E-Learning Personalization Using Triple-Factor Approach in Standard-Based Education

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Abstract. E-Learning can be a tool in monitoring learning process and progress towards the targeted competency. Process and progress on every learner can be different one to another, since every learner may have different learning type. Learning type itself can be identified by taking into account learning style, motivation, and knowledge ability. This study explores personalization for learning type based on Triple-Factor Approach. Considering that factors in Triple-Factor Approach are dynamic, the personalization system needs to accommodate the changes that may occur. Originated from the issue, this study proposed personalization that guides learner progression dynamically towards stages of their learning process. The personalization is implemented in the form of interventions that trigger learner to access learning contents and discussion forums more often as well as improve their level of knowledge ability based on their state of learning type.

1. Introduction
Learning is a continuous process performed with the purpose in achieving learning objectives in a specific time period. In standards-based education, there are mechanism in targeting competencies as learning objectives and evaluation to assess the learners’ achievement toward the objectives. Learners evolve over time, consequently learning process should also be well prepared to help learners meet the standard.

In the other hand, e-Learning can help learners to learn the way they want without limitation in place and time. Unfortunately, e-Learning commonly does not consider the diversity of learners in term of their ability and characteristics. Usually, the learning paths and contents are given identically for all learners in the same course despite the fact that learning type may differ on one another. To accommodate the variation of learning types, the learning paths and learning contents can be adapted to meet personal needs [1]. Personalization in e-Learning enable learners to have a learning process that is suitable to their learning type. By learning with the appropriate paths and contents, learners are expected to achieve the targeted competency optimally.

Learning types can be identified by taking into account several factors, such as: learning motivation, learning styles, knowledge ability, and others. According to Triple-Factor Approach, there is a close relation between motivation and learning styles with knowledge ability levels. These factors can influence the learning process, which in turn can determine learning outcomes [2].

The factors can be identified through learner’s activities in using e-Learning. Learning styles can be identified through the intensity of learning activities on e-Learning [3]. Motivation to learn shown by
how often learners interact in discussion forum[4]. Meanwhile, knowledge ability can be known through a series of assessments to figure out learners’ the level of knowledge on a particular learning topic[5].

Learning style, motivation, and knowledge ability of learner are very likely to be changed according to their condition at every stage. The intensity of one's learning at the end of the course can be increased or decreased compared to the activities in early topic, as well as learning motivation. In the meantime, the level of knowledge can increase over time and related to learners’ knowledge on the discussed topic. Considering that factors in Triple-Factor Approach are dynamic, personalization is better to be flexible with changes that may occur on motivation, learning styles, and knowledge ability of learners. This study highlights the challenge to provide learning process that helps learners’ improvement in achieving expected competency, while also raises the need for personalization that can be presented dynamically according to the situation experienced by learners at every stage of learning.

2. Literature Review

2.1 Personalization

In the context of e-Learning, personalization is a strategy in which the system will be able to provide individual learning for each learner. Personalization in e-Learning enables system to present a scenario adapted to the characteristics of learners[6]. Personalization generally comes from the selection or customization of learning content and learning sequences of activities that are being prepared to meet the needs of individual learners[7].

In recent years, many studies have discussed about personalization in e-Learning through a variety of approaches and techniques. Automation of learning begins with defining the relationship between competence, subject, topic, and learning units. Knowledge domain [8] or knowledge model [9] are the most popular terms to describe this component. Other scholars mentioned it with different terms but essentially described the same meaning. For example, one scholar used the term competency structure [10] while another scholar named this curriculum component as a unified repository [11]. In a study conducted by Gamalel-din [8] ontology is used to represent concepts and relationships concepts. Knowledge domain also represents object of teaching by means of concepts, relations among concepts and teaching preferences connected with concepts[9]. Besides concepts and their relationships, knowledge domain can be used to define competencies and capabilities as the objective of learning process [10]. Knowledge domain is described as relationship between courses, topics, subtopics, and competencies[11].

Most common reference for personalization is learning style, knowledge level, and affective state of learner. Learning style refers to habit or preferred way for learning [3]. There are many learning style models that can be used for personalization, for example Felder-Silverman Learning Style Model (FSLSM) as discussed in [12] and [8]. Myers-Briggs Type Indicator (MBTI) as implemented in [13] and Kolb's Model mentioned in [14].

Besides learning styles, personalization can be delivered based on information regarding learners' level of knowledge. Learning Object (LO) can be classified based on its difficulty level, then LO will be presented based on the learner's ability level [15]. Another popular approach is based on affective state of learner such as motivation, effort, and confidence[16].

Personalization can be presented in various forms, among others: personalized interfaces, personalized learning scenarios, as well as personalized learning content. Personalized interface among others proposed by [12] and [17]. Neural networks was applied for learning styles classification in [12], while [17] used support vector machine. Both studied adopted Felder-Silverman learning style model in adjusting the interface of e-Learning system.

Personalization can also be presented as individual learning scenarios [8]. System will analyze the learning style of each learner. The identified learning styles then determine the order of learning unit given to learners individually. For example for global learner, the system will present the general overview at the beginning of each chapter or section and then present the sequence of learning object[8].
Meanwhile a recommender system approach can be utilized for personalizing learning content. System can first analyze the preference of students to this type of learning content. The system will then recommend the learning content that similar to the preference of such learners. We can use the concept of preference score and similarity score to recommend learning content [18]. Preference score is calculated based on the matched object between the learning contents presented by system and learning contents that accessed by user. The similarity score can be derived by the number of same object that accessed between two users. System will recommend learning contents with highest recommendation score based on preference score and similarity score. Learning content recommendation can also be calculated using collaborative filtering. Collaborative filtering is used to predict the preference of one user based on previous ratings by other users to the object[19].

Assessment component also generally implemented in personalized e-Learning. Assessment is used to find out the effectiveness of the learning process. Assessment can be implemented through e-portfolio which include tasks that can be evaluated and provide feedback to learners [20].

In studies that discuss personalization, there are two terms that are often mentioned: adaptive and dynamic. The two terms are often discussed overlapping one to another. The term of adaptive learning denotes to a learning process where the learning contents that are presented “adapts” to individual needs of learner [21]. Thus, adaptive e-Learning system can be defined as system that has ability to deliver learning sequences and contents in accordance with learners’ individual characteristics [22]. In the other hand, dynamic refers to something that is not constant. Dynamic approach can be applied, among others, to learner modelling [23] and learning sequence of object [24].

Focusing on personalization techniques, most of the learning scenarios are generated at the beginning of the term and rarely notice to learners’ progress in the learning stages. Only few studies re-adjust the given learning scenario throughout the whole learning process, among others utilize Multi-Agent Memetic Algorithm [9]. However, the study only considered cognitive state and preferences of learners in learning presentation (sequences of learning activities) that will be given.

2.2 Triple-Factor Approach
The current study adapts Triple-Factor Approach [3] which uses learning type that consists of learning styles, motivation, and knowledge ability as factors that affecting learning process. This approach was selected since it includes the affective factor (indicated by motivation) and learning styles that reflect the character of learners, in addition to knowledge ability level. Another consideration is that previous studies have shown a close association between factors in the approach [2].

Triple-Factor Approach is based on previous studies which mentioned that there are linkages between factors in the process of e-Learning. Some studies show that learning styles affect learners' learning strategies [25] and ultimately have an influence on learning achievement [25][26]. In addition to learning styles, motivation also has a significant relationship to knowledge ability demonstrated by the results of the assessment [5]. Based on the results of these studies, there had been an analysis of three factors: motivation, learning styles, and the ability of knowledge [2].

The results of the correlation tests showed that motivation to learn affect the level of knowledge ability. Similarly, learning styles have a relationship with the level of knowledge ability. The test results are then led to the learning type in e-Learning process namely Triple-Factor Approach.

Learning style is shown through intensity of learning activity on e-Learning: low, medium, and high intensity. In Triple-Factor Approach, motivation is classified into three levels: low, medium and high. Meanwhile, the learner is based on four levels of knowledge ability, namely: poor, average, good, and excellent[3]. Furthermore, 36 learning types could be obtained from a combination of (3 characteristic learning style: low, medium, and high intensity) * (3 characteristic motivation: low, medium and high) * (4 characteristic knowledge ability: poor, average, good, and excellent).

3. Research Methodology
The present study is conducted through the following steps:
1) Personalized E-Learning System
In this step, the authors analyze the functional requirement of the personalized e-Learning system. The proposed system should cover some components that support personalized learning process from course planning to assessment.

2) Personalization Rule

The next step is designing rules in presenting personalization to user. The personalized learning is based on learning type and intended to improve learner’s state in every stage of learning process. The rules are applied topic by topic, to help learner’s progress in learning styles, motivation, and knowledge ability.

3) Intervention to improve learning type

The personalization rules are equipped with some additional activities to trigger learner’s progress. The intervention cover activities to improve learner’s intensity in learning activities and accessing discussion forums, as well as improve their level of knowledge ability.

4. Proposed Design and Discussion

4.1 Proposed Personalized E-Learning

In order to accomplish the objective of enabling learner to learn based on their individual needs and to monitor learner’s progress toward targeted outcomes, the authors propose personalized e-Learning system that complies with standards-based education. Personalization provided in the system is driven by learning type based on Triple-Factor Approach that consists of learning style, motivation, and knowledge ability. We can identify learner’s learning styles through the intensity of their learning activities on e-Learning. Learning motivation can be seen from the frequency of learner’s activity in discussion forum. Knowledge ability can be found through a series of assessments to figure out learners’ knowledge on a particular learning topic.

The personalization is presented topic by topic within a subject and completed with an assessment to see how far learner has mastered the targeted competencies. In addition, the assessment is also done to see whether the personalization gives expected results. At the end of each assessment, the system identifies the next state of each learner as the beginning of the new iteration of personalization for the next topic. Thus, personalization operates adaptively to the needs and character of learner as well as dynamically accommodates the state changes of learner in every stage of learning process. Figure 1 describes the proposed personalized e-Learning system.

![Figure 1. The Proposed System](image-url)

The proposed system covers several components: knowledge domain, learner model, personalization, and assessment. Targeted competency will drive the knowledge domain as it defines the relationship between competencies, subjects, topics, and learning units. To accommodate learner’s personal needs, systems have to understand the characteristics of learners. Our study adapts the Triple-
Factor in learner modeling. As mentioned earlier, that the standards-based education requires a standard of assessment to measure the learner achievement. Thus, in order to identify the progress of a learner, our study proposes portfolio-based assessment.

4.2 Personalization Rule

The study proposes rules that could be applied in implementing dynamic personalization. The main idea of dynamic personalization is not only the system adaptive to learners’ learning type, but also adaptive to learners’ change in every stage of the learning process. Considering that learning type are dynamic, the current study proposes that the learning process are evaluated and adjusted at each stage. The next iteration of personalized learning is determined based on the results of learning type identification at the previous stages.

The personalization rules are equipped with some interventions to trigger learner's progress. The intervention cover activities to improve learner's intensity in learning activities, discussion forums, and assessment. In general, the proposed personalization rules shown in Figure 2.

![Figure 2. Personalization Rule to Improve Learning Type]

The intervention in learning styles can be in form of additional contents such as video, animation, or video conference. The material can be varied by extended explanation and examples. These action is expected to increase learner’s learning intensity.

In motivational factor, this study considers some strategies to improve learner’s interest in accessing discussion forum, among others: create stimulating threads that trigger learners to read (for example: discussing about the answer of the latest quiz/assignment), posting threads that require learners to respond (for example: discussing about the mechanism and themes of next topic/assignment), and bonus points for every valid action on discussion forum.

To improve knowledge ability, the system can provide exercise activities and try-out just before the quiz period. Exercise and try-out quiz trigger learners to practice more in order to achieve better results in assessment. To excite learner's interest, learners who complete the exercise and try-out quiz can get extra points. Learning contents presented to each learner are adjusted to their level of knowledge ability. Figure 3 illustrates the possible change on the learner's learning type and given personalized learning.
The proposed system offered an approach that could help learners to always improve their selves with the aim to accomplish expected result. The rule is to give learning path and learning contents to improve their state of learning type. As shown in Figure 3, the system offers personalized learning to improve their learning style, motivation, and knowledge ability to a higher level. The personalization is presented in order that the learner would making progress step by step towards the expected learning outcomes.

5. Conclusion
This study proposed personalization that refers to Triple-Factor Approach. The approach identified learners’ learning type based on learning style, motivation and knowledge ability. This study considered the possibility that intensity of learners in using e-Learning can fluctuate over time. Moreover the assessment results may differ depending on learners’ ability and effort at the time of assessment. Accordingly, this study proposed rules that could be applied in implementing dynamic personalization. The main idea of dynamic personalization is not only a system adaptive to learners’ need, but also adaptive to the learners’ change that may occurs. The rules are applied topic by topic and implemented in the form of interventions that trigger learner to access learning contents and discussion forums more often, as well as improve their level of knowledge ability.

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