A Decision Making Approach to Evaluation of Learning Components in Adaptive Educational Systems

Full Paper

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Abstract. Personalized learning models are developed to cater for the differentiation in learner styles and needs. Tutors determine the most appropriate learning components for each student. The learning units (LUs) are adapted to learners based on their contexts. However, there are no methods that adapt learning objects to learners based on their personalized learning styles. There also does not exist appropriate techniques that employ decision making approaches to evaluate the LUs. This study presents a model that uses learning styles to determine the appropriate learning information by employing learning analytics. Its proposed evaluation model, facilitates evaluation of how suitable, acceptable and usefulness of personalized learning in the LUs. To test the model, varying evaluation criteria weights are employed. It is proposed that the model can be used by tutors to assist learners in creating and applying LUs that are most suitable for their needs thereby improving the quality of learning.

Keywords: Educational Data Mining, Adaptive Educational System, Suitability Evaluation, Personalized Learning.

1 Introduction

1.1 Overview

One of the key objectives for educational systems is to enhance students' learning performance and satisfaction. Trainers are required to carry out accurate evaluations of learners' varying competencies to enable them tailor the teaching process to personalized learner requirements. Learners can differ based on their knowledge level, interests, how they are socialized, and the motivation level [1, 2]. To create personalized learning systems, designers and developers should consider artificial intelligence (AI) techniques that have been extensively used in creating near human like applications. While AI is the broad science of mimicking human abilities, machine learning is a specific subset of AI that trains a machine how to learn. Its applicability in educational settings is also gaining prominence with growing volumes of available learning data [3].

Machine learning skills are necessary for developers of predictive applications. Current practices show that machine learning skills are taught primarily via a teacher-centered approach [4] limiting the ability of trainers being able to identify problems faced by individual trainees. This calls for innovative ways of training learners to solve their own problems during learning. Learners should be assisted to be able to identify their learning styles. Training modules should be evaluated by domain experts for appropriateness to particular learners according to their learning styles.

There is utmost need for methodologies for evaluating how suitable, acceptable and useful personalized learning units (LUs) are for each student in addition to methods for evaluating the learning objects (LOs). LOs can be defined as a series of learning components, learning tasks, and learning settings. An acceptable LO should entail learning components which are appropriate for certain learners depending on their learning styles.

Emphasis on the individual learner differentiation while modelling ideal online setting is a major component in adaptive educational systems (AES). Successful provision of adaptive learning models depends on the identification and ability to meet learners' needs. Enabling these features is key if AESs are to provide methods and content that are suitable for their users [5]. Importantly, accurate learner profiles and models should be created after analyzing learner affective states, knowledge type, skills and personality traits. This information should then be employed in the creation of adaptive learning settings [5].

E-learning courses can be delivered using several existing learning management systems (LMS) like Sakai and Moodle and learning portals like Dream-box and massive open online courses [6]. Being online and hosted in large database systems, the platforms store massive data. The continuation of the learning process by student is based on his/her individual learning style and the results of his/ her performance evaluation [6]. In literature, educational data mining (EDM) and learner analytics (LA) fields of research have specialized in the analysis of online learning systems' stored data to create personalized profiles that can be used by interested parties to develop personalized adaptive educational systems [6]. Formal definitions and applications of EDM and LA are found in [7].

1.2 The Problem

Lack of knowledge and limited awareness by majority of educators in the application LA and EDM methods [6] has been a great impediment to the successful learning. Educators are handicapped in the correct analysis of the results and correct inference deciphering. In dealing with these challenges, a key point is the creation of a positive environment for cultivating a data centered approach in the educational sector [8, 9]. In this regard, the environment should facilitate learner analytics for personalized recommendation of learning objects based on learners' learning styles.

According to Kurilovas [10], the concept of personalized learning styles became popular in the 1970s. Since then, the concept has had great influence in education sector despite some researchers criticizing it. However, its proponents have suggested that trainers should evaluate their learners' learning styles and make their teaching methods adapt to each learner's preference. Notably, evidence exist suggesting that individual learners have preferences on how they would like to receive information. However, seldom works have tried to validate use of learning styles to adapt course materials. Possible reason for this could be the lack of evidence of learners' learning outcomes improvement when learning styles is the basis of developing learning activities [11].

In the authors' assessment, the criticism by these researchers has nothing to do with the validation of the construction of learning objects based on learning styles. It is the opinion of the authors that the application of learning styles constructs for efficient learning personalization, could be the genesis of the criticism. This can be attributed to existing varied learning styles, impracticality of having enough trainers to personalize learning materials based on possible numerous learning paths that are dependent on learning styles. Moreover, some researchers have stated that personalization of learning when based on learner's learning styles can be effective when intelligent technologies are properly applied to develop optimal personalized learning paths.

In this study, learners fill the psychological questionnaire to identify their learning style. Thereafter, employment of learning analytics techniques to identify and correct the discrepancies in the outcome is done (sometimes the outcome of filling the questionnaire differ from the existing defined learning styles). This results in better identification of individual learning styles. In this work, personalized LUs encompass learning components with the highest probabilistic suitability indices (PSI) to particular learners based on the Felder-Silverman Learning Styles Model (FSLSM) [12].

This study also proposes to evaluate suitability, acceptance and use of personalized LUs by using a multi-criteria decision making (DM) method. The method employs DM criteria proposed in Educational Technology Acceptance and Satisfaction Model (ETAS-M) [13] that is based on the Unified Theory on Acceptance and Use of Technology (UTAUT) model [14]. This study defines LU as a sequence of learning objects (LOs), learning tasks (LTs) and learning settings (LSs) which according to some authors, has been frequently referred to as either virtual learning settings (VLSs) or virtual learning environments (VLEs). This study adopts the former reference.

2 Previous Works

2.1 Employment of Artificial Intelligence Methodologies in Adaptive Educational Systems

The success of any adaptive educational systems (AES) is dependent on how the systems are able to cater for each learner's needs [15]. This becomes possible when learners' profiles and learner objects are created accurately after considering their affective states, knowledge level, personality attributes and skills. All these information is utilized in creating the adaptive learning setting [15]. AI being the approach that is most applied in creating decision making processes that have largely been adopted by people [16], is also seen as a valuable tool for developing AES.

Use of AI approaches in AES has been in examining and assessing learner attributes for generation of their profiles. Using the personalized profiles, the overall knowledge level is determined which is used as basis for prescribed software pedagogy [17]. Similarly, diagnostic process completion is facilitated by using these approaches. Adjustment of course content to cater for individual learner needs is done. Analytics of learner behavior is carried out and the prescribed software pedagogy [18] is adjusted accordingly.

It can be considered time consuming or costly to rely on designer or expert knowledge to guide the pedagogy of the AES. Furthermore, because of incomplete knowledge on what entails effective teaching, dealing with varied characteristics of students is sometimes not possible. It can be more convenient and effective for adaptive e-learning system designers or experts if they consider learner behaviors for automatic learning. It may save their time and effort in the design of suitable pedagogy according to the learner needs. In the design, learning models which can be continuously edited and modified without difficulties can be generated. Therefore, AES can be developed based on how learners define their styles of learning and the experts' evaluation of the learning units. Experts' evaluations are inherently uncertain.

The AI techniques, such as fuzzy logic, decision trees and neural networks can manage the uncertainty that is inherent in human decision making. These techniques have been touted as being able to deal with imprecision and uncertainty and thus can be used to build and automate accurate teaching-learning models [19].

2.2 Learning Units' Personalization

Research works in recent times have shown personalization of learning attracting a lot of attention from researchers [20, 21]. Popular topics in this domain have been (or include), creation of LUs [22], learning objects (LOs) [23], LTs [24] and LSs [25] that should be most appropriate for individual learners. Seemingly high demand of these techniques have seen a lot of proposals coming forward from researchers.

In [24], it is stated that going into the future, educational systems will have to adopt both personalization and intelligence. Personalized learning refers to learner ability to receive learning materials based on their personal learning needs. This is achieved by creation and implementation of personalized LUs. In other words, the adaptive system should recommend the most suitable learning components to learners. Intelligent technologies, the likes of resource description framework (RDF) can be applied in AES to improve learning quality and efficiency in personalized learning.

The steps for implementing personalized learning include, 1) implementation of learner profiles (models) based for instance, on FSLSM where a dedicated psychological questionnaire like Soloman and Felder's Index of Learning Styles Questionnaire (SFILSQ) [26] is applied, and 2) integration of other features like knowledge, goals, learning behavioral types, interests and cognitive traits in the learner profile. In [27], it is stated that FSLSM learning styles model is suitable for technology-based related learners. Hence its adoption in this study.

Literature reveals that FSLSM, uses number scales to categorize learners according to how they receive and process information. For instance, in [10], the categories are by: a) Information type, b) Sensory channel, c) Information processing, and d) Understanding. Descriptions of sub categories for each category can be found in [10].

Explanations given in [28] on the steps of implementing personalized learning indicates that step three (3), entails filling the SFILSQ, to obtain a learning style that is currently stored in (or represents) learner's profile. The outcome of this step is checked against the results described in Table 1 and appropriately modified using the correct learner's information as determined in this personalized learning implementation step by application of LA methods. The application of the process to create suitable LUs for individual learners should be carried out as per the descriptions given in [29]. Ultimately, implementation of integrated learner profiles is done. Further, creation of ontologies-based recommender systems that adapts appropriate learner components according to individual learner's FSLSM-based profiles is also carried out.

Table 1. An instance of learner's learning style stored in his/her profile (as provided in [10]) that should be modified.

Styles of Learning							
Information type		Sensory channel		Information processing		Understanding	
Sensory	Intuitive	Visual	Verbal	Active	Reflective	Sequential	Global
0.639	0.361	0.821	0.179	0.731	0.269	0.449	0.551

From the preceding steps, each learner should have a personalized LU for each learning task/activity he /she engages in. The personalized LU should be created using existing AI technologies. These intelligent technologies can be useful in evaluating quality and suitability of the learning components. Among these technologies are ontologies and recommender systems which should work by linking learner profiles (LP) to learning components (LCo). There exists established interlinks between LP and LCo that can be exploited in these cases even as experienced experts participate in creating appropriate learning environment to facilitate proper guidance to learners or creation of appropriate learning components / objects.

2.3 Evaluation Approach: UTAUT Model Application in Learning

There are a number of decision making techniques (evaluation approach adopted in this work) in literature. As highlighted in [30], they include 1) Analytical Hierarchy Process (AHP), 2) VIsekriterijumska optimizacija I KOmpromisnoResenje (VIKOR), 3) Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) among others. Any of these can be employed in the design and development of models suitable for use in evaluating the quality of learning components as per defined criteria. However, only a few research works have investigated the application of these techniques in AES.

One of the consistent concept in decision making, has to do with identification of decision / evaluation criteria. These criteria are usually relatively precise but can be conflicting at times. Each criterion is evaluated by comparing it against another criterion with respect to a given objective, where weight of importance is assigned based on a defined crisp or fuzzy scale. These criteria are also referred to as alternatives.

The identification of criteria in the decision making techniques, as stated by Kurilovas and Zilinskiene [22], should be based on among others the following principles: 1) Relevance of value; 2) Comprehensibility; 3) Ability to be measured; 4) Not redundant; 5) Independent of any judgment; and 6) Operational aspect. All these principles are relevant to a number of multiple criteria decision making (MCDM) models.

In [22], Kurilovas and Zilinskiene present the measure of performance model for LU quality that is based on the preceding principles of MCDM identification criteria. LU is Educational Modelling Language and IMS LD [31] based technology consisting of learning objects, learning tasks and learning settings.

Authors state that the same criteria-based evaluation can be applied by educators in the virtual learning settings. The basis of this evaluation is the Unified Theory on Acceptance and Use of Technology (UTAUT) model [14]. The focus on UTAUT model has been on its application in education as regards to the acceptance and use of information technology (IT) in the design and creation of personalized learning applications. While examining UTAUT as applied in IT acceptance research, it is glaringly shown that there exist several models (that are competing). Each of them have acceptance determinants of varying sets.

In the examination alluded to in the preceding section, a review of the following models among others was done, the theory of reasoned action, the technology acceptance model, the motivational model, the theory of planned behavior, a model combining the technology acceptance model and the theory of planned behavior, the innovation diffusion theory, and the social cognitive theory. The results of the review of the models as relates to UTAUT, were converging to a few constructs that were appearing like they were significantly determining the usage in at least one of the models. Researchers in this study have determined that four of the constructs are critical and as a result have employed them as direct determinants of user acceptance and usage behavior. They are adapted from Venkatesh et al. [14] and include: a) Performance expectancy (PE), b) Effort expectancy (EE), c) Social influence, and d) Facilitating conditions (FC) as presented in Fig. 1.

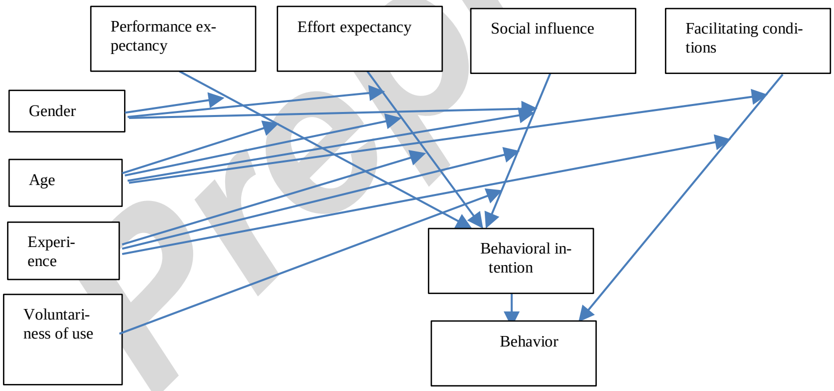

Fig.1. UTAUT model (Adapted from Venkatesh et al. [14]).

2.4 Learning Personalization by Use of Learner Analytics Methods

A selected review of recent works in [32, 33, 34], on learning analytics reveals the following issues. The list is non-exhaustive. The application entails: 1) Learners categorization in predefined set of learners group; 2) Course materials clustering for provision to particular learners based on their profiles; 3) Discovery of interesting relations between course elements used by specific learners; 4) Adaptation of learner profiles to personalized learning objects affecting the eventual learning outcomes; and 5) Creation of decision tree based on learners' actions. Decision trees are widely applied in data mining as they are easy to comprehend and use. The proposed method resembles decision tree where the branches represent correct responses to questions sought. A response can also be a state. The study divides datasets into branches at the initial steps progressively leading into a homogeneous state. The states assist in the identification of the data used to base the final decision.

3 Methodology

3.1 Using Learning Analytics in Learning Personalization

Use of learning analytics for personalized learning in education sector has been successful from what literature reviewed has shown. Literature has also shown that there are large volumes of data depicting learner behaviors which can be used in creating individual learner profiles. Appropriate learning objects can be designed to be adapted to the correct profiles in real-time, enabling successful learning activities thus improving performance in knowledge and skills acquisition.

When data analytics methods are employed in learner data in a learning institution, using the data obtained from students depicting their real behaviors, learner profiles as shown in Table 1 can be corrected based on this obtained data. This profile's correction can be achieved using a developed learning analytics (LA) software agent. It corrects the learner profile based on the learner behavior in the learning environment essentially implementing the recommended LUs.

In a learning institution or learning setting like multi-agent system or virtual learning setting (VLS), as learning takes place, learning objects and tasks can be associated with particular learners before identifying appropriate PSIs and recommending suitable LUs. Authors perceive that due to the foregoing discussion, it seems that learners' preference is to employ particular learning activities or use appropriate learning objects for their specific learning needs. Hence, usage of suitable LA methods, could facilitate easy analysis of learning activities and objects particularly used by the learners in the learning setting, and also determining the extent of usage.

Step one of using learning analytics in personalizing learning, authors propose the use of FSLSM-based approach and expert evaluation method [24]. FSLSM is widely used in higher learning institutions, as the appropriate learning style model. Furthermore, in [22], analysis of expert evaluation methods for learning components is presented. Secondly, SFILSQ is filled by learners and analyzed to determine their personalized learning styles. In the third step, it is proposed that the use of experts' evaluation methods should be employed to determine the suitability interlinks between learning styles and VLS learning activities. Thereafter, computation of PSIs [28] is carried out for each learner behavior analyzed. Additionally, the same process is applied to each VLS-based learning activity so that appropriate learning activities for particular students are identified. It is stated that when suitability index is high, the learning activity is presumably better. The same applies to learning objects used by learners. The higher the index, the better or more appropriate, the learning object is considered.

Fourthly, after the learners have been through a learning process, use of appropriate learning technique is recommended for analyzing the exact learning objet and tasks by students. Essentially, the information on the exact nature on how the learner used VLS-based learning tasks is then compared to their PSIs that resulted in the second step as discussed earlier. Discrepancies could have resulted during the comparison, in which case, the analyst (the teacher for the purposes of this study), is required to correct the learners' personal LUs in VLS based on the obtained information as a result of the process. This new information is attributable to the discovery of the differences in students' learning styles in their profiles as per their PSIs identified from the evaluation.

If there are still any glaring discrepancies that results when learning units are created based on the identified learners' learning styles from the filled questionnaire and when their real historical behavior is identified based on learner analytics, the analyst can either request the learners to refill the questionnaire or in the case that the results of historical behavior are good, learner analytics approach is employed to create optimal LUs. In the latter case, students learning quality and effectiveness can be enhanced.

3.2 Evaluation Approach Adopted for Suitability, Acceptance and Personalized Learning Units' Usage

Previous related works have employed MCDA based evaluation models to identify criteria for analysis. They base their arguments on the principles proposed in [22]. Authors borrow from this precedence and propose to use the same approach to evaluate LU model in the current work. This study uses the ETAS-M (as shown in Fig. 2), and PSIs to identify learning components' suitability to particular students' needs according to their learning styles [28].

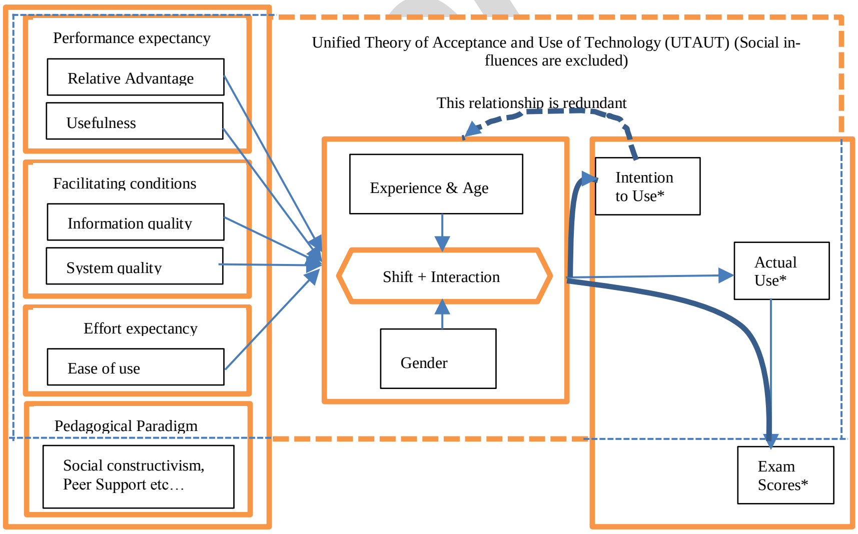

Fig. 2. ETAS-M (Adapted from Poelmans et al. [13]).

The proposed model is both component- and ETAS-M-based. Evaluation criteria for the model include, PE, EE, FC and pedagogical paradigm influence (PPI). In ETAS-M, PPI criteria replaces social influence used in UTAUT. When PPI in ETAS-M is compared with component based model mode in [22], it is shown that the operation convenience is enhanced. It is believed that the enhanced convenience level manifested in the comparison is attained because the described comparison is solely based on the evaluation of acceptance in addition to the use of LU the participants have developed or prepared, which fully reflects the participants' needs and perspectives.

4 Study Results

4.1 Application of the Proposed Learner Analytics Technique

To demonstrate the applicability and validity of the proposed learning analytics technique, an analysis of a sophomore class of 42 students enrolled in the Bachelor of Science in Computer Science at Dedan Kimathi University of Technology in Kenya was carried out. As much as this was a moderate class size suitable for such experiments, the focus was not so much on the class size but rather the sufficient differentiation in terms of their learning styles. The learners were put in six categories of seven members each, labeled as A, B, C, D, E and F (see Table 2). The university offers a number of its courses in the moodle-based e-learning platform[1] which is integrated with the now well-known and used big blue button platform[2] which is offered to all universities in Kenya by Kenya Education Network (KENET)[3]. The department of computer science has a number of select courses offered by either face to face or online.

The experimental class participated in the VLS-based digital image processing course for one semester during the August- December 2018 semester. It took fourteen weeks with each session lasting three hours per week. Researchers used this class having identified the differences in the learning styles for illustration purposes though the sample size is acceptable as it is the whole class which represent 25% of the students of the entire program which is studied in four academic years, hence a quarter of the entire population for the programme in the department. It should be noted that these results can be different in other universities but they can be generalized. Generalization is possible because in Kenya, students in majority of universities are government sponsored and are therefore allocated through Kenya Universities and Colleges Placement Services (KUCCPS) which is a state agency. The characteristics of students across most universities are majorly similar if not the same due to similar origins and backgrounds. Similarly, generalization is possible because the study has sufficiently analyzed different learning styles.

After determining the students to participate in the evaluation process, learners responded to the forty-four (44), two answer questions in the SFILSQ. It is shown from the analysis of the responses that 28 students preferred active information processing while the remaining 14 preferred the reflective mode; Similarly, 28 learners were mostly Sensory, with only 14 of them being intuitive learners; Finally, 28 learners were mostly Visuals versus 14 that were Verbal learners by sensorial channel; and 7 were either Sequential or Global learners by understanding (Table 2).

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[1] Moodle-based e-learning platform at Dedan Kimathi University of Technology. Available at: https://elearning.dkut.ac.ke

[2] Big blue button platform. Available at: https://bigbluebutton.org

[3] Kenya Educational Networks. Available at: https://www.kenet.or.ke

Table 2. Ratios of learner' learning styles for each category.

		Information processing		Information type		Sensorial channel		Understanding	
Category	Learners' Identification	ACT	REF	SEN	INT	VIS	VER	SEQ	GLO
A	1,9,15,16,30, 32,34	0.724	0.276	0.544	0.456	0.728	0.272	0.544	0.456
B	5,12,20,22,26,39,40	0.456	0.544	0.272	0.728	1.000	0.000	0.184	0.816
C	4,6,17,21,27,35,38	0.728	0.272	0.365	0.635	0.365	0.635	0.454	0.546
D	2,10,23,24,33,37,42	0.728	0.272	0.635	0.365	0.272	0.728	0.456	0.544
E	8,11,14,18,19,28,36	0.635	0.365	0.728	0.272	0.544	0.456	0.456	0.544
F	3,7,13,25,29,31,41	0.272	0.728	0.728	0.272	0.908	0.092	0.728	0.272

NB: ACT-Active, REF-Reflective, SEN-Sensing, INT-Intuitive, VIS-Visual, VER-Verbal, SEQ-Sequential, GLO-Global

After the identification of learner styles from analyzing the responses in the questionnaires, expert evaluation methods are used to help determine the activities in VLS Moodle appropriate for FSLSM-based learning styles. This is shown in the third column of Table 3. In Table 3, column 4, it is shown the outcome of using learning analytics methods to identify the particular learning tasks that each member of the experimental class exhibited. Decision tree technique was used to analyze the data using the learner identification (in clusters) as the target. In decision trees, different learners are shown using colored blocks where the records appropriate for each learner is represented by length of the line.

Table 3. Appropriate learning styles for learners' participation in moodle-based tasks (Adapted from Kurilovas [12]).

Moodle-based tasks	Description	Appropriate learning style	Number of learners
Assignments	Enable teachers to grade and give comments on uploaded files and assignments created on and off line	Reflective	I(35)
Chat	Allows participants to have a real-time synchronous discussion	Active	J(35)
Forum	Allows participants to have asynchronous discussions	Active	K(21)
Lesson	For delivering content in flexible way	Sensory, Sequential	L(21)
Quiz	Allows the teacher to design and set quiz tests, which may be automatically marked and feedback and/or to correct answers shown	Reflective, Sensory, Sequential	M(35)

From additional observations from Table 3, it can be noted that J is identified as the elements of the modules with the most active students, which is the target group with the highest averages scores. Similarly, students' participation in chat rooms characterizes their activities. To know the worst state of the learners' average values with the highest activity, one looks at the tasks and test course elements.

From the analysis, it could be deduced that there was a direct relationship of the learners' grade scores on the study module with their activities. It was then important that during the study process, more attention was paid to the learners' behavior in addition to their style of learning while at the same time facilitating active involvement in the course. The moodle-based activities like chats and fora registered majority of the activities confirming learners learning in correspondence with their styles of learning.

4.2 Application of the Proposed Evaluation (Decision making) Technique

Fig. 3 shows the proposed evaluation model for suitability, acceptance and use of LU.

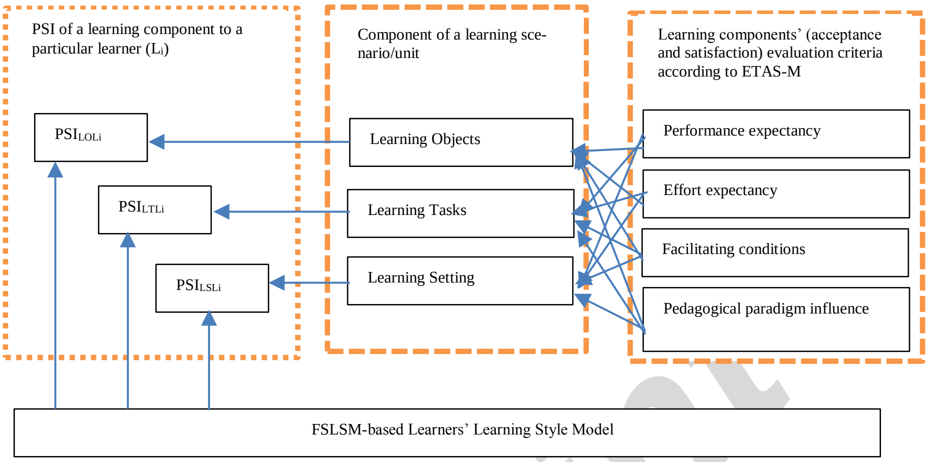

Fig. 3. A proposed evaluation model for suitability, acceptance and use of LU.

The evaluation model is used to evaluate a particular LU. Equation 1 is used to express the evaluation model:

$$f(x) = \left(\frac{\sum_{l=1}^{c} PSI_l}{c}\right)\left(\sum_{s=1}^{p} \alpha_s f_s(x)\right) \quad (1)$$

Where, *l* is the learning component (LO, LT or LS), c =3, PSI_l is the probability suitability index of corresponding learning component *l* to particular learner, α_s is a weight of criterion s, and $f_s(x)$ is a value of criterion *s*, p= 4 (PE, EE, FC and PPI).

To compute the LU evaluation function numerical value, first, get the product of all ETAS-M-based evaluation criteria and their weights. Secondly, get the sum of the results from the first step. Thirdly, the product of these sums with their corresponding learning components' probability suitability indices is done and the final step is the computation of the overall sum. For LU of a particular learner to be considered appropriate, then its numerical overall weight, should be higher than the weights of other LUs.

In equation 1, the weights α_s of evaluation criteria *s*, $s = 1,2,3,4$ might have been either equal or not, depending on how each evaluator views the criteria in terms of their importance in relation to each other. As pointed out by Kurilovas and Zilinskiene [34], when according to the evaluators', the criteria are of equal importance, i.e., $\sum_{l=1}^{p} a_l = 1, a_l > 0$, the weight of evaluation criteria $\alpha_s \cong 0.249$. Computing f(x) in equation 1, then becomes simple.

For demonstration purposes, the following section use a particular learner L_i, whose profile is shown in Table 1. It is imagined that a recommender system had recommended that its suitable learning units are LU_1 and LU_2 with the aggregated learning components (*LO, LT and LS*) *l* = 1, 2, 3 having the highest suitability indices for the learner L_i. Also, it is imagined that the values of $f_s(x)$ of evaluation criteria s = 1, 2, 3, 4 (PE, EE, FC and PPI) using trapezoidal fuzzy numbers [24], respectively are:

LU_1: *(0.999 0.799 0.799 0.499)*

LU_2: *(0.899 0.899 0.699 0.599)*

Computation results when all the weights have equal values becomes:

$$LU_1(\sum_{s=1}^{p} \alpha_s f_s(x)) = 0.249*0.999 + 0.249*0.799 + 0.249*0.799 + 0.249*0.499 \cong 0.775$$

$$LU_2(\sum_{s=1}^{p} \alpha_s f_s(x)) = 0.249*0.899 + 0.249*0.899 + 0.249*0.6999 + 0.249*0.599 \cong 0.775$$

The following are the computation results when weights have different values (for instance, the weights of PE = PPI = 0.20; EE = FC = 0.25):

$$LU_1(\sum_{s=1}^{p} \alpha_s f_s(x)) = 0.200*0.999 + 0.250*0.799 + 0.250*0.799 + 0.200*0.499 \cong 0.700$$

$$\mathrm{LU}_2(\sum_{s=1}^{p} \alpha_s \mathrm{f}_s(\mathrm{x})) = 0.200*0.899 + 0.250*0.899 + 0.250*0.699 + 0.200*0.599 \cong 0.700$$

To identify learning components' probability suitability indices, trapezoidal fuzzy numbers can be applied on a select simple and convenient expert evaluation method and used to identify the learning components suitable for particular learners' FSLSM-base styles of learning.

A reference was made to an adaptive e-learning model (AeLModel) developed in [35]. The model allows social interactions such as content annotation, blogs, and tagging. Noting the use of the AeLmodel by learners (as described in the preceding section), twenty (20) expert evaluators were asked to give their opinions on how they rated the suitability level of learning activities based on the application of remodeled/enhanced (augmented) reality and social networks to Felder-Silverman learning styles. They filled in the questionnaire by selecting one of the following linguistic variables as proposed in [10]: excellent, good, fair, poor, or bad. Table 4 shows results of expert evaluation method

Table 4. Results of application of decision tree method.

	Students identification by category and their ratio values for each task						
	No. of records	A	B	C	D	E	F
Activity	2827	0.3033	0.1113	0.1953	0.1205	0.1200	0.0441
Lesson	99	0.2800	0.0900	0.0100	0.1201	0.0000	0.4002
Test	667	0.1592	0.1802	0.1907	0.1412	0.1425	0.0588
Assignments	375	0.2371	0.1122	0.1527	0.1414	0.2424	0.0113
References	330	0.2315	0.0875	0.2165	0.1267	0.1867	0.0000
Chats	129	0.4908	0.1746	0.0955	0.0322	0.1348	0.0000
Other activities	1228	0.4035	0.0755	0.2294	0.1102	0.0608	0.0337

on the suitability indices of using social networks and augmented reality as media for learning. This is as determined by learning activities in learners' FSLSM-based learning styles (see Table 5).

Table 5. Results of expert evaluation method.

Learner Style	Sensory	Intuitive	Visual	Verbal	Active	Reflective	Sequential	Global
Value	0.740	0.750	0.910	0.600	0.870	0.450	0.670	0.780

As shown in Table 5, use of social networks and augmented reality as learning media is most suitable for Visual and Active learners with numerical values of 0.91 and 0.87 respectively. However, the suitability indices of Verbal and Reflective learners are 0.60 and 0.45 respectively. Computing the product of probabilistic values (PV) of learners' learning style from Table 1 and suitability values (SV) of learning styles & learning tasks from Table 5, results in probabilistic suitability values PSI, of suitability of certain learning tasks to certain learners (see equation 2 for active learning style).

$$PSI_{Active} = PV_{Active} * SV_{Active} \qquad (2)$$

Computation of probabilistic suitability indices of other learning styles of a certain learner is carried out in the same way. Using Tables 1 and 5, these computations are done for a particular learner *Li*, as shown in the following section.

$PSI_{SEN} = 0.639 * 0.740 = 0.4736$; $PSI_{VIS} = 0.821 * 0.910 = 0.7462$; $PSI_{ACT} = 0.731 * 0.870= 0.6351$;
$PSI_{INT} = 0.361 * 0.750 = 0.2700$; $PSI_{VER} = 0.179 * 0.600 = 0.1080$; $PSI_{REF} = 0.269 * 0.450 = 0.1215$;
$PSI_{SEQ} = 0.449 * 0.670 = 0.3015$;
$PSI_{GLO} = 0.551 * 0.780 = 0.4290$.

The mean weight of this particular learner, $PSI_{Li} = 0.3856$.

Similarly, computation of suitability indices for LOs and LSs is done in the same way. For instance, PSI_{Li} for LOs in LU_1 could be equal to 0.499, and PSI_{Li} for LSs in LU_1 could be equal to 0.599.

Therefore, *PSI_{Li} for LOs in LU_1 = 0.499; PSI_{Li} for LTs in LU_1 =0.3856; and PSI_{Li} for LSs in LU_1 = 0.599. The average PSI_{Li} for LU_1 = 0.4951.* Thus, $f(x) = (\frac{\sum_{l=0}^{c} SI_l}{c})(\sum_{m=1}^{p} \alpha_m f_m(x))$ = 0.4951 * 0.775 = 0.3837

5 Conclusion

It has been demonstrated that there is the possibility of applying learning analytics techniques to learning personalization. A methodology is presented for enhancing the quality and effectiveness of learning by learners. It is proposed that the use of FSLSM and appropriate learning styles questionnaire can be used for identifying learning styles of certain learners. Establishment of suitability indices of learning tasks for certain learners is done through evaluation by experts.

Additionally, learning analytics are employed to establish the exact LOs and activities carried out by the learners in the VLS and the extent of use. If it is noted that personal learning styles of learners and optimal LUs show some mismatch, appropriate adjustments are done. Practically in the learning institutions, the level of application of personalized LUs in the pedagogy determines the level of competences exhibited by learners in terms of knowledge, skills and attitudes.

The study has proposed a model based on MCDM criteria identification principles for personalized LUs' suitability, acceptance and use. Also proposed are: an evaluation model based on learning components and an UTAUT model based on ETAS-M. Authors argue that to personalize LU's components and the whole LU, correct identification of corresponding probabilistic suitability indices should be carried out. At the same time, learning analytics should be applied in a proper manner. The model in this study is both component- and ETAS-M-based. The model is more convenient when compared to purely components based ones. It is believed that the enhanced convenience level manifested in the comparison is attained because the described comparison is solely based on the evaluation of acceptance in addition to the use of LU developed / made / prepared by the participants, which fully reflects the participants' needs and perspectives. Even better is the fact that high-level technological expertise is not required for this kind of model.

Tutors of all cadre can use their specific domain knowledge to create optimal LUs by establishing learners' profiles based on FSLSM. Tutors can create learning styles by letting learners fill Soloman-Felder questionnaire with immediate output for analysis. Computation of learning styles' suitability indices can be easily done using mathematical formulae in an excel workbook.

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