factors in learning process. For instance, the taxonomy of learning styles developed by Curry, in [1] "used the concepts of learning styles, student achievement, and motivation to explain the process of learning". Then, based on psychological learning view, learning style and motivation basically aims to improve learning performance and influence student achievement.

Each student learns in different learning styles. A better understanding of learning styles can benefit not only to the teachers but also their students. For example in [2], "the students show a positive response and higher achievement when their learning preferences and needs are accommodated by their lecturers". According to Felder and Spurlin, when mismatches exist between most of students learning style and teacher teaching style, the students may become bored, inconvenient learning situation, less optimal in exams, etc. [3].

On the other hand, motivation improves student's learning spirit. Thus, motivated students will have more spirit to learn than those who are less motivated. A student with a higher degree of motivation in a course will likely produce greater achievement [4]. In addition, in the study of relationships between student achievement and variables such as attitude, motivation, learning styles, and selected demographics, student motivation seemed to play a very important role [1].

Hence, many researchers agreed that adopting learning styles and motivation will increases knowledge ability and makes learning easier for students. In order to develop an e-Learning system, one should understand the importance of learning style and motivation so as to enhance student achievement. E-Learning system provides an opportunity to achieve the goals by considering factors of learning style, motivation and knowledge ability to personalise learning process.

In this study, we propose the influence factors of inherent structure and design an e-learning framework for identifying learning style, motivation and knowledge ability in e-Learning system. The paper is structured in the next sections as follows: theoretical background, and preliminary study are described; subsequently, approach and design of framework; last section concludes our study.

II. Theoretical Background

This section covers theoretical background, especially related to factors of learning process, adaptive e-Learning system and personalization

A. Factors of e-Learning Processes

Many studies had explored the influence factors in learning processes. According to Huitt [5], a learning process has many influencing factors, such as community, family, teacher, student, school policies, and state policies. Each student has different degree of influenced factors that related to how to get and process the information in the learning process. Some students respond to learning style in the form of visual or verbal faster than others. Some others have lower or higher learning motivation. Meanwhile, some have wider or narrow knowledge to learn. When these varied factors are not properly addressed in the learning process, some previous research argues that this can cause the decrease of willingness to study.

Learning style defined as "the attitudes and behaviours which determine an individual's preferred way of learning"

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[6]. Educational psychologists have developed several models of learning styles, such as The Myers-Briggs Type Indicator (MBTI), Herrmann Brain Dominance Instrument (HBDI), model by Kolb, Felder-Silverman Learning Style Model (FSLSM), etc. Each model proposes classifications of learning styles. This study focuses on FSLSM for a reason. FSLSM is used often in research related to learning styles in e-Learning, as one of the adaptability than tailors to learning differences and individual needs, particularly in visual/verbal dimension [7].

FSLSM dimensions can be categorized into four dimensions, namely: (1) active (trying things out and working in groups) or reflective (thinking things and prefer to learn alone); (2) sensing (concrete material, like example, practical, facts, and procedure) or intuitive (abstract material, like challenges and are more innovative); (3) visual (picture, diagram, flowchart and etc) or verbal (learning from written and spoken); and (4) sequential (linear thingking process and explore the material in sequence) or global (holistic thinking process, and students learn in large leaps) [3].

Meanwhile, several researchers (Pintrich, 1995; Pintrich & Schunk, 1996; Garcia, 1995; Bandura, 1986; Zimmerman, 1989) in [1], "believed that students should monitor their learning motivation, regulate emotions, and use motivational strategies for active involvement in learning". Thus, a student with higher motivation to struggle towards success in a course will likely caused higher self ability, than low motivation to struggle.

In [8], Vincente and Pain divided the students learning motivation into five categories: effort, confidence, satisfaction, sensory interest and cognitive interest. From these categories, effort is a fundamental indicator of a student's motivation. The exertion of effort in learning can be as a positive parameter although they are not successful [9]. Hence in our study, we can assume that a student's effort as the amount of time the learner spends on learning and participation in the discussion forum.

The student's ability is also another factor that should be considered. The student's ability can be seen from the level of knowledge in their learning performance. One way to measure the learning performance is recognising the knowledge objectively through evaluation, such as quiz, class exercise, and exam. Hence, students' factors: learning style, motivation, and knowledge ability should be considered in the adaptive e-Learning development in order to optimize learning process.

B. Adaptive e-Learning System

An adaptive e-Learning system is defined in [10], "The adaptive e-Learning systems are built to personalize and adapt e-Learning content, pedagogical models, and interactions between participants in the environment to meet the individual needs and preferences of users if and when they arise". Thus, the adaptive hypermedia application model (AHAM) is a reference and basis of the adaptive e-Learning systems. AHAM focuses on the three components, i.e. user model, adaptation model, and domain model [11].

The user model explains user's features which are used in the adaptation [12]. To develop an adaptive e-Learning system, the user model has to gather some data about learning style, motivation, and knowledge ability, etc. The methods of gathering those data can employ direct questions or learner-system interaction [13].

1) Using direct questions method, as primary information to develop user model can be collected through questionnaire. For example, Index of Learning Style (ILS) can be used to identify hints at detecting learning styles for each dimension of the FSLSM [14].
2) On the other hand, the learner-system interaction method makes use of student's interaction based on student's learning behaviour (log file learning activities) during an online course. Analyzing and interpreting log file learning activities is a valuable source of information about student's learning behavior, i.e. learning patterns such as time spent on the course, total time spent on taking a test, total time spent in forum, number of visits into the forum, etc. [15]. Based on this information, data about students' behaviour can be used to indentify hints for specific learning style preferences, degrees of motivation, and knowledge levels. For example, if a learner often visited forum discusstion, this gives us a hint that the learner is a higher degree of motivation in a course.

An adaptation model provides a foundation for personalized functions related to other models because a domain model consists of those personalized learning materials that will be transmitted to the students based on some data from a user model [12]. Therefore, the adaptation model is employed to support the personalisation of learning materials. The main issue in personalisation is how the Learning Management System (LMS) can match the learning materials with learning style, motivation, knowledge ability, etc.

Finally, Domain model describes the structure of the information content of adaptive system application [12]. According to Carchiolo [16], a domain model consists of three databases: (1) Domain Database (DDB) has the information of learning material modules for learning and grading; (2) Teaching Material Database (TMDB), has all learning materials which are used in the learning process (presentation files, quiz, exam, etc.); (3) Profile Database (PDB) has the information of student (e.g. knowledge, available time, etc.), used to build course tailored learning materials. Hence, the domain model in the adaptive e-Learning system has learning materials, student evaluation, and information of student factors such as learning style, motivation, knowledge ability, and so on. The information is stored and managed in a database to support the personalization of learning materials.

C. Personalization

Fig. 1 describes the structure of adaptive system for a basis in the process of user modelling by Brusilovsky [17]. The structure consists of three processes, i.e. collecting user data, user modelling process, and adaptation process. The process starts when the adaptive system collects data about student's learning behaviour. Then, in the user model, the data will be processed by the system (user modelling) to gather the influence factors of students such as learning style, motivation, knowledge ability, and so on. Finally, the system will perform adaptation process to support the personalization of learning materials based on those factors.

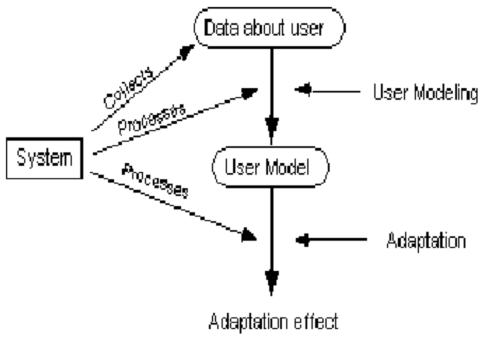

Fig. 1 The structure of adaptive systems [17]

According to Giridharan [18], personalization model for adaptive e-Learning is a way to distribute learning materials into three levels, namely: level-1, level-2 and level-3. All three of these levels will be personalized based on divergent knowledge levels (novice, average and excellent).

Thus, in the adaptive e-Learning environment, the influence factors of students must be identified for the purpose of personalization.

III. Preliminary Study

In the previous study [20], we have held a study at Faculty of Computer Science, University of Indonesia. Preliminary data for this study were extracted from a graduate course on strategic planning for information systems (SPIS) that was taught to Master Program in Information Technology students. The lecture delivered the course using dual-mode (combination of face-to-face and online) at Student Centered E-Learning Environment (SCELE), which was developed by e-Learning team at Fasilkom UI [19].

SCELE facilitates students forum for discussion, learning log to identify the number of content which accessible using the system, and grade of the course to indicate the student ability, etc. Participation in the forum discussion and learning log indicates motivation and learning style, whilst grade obtained indicate knowledge ability.

In order to obtain the preliminary data in this study, one hundred (100) students were involved in the 16-week-course. As shown in Table I, from the total participants, we gathered data of 9167 activities of learners using SCELE system for each student's profile. The respondents were 85 male students (7555 activities) and 15 female students (1612 activities). The groups were also divided into 3 groups, depending on the students' age: group I, 21-30 years old (6586 activities); group II, 31-40 years old (1848 activities); and group III, 41-50 years old (733 activities). In addition, there were 28 working students (2070 activities) and 72 non-working students (7097 activities). The students were from various university graduates in Indonesia: 60 persons (5758 activities) from Jabodetabek (Jakarta, Bogor, Depok, Tangerang, and Bekasi), and 40 learners (3409 activities) from outside Jabodetabek (Java, Sumatra, and Sulawesi). Meanwhile, in the groups of grading, 25 learners (2307 activities) obtained grade A, 40 learners (4078 activities) obtained grade A-, 29 learners (2567 activities) obtained grade B+, 4 learners (183 activities) obtained grade B, 1 learners (21 activities) obtained grade D, and 1 learners (16 activities) obtained grade E.

TABLE I. THE ANALYSIS OF PRELMINARY DATA FROM ACTIVITIES OF

Students' Profiles		Total students	Activities of SCELE (%)		Total activities
			Learning log	Forum	
Gender	Male	85	81.67	85.99	7555
	Female	15	18.33	14.01	1612
Age	21-30	72	72.46	68.86	6586
	31-40	22	18.88	26.32	1848
	41-50	6	8.66	4.82	733
Working	Yes	28	76.94	79.71	7097
	No	72	29.97	25.46	2070
University Graduates	Jabodetabek	60	63.21	60,88	5758
	Outsite Jabodetabek	40	36.79	39.12	3409
Grade	A	25	25.90	21.62	2307
	A-	40	42.04	56.25	4078
	B+	29	29.46	20.67	2567
	B	4	2.17	1.14	183
	D	1	0.28	0.00	21
	E	1	0.14	0.32	16

The overall Grades obtained by students to indicate: A- (learning log 42.04%, and forum 56.25%) were involved in the most activities than A (learning log 25.90%, and forum 21.62%), B+ (learning log 29.46%, and forum 20.67%), B (learning log 2.17, and forum 1.14%), D learning log 0,28%, and forum 0.00) and E (learning log 0.14%, and forum 0.32%).Thus, from preliminary data investigation and analysis results, shows that there is a tendency that the higher the frequencies of learning log and participate in discussion forum, the higher the grade the student will get [20].

In addition, we also analyzed the data of the learning activities of students that used SCELE system (see Table II). We provide the preliminary data collected from students' activities and final grades conducted at SCELE. In the tables, we define the students groups, namely, SM and SF denote male and female students respectively; A21-30, A31-40, A41-50 denote the range 23-30 year, 31-40 year, 42-50 year students respectively; WY and WN denote students who are working and non working people; and JBY and JBN denote student who are living in Jabodetabek and outside Jabodetabek. NStd denote the number of students, NLog denote the percentage learning log activities, NFrm denotes percentage of the number of activities in the learning forum, NAct denotes the total activities of each student categories, and Avg-Grade denote average students grade which based our grade standards is computed by substituting the grade A, A-,B+,B,D, and E with values 4, 3.7, 3.3, 3, 1, and 0 respectively.

We do not use NAct as the measure the students activities in the process because the larger number does not truly indicate the quantity of the students' activities. For example, Male students has total 7555 activities compared with 1612 of the female, but in average the male student is less active (88.88) than the female (107.47). As an alternative we use the average number of activities (Avg-NAct) as the measure.

From the table, it is obvious that:

1) Even though the female students are more active than the male, their grades (3.38) are less than those of the male (3.60),
2) The A31-40 year students is lest active compared with the other and their grades are the smallest, but even though the A41-50 year students are more active (122.17) than the A21-30 year students, their grades (3.57) are less than that of the A21-30 year students (3.61),
3) The working students are more active (98.570 than the non working students (73.93), and their grades (3.63) are much better than those of non working students (3.40),
4) Finally, the students who are university graduates living in Jabodetabek are more active (95.97) than those who are living outside of Jakarta (85.23), but their grades in contrary (3.52 versus 3.64).

In the near future, we need to further collecting more data and reanalyzing to see whether there is a relation between the activities of the students and their grade in each of the student categories and how strong is this relation.

TABLE II. THE ANALYSIS OF PRELIMINARY DATA FROM ACTIVITIES OF SCELE BASED ON ACTIVITIES AND GRADE

	NStd	NLog	NFrm	NAct	Avg-NAct	Avg-Grade
SM	85	81,7	85,99	7555	88,88	3,60
SF	15	18,3	14,01	1612	107,47	3,38
A21-30	72	72,5	68,86	6586	91,47	3,61
A31-40	22	18,9	26,32	1848	84,00	3,41
A41-50	6	8,66	4,82	733	122,17	3,57
WY	72	76,9	79,71	7097	98,57	3,63
WN	28	30	25,46	2070	73,93	3,40
JBY	60	63,2	60,88	5758	95,97	3,52
JBN	40	36,8	39,12	3409	85,23	3,64

Thus, SCELE has provided facilities: learning log, forum discussion and students assessment to support online courses activities. These facilities indicate the existence of inherent structure that reflect relationship among learning style, motivation and knowledge ability. But on the other hand, SCELE still treats all students equally the same in providing materials for the courses. This is due to, SCELE does not have facilities to identify the influence factors of inherent structure (learning style, motivation and knowledge ability) .

Based on that preliminary study, in the next section we proposed an approach and the design of framework in e-Learning systems that consider those influence factors to support personalization learning materials.

IV. APPROACH AND DESIGN OF AN E-LEARNING FRAMEWORKS

In the previous study [20], we proposed triple characteristic model (TCM) to support e-Learning system. The TCM model accommodates students' learning style, motivation and knowledge ability in their personalized learning activities. It consists of three layers, i.e. learning layer, characteristic layer, and personalization layer. The relationship between the three layers are learning layer which provides learning behavior patterns to support identification of students' characteristics on characteristic layer. Then, it provides the basis for personalization functionality on personalization layer.

As shown in Fig. 2, we propose the influence factors of inherent structure in e-Learning that are based on factors reflect inherent structure among learning style, motivation and knowledge ability. Our approach integrates information about learning styles, motivation and knowledge ability factor, in order to enable e-Learning systems to identify and personalise the learning materials based on those factors.

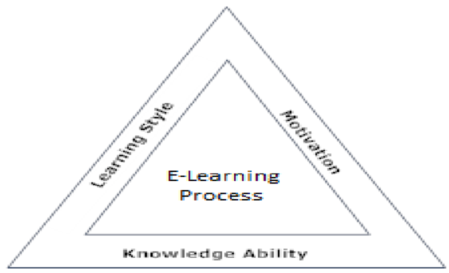

Fig. 2 The Influence factors of inherent structure in e-Learning process

Then a framework for the influence factors of inherent structure in e-Learning process can be created as shown in Fig. 3.

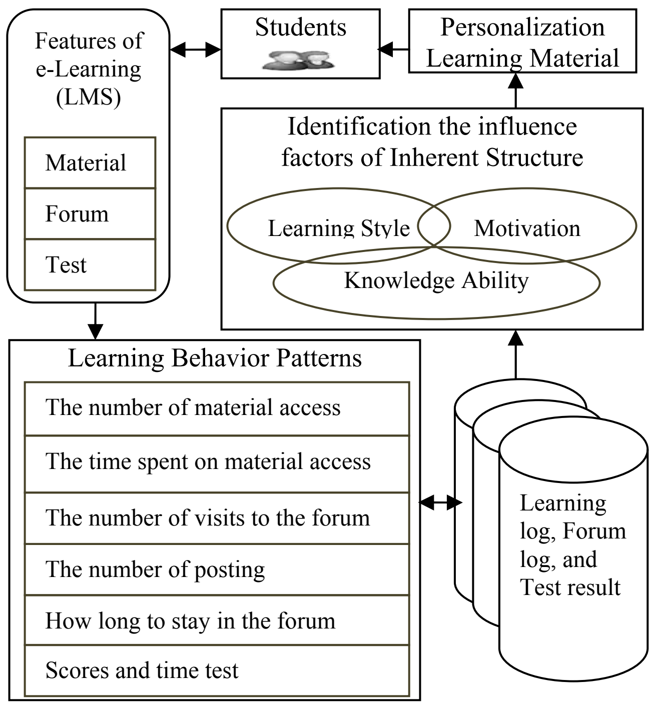

Fig. 3 The e-Learning framework design for factors of inherent structure in e-Learning process

The students will interact with the e-Learning (Learning Managemen System-LMS) through variety of features to support students in online course, in order to gain the learning materials that suit their needs, forum for discussion, take all the tests, etc. We focused on commonly used features, such as material, forum and test. The LMS (Moodle, Atutor, WebCity, Blackboard, Dekeos, Ilias, Sakai, etc) is e-Learning software as well as an organizer of those features and a tool to provides information about learning behavior patterns in an online learning situation.

The information of learning behavior patterns is stored and managed in a database (learning log, forum log, and test result). A Learning log contains learning patterns, such as the number of content access, the time spent on content access. Then, the log of forum discussion consist of the number of visits to the forum, number of posting, how long to stay in the forum. Whereas, assessment comprises scores and time test.

Each of those patterns gives an indication related to identification the influence factors of inherent structure in e-Learning process. The identification of those factors aims at inferring the learning styles, motivation and knowledge ability states. Then, it provides the basis for personalization functionality. In order to identify students' learning styles, motivation and knowledge ability, it uses a learning behavior patterns in the database as mentioned earlier. These patterns will indicate learning style and motivation (learning behavior pattern in learning log and forum log) and the student knowledge ability (using scores and time test).

In our previous study [20], we showed how to identify students' characteristicsc from the TCM in e-Learning based on learning style (active/reflective, sensing/intuitive, visual/verbal, sequential/global), motivation (high/low), and knowledge ability which is classified based on test score: poor (0-64) / average (65-74) / good (75-84) / excellent(85-100).

The result from this identification can be used to generate personalization. In our previous study [20], the personalization layer have provided a hierarchy of learning materials that suit to student's learning style, motivation, and knowledge ability (Triple-Characteristic) approach as described previously. Category personalization is learning materials of level-1 (easier), level-2 (moderate), and level-3 (advanced).

V. Conclusion

In this study, we have shown that there is an existence of the influence factors of inherent structure in e-Learning system (SCELE) but does not yet support personalization learning materials. We also have explained an approach of these influence factors, such as learning style, motivation and knowledge ability in e-Learning process. Based on those factors, we proposed a framework to support identification and personalization of learning material in e-Learning process. The framework consists of six main components: students, features of e-Learning (LMS), learning behavior patterns, database, identification the influence factors of inherent structure, and ppersonalization learning materials. Each component will dynamically guide the student to achieve the goal of learning. Our future research is to implement the influence factors of inherent structure in e-Learning process and test it on various courses.

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