# On the methodology of evaluating the acceptance, use and suitability of personalized learning units

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*The aim of this paper is to present the methodology (i.e., the model and method) for evaluating the acceptance, use and suitability of personalized learning units/scenarios for particular students. Learning units/scenarios are referred to here as the methodological sequences of learning components (learning objects, learning activities and the learning environment). High-quality learning units should consist of learning components optimized for particular students in accordance with their personal needs, e.g., learning styles. In the paper, optimized learning units mean learning units composed of the elements having the highest probabilistic suitability indexes for particular students in accordance with the Felder-Silverman learning styles model. The personalized learning unit evaluation methodology, presented in the paper, is based on (1) the well-known principles of the Multiple Criteria Decision Analysis for identifying evaluation criteria; (2) the Educational Technology Acceptance & Satisfaction Model (ETAS-M) based on a well-known Unified Theory on Acceptance and Use of Technology (UTAUT) model and (3) probabilistic suitability indexes for identifying learning component suitability to the needs of particular students, all in accordance with their learning styles. The methodology for evaluating the acceptance, use and suitability of personalized learning units for particular students, which is presented in the paper, is absolutely new in scientific literature. In the paper, there are also examples of implementing the methodology using different weights of evaluation criteria. This methodology is applicable in real life situations, where* *teachers have to help students create and apply learning units that are most suitable for their needs and thus to improve education quality and efficiency.*

***Keywords:*** *learning styles, personalization, learning units, probabilistic suitability indexes, evaluation, UTAUT model.*

## 1. Introduction

The methodology for evaluating the acceptance, use and suitability of personalized learning units/scenarios for particular students is referred to here as a model and method to evaluate learning units (or Units of Learning, UoLs). UoLs are referred to here as methodological sequences of learning components (learning objects (LOs), learning activities (LAs) and learning environments (LEs) that are often referred to as virtual learning environments. High-quality UoLs should consist of the learning components optimized for particular students in accord with their personal needs, e.g., learning styles. In the paper, personalised UoLs are referred to as UoLs composed of the learning components having the highest probabilistic suitability indexes (Kurilovas, Kurilova and Andruskevic 2016) for particular students in accordance with the Felder-Silverman Learning Styles Model (FSLSM, Felder and Silverman 1988).

Methodology reported in this paper is partly based on the construct of learning styles. This construct is very popular in scientific literature, e.g., Semantic Scholar shows that 27 843 papers on the topic "learning styles" were published in scientific literature during the last 5 years, while the first publications on the topic appeared in 1950. The idea of individualized learning styles became popular in the 1970s, and it has greatly influenced education despite all the criticism that the idea has received from some researchers. Proponents recommend that teachers assess the learning styles of their students and adapt their classroom methods to best fit each student's learning style. Although there is ample evidence that individuals express preferences for how they prefer to receive information, few studies have found any validity in using learning styles in education, mainly in terms of the lack of evidence on improving students' learning outcomes while constructing learning according to student learning styles.

We think that the criticism reported in some papers on educational psychology mainly during the last 5 years has nothing in common with the validity of the construct of learning styles, which was put to question in those papers. We think that this criticism is based mainly on the problems that appear while educators try to apply the learning styles construct to personalize learning in an efficient way, e.g., (1) there are many different learning style models presented in scientific literature (we found over 70 different models); (2) within the traditional education paradigm, it's almost impossible to personalize learning in the proper way, since it's impossible to appoint a separate, well-prepared teacher to construct and implement learning paths/units for a particular student in accord with his/her learning styles, and, last but not the least – (3) learning personalization based on student learning styles becomes effective/efficient only when properly applying intelligent technologies to create and recommend an "optimal" personalized learning path/unit. The last problem deals with the necessity of interdisciplinary research, by properly applying computer science, engineering methods and tools together instead of purely educational or psychological ones. One of these interdisciplinary approaches is presented further in the paper.

According to Kurilovas, Kurilova and Andruskevic (2016), the probabilistic suitability index is the main value that is used to establish the preference list of learning components in accordance with their suitability level to student learning styles. It is based on the probabilistic model of student learning styles and the ratings (values) of the suitability of learning components to particular students in accord with their learning styles.

Finally, the methodology analyzed in the paper is based on criteria proposed by the Educational Technology Acceptance & Satisfaction Model (ETAS-M, Poelmans et al. 2009), which, in its turn, is based on the well-known Unified Theory on Acceptance and Use of Technology (UTAUT) model (Venkatesh et al. 2003).

The rest of the paper is organized as follows: related research is presented in the following section, proposed methodology is presented in Section No. 3, Section No. 4 presents examples of implementing the methodology by using different weights of evaluation criteria, and Section No. 5 concludes the paper.

## 2. Related Research

### *2.1 Personalization of Learning Units*

Learning personalization became a very popular research object in scientific literature in the last years (Arimoto et al. 2016; Dorca et al. 2016; Juskeviciene et al. 2016; Kurilovas and Juskeviciene 2015; Lytras et al. 2014; Lytras and Kurilovas 2014). The research topic on creating full learning units (Kurilovas and Zilinskiene 2012) and smaller learning components – LOs (Kurilovas 2009; Kurilovas and Serikoviene 2013), LAs (Jasute et al. 2016) and LEs (Kurilovas et al. 2014; Kurilovas and Dagiene 2016) – which should be optimal (i.e., the most suitable) to particular students based on expert evaluation methods and techniques, has also become highly demanded, and there are some relevant methods and techniques proposed in the area (Kurilovas et al. 2011; Kurilovas, Serikoviene and Vuorikari 2014; Kurilovas, Vinogradova and Kubilinskiene 2016).

According to Kurilovas (2016), future education means *personalization plus intelligence*. Learning personalization means creating and implementing personalized UoLs that are based on a recommender system, suitable for particular learners and their personal needs. Educational intelligence means the application of intelligent (smart) technologies in enabling personalized learning, done to improve learning quality and efficiency.

In personalized learning, first of all, integrated learner profiles (models) should be implemented. It should be based on, e.g., the FSLSM model. Dedicated psychological questionnaires, like the Soloman and Felder Index of Learning Styles Questionnaire, should be applied here. After that, one should integrate the rest of the features in the learner profile (knowledge, interests, goals, cognitive traits, learning behavioural type etc.).

FSLSM is the most suitable learning styles model for Science, Technology, Engineering and Math and e-learning (Jevsikova et al. 2017). It classifies students based on where they fit on a number of scales, pertaining to the ways they receive and process information:

(a) By information type: (1) Sensory (SEN) – concrete, practical, oriented toward facts and procedures vs. (2) Intuitive (INT) – conceptual, innovative, oriented toward facts and meaning;
(b) By sensory channel: (3) Visual (VIS) – prefer visual representations of presented materials, e.g., pictures, diagrams, flow charts vs. (4) Verbal (VER) – prefer written and spoken explanations;
(c) By information processing: (5) Active (ACT) – learn by trying things out, working with others vs. (6) Reflective (REF) – learn by thinking things through, working alone;
(d) By understanding: (7) Sequential (SEQ) – linear, orderly, learning in small incremental steps vs. (8) Global (GLO) – holistic, system thinkers, learning in large leaps.

According to Kurilovas, Kurilova and Andruskevic (2016), after filling out the Soloman and Felder's Index of Learning Styles Questionnaire, one could obtain, for example, the following learning style, initially stored in his/her student profile/model:

After that, the methodology on creating optimal UoLs for particular learners based on expert evaluation and intelligent technologies should be applied.

According to Kurilovas (2016), in personalized learning, first of all, integrated learner profiles should be implemented, and ontologies-based recommender systems should be created to suggest learning components (LOs, LAs and LEs) suitable to particular learners in accordance with their FSLSM-based profiles. Thus, the whole of the personalized UoLs could be created for particular learners and dedicated to each topic based on study programs at universities or curriculum programs at schools. A number of intelligent technologies should be applied to implement this approach, e.g., ontologies, recommender systems, intelligent software agents, multiple criteria of decision-making models, methods and tools to evaluate the quality and suitability of the learning components etc.

Ontologies and recommender systems should be based on established interlinks between student profiles and learning components. While establishing those interlinks, learning style models and high-quality vocabularies of learning components should be used on the one hand, and experienced experts should participate in this work generating collective intelligence on the other.

Since the aim of the paper is to present the UoLs of evaluation methodology, first of all, one should identify a system of decision (evaluation) criteria (i.e., a model).

According to Kurilovas and Zilinskiene (2012), decision criteria are rules, measures and standards that guide decision-making. A quality criterion is a tool allowing the comparison of alternatives based on a particular point of view. When building a criterion, the analyst should keep in mind that it is necessary that all the actors of the decision

*Table No. 1.* ***An example of a learning style stored in student profile*** *(according to Kurilovas, Kurilova and Andruskevic 2016).*

| *Learning styles* | | | | | | | |
|---|---|---|---|---|---|---|---|
| *By Information Type* | | *By Sensory Channel* | | *By Information Processing* | | *By Understanding* | |
| SEN | INT | VIS | VER | ACT | REF | SEQ | GLO |
| 0.64 | 0.36 | 0.82 | 0.18 | 0.73 | 0.27 | 0.45 | 0.55 |

process adhere to the comparisons that will be deduced from that model. Criteria (relatively precise, but usually conflicting) are measures, rules and standards that guide decision-making, which also incorporates a model of preferences between the elements of a set of real or fictitious actions.

According to Kurilovas and Zilinskiene (2012), in identifying criteria for the decision analysis, the following considerations (i.e., principles) are relevant to all the multiple criteria decision analysis (MCDA) approaches: (1) value relevance, (2) understandability, (3) measurability, (4) non-redundancy, (5) judgmental independence, (6) balancing completeness and conciseness, (7) operationality and (8) simplicity as opposed to complexity.

A UoL quality evaluation model, based on these MCDA criteria identification principles, is presented in a 2012 study by Kurilovas and Zilinskiene. A UoL is an Educational Modelling Language and an IMS LD-based (2003) technology consisting of LOs, LAs and LEs. Therefore, the UoL quality criteria should consist of the quality criteria identified for all its components.

## *2.2 The Application of UTAUT Model in Education*

The component-based UoL evaluation model presented in the 2012 study by Kurilovas and Zilinskiene has its shortages; e.g., there are different types of criteria to evaluate different UoL components. This approach is quite time-consuming and requires different and high-level expertise from the evaluators. As stated in Section No. 2.1, personalized UoLs are considered as high-quality as they fit the personal needs of students, which are judged based on the FSLSM. Therefore, we could apply the same criteria-based evaluations of all components by the users.

This kind of evaluation is based on the Unified Theory on Acceptance and Use of Technology (UTAUT) model (Venkatesh et al. 2003). In the paper, the UTAUT is examined while being applied in education in terms of the acceptance and use of ICTs for personalized learning purposes. In this section, the original UTAUT model is analyzed and supplemented by several carefully selected studies on the UTAUT application in education.

According to Venkatesh et al. (2003), IT acceptance research has yielded many competing models, each with different sets of acceptance determinants. The eight models reviewed by Venkatesh et al. (2003) are the theory of reasoned action, the technology acceptance model, the motivational model, the theory of planned behaviour, a model combining the technology acceptance model and the theory of planned behaviour, the model of PC utilization, the innovation diffusion theory and the social cognitive theory. In the mentioned study (Venkatesh et al. 2003), seven constructs appeared to be significant direct determinants of intention or usage in one or more of the individual models. Of these, the authors theorize that four constructs will play a significant role as the direct determinants of user acceptance and usage behaviour: (a) performance expectancy (PE), (b) effort expectancy (EE), (c) social influence (SI) and (d) facilitating conditions (FC), all as presented in Fig. No. 1.

Hsu (2012) aimed to investigate student acceptance and the use of Moodle employing the model of UTAUT and to further understand the four constructs of the model. Data collected revealed that PE, EE, and SI were the major three keys of the UTAUT

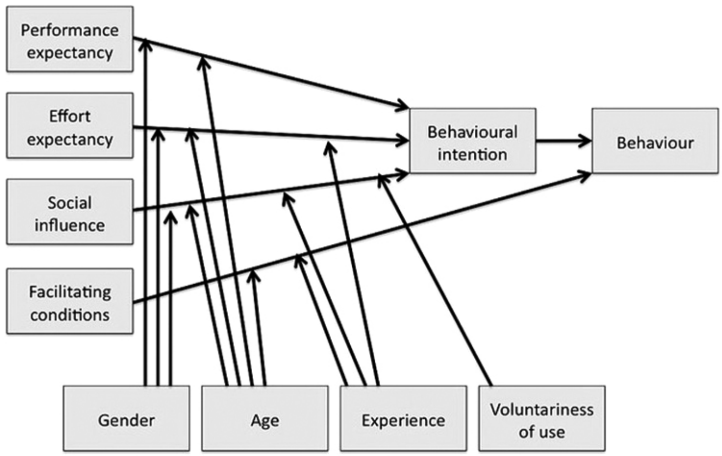


*Fig. No. 1.* ***The UTAUT model*** *(according to Venkatesh et al., 2003).*

model to assess the acceptance of Moodle. Behavioral intention acted as a mediator to urge students to get involved in the use of Moodle.

According to Taiwo and Downe (2013), the UTAUT proposes that PE, EE, and SI predict behavioral intention toward the acceptance of IT. The theory further proposes that FC and behavioral intention predicts usage behavior in the acceptance of IT. Ever since its inception, the theory has been assessed using different applications. The outcome of the study suggests that only the relationship between PE and the behavioral intention is strong, while the relationships between EE, SI and the behavioral intention are weak. Similarly, the relationship between FC, behavioral intention and usage behavior is also weak. Furthermore, the significance of the relationship between FC and usage behavior does not pass the fail-safe test, while the significance of the relationship between behavioral intention and usage behavior does not pass the fail-safe test satisfactorily enough.

The review (Attuquayefio and Addo 2014) evidently shows that variables that need to be applied to determine user acceptance or adoption of technology do vary. The effect of exogenous variables – EE, PE, SI – on the endogenous variable Behavioral Intention is not consistent across countries, within a country and the unit of studies. According to the results of the review, EE (0.4, $p < .05$) significantly predicted Behavioral Intention to use technology; SI and PE were statistically insignificant, as was the Behavioral Intention on Use Behavior. However, FC ($\beta = .26$, $p < .01$) significantly influenced Use Behavior.

According to Samaradiwakara and Gunawardena (2014), among the fourteen theories reviewed in the paper, the UTAUT seems to be an improved theory that could provide a useful tool in assessing the likelihood of success for technology acceptance studies.

Masa'deh et al. (2016) seek to explore the factors that influence student usage behavior of e-learning systems. Based on the strong theoretical foundation of the UTAUT and using structural equation modelling, this research paper examines the impact of PE, EE, hedonic motivation, habit, SI and trust on a student's behavioral intention, which is later examined along with the FCs on a student's usage behavior of e-learning systems. The results revealed a direct, positive effect of PE, hedonic motivation, habit and trust on a student's behavioral intention to use e-learning, explaining around 71% of overall behavioral intention. Meanwhile, behavioral intention and FC accounted for 40%, with strong positive effects on a student's usage behaviour of e-learning systems. However, both EE and SI influence did not impact a student's behavioral intention.

This review shows that the UTAUT was never applied earlier to evaluate technology like the UoL. The only study that proposed a UTAUT-based model, which could be applied to evaluate personalized UoLs, was found in scientific literature to be conducted by Poelmans et al. (2009). Poelmans et al. (2009) examine various extensions of the UTAUT and related frameworks from theoretical and empirical points of view. The theoretical contribution of the paper consists of substantial extensions/improvements of the UTAUT, which are embedded within the theoretical paradigm of social constructivism. It is argued that the usability aspects of e-learning systems cannot be treated independently from their impact on learning behavior and the pedagogical setting in which they are implemented. Based on new empirical data from an experimental, undergraduate statistics course, the authors provide strong support for a newly proposed Educational Technology Acceptance & Satisfaction Model (ETAS-M).

## 3. Personalized Learning Units Evaluation Methodology

Based on a related research analysis, the authors propose a UoL evaluation model,

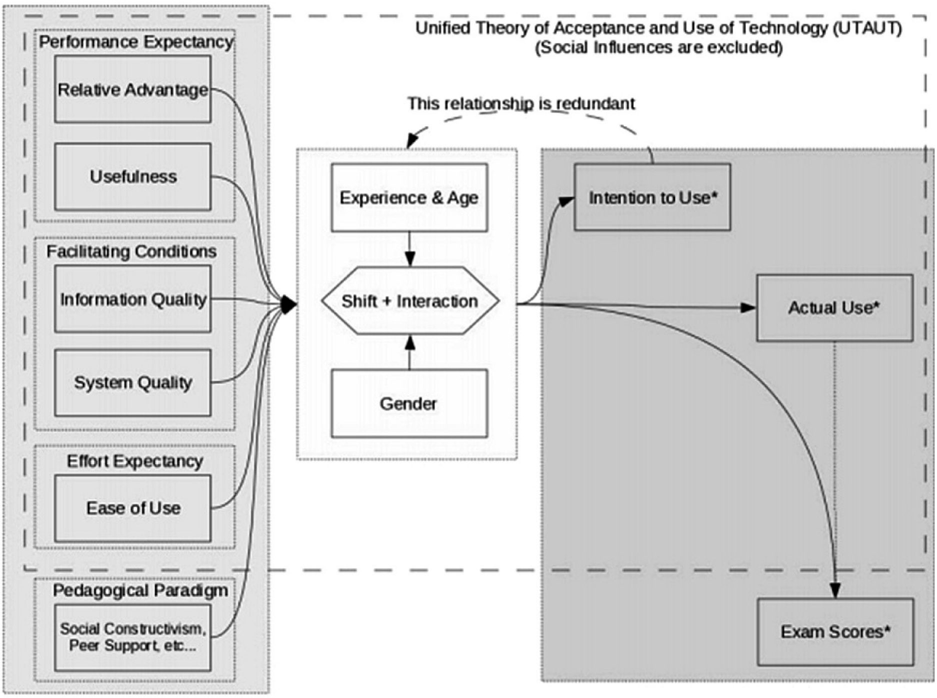


*Fig. No. 2.* ***ETAS-M*** *(according to Poelmans et al., 2009).*

based on MCDA criteria identification principles, which are proposed by Kurilovas and Zilinskiene (2012), the Educational Technology Acceptance & Satisfaction Model (ETAS-M, Fig. No. 2) and the probabilistic suitability indexes (SI) to identify the suitability of learning components for the needs of particular students, which would also be in accordance with their learning styles (Kurilovas, Kurilova and Andruskevic 2016).

The proposed model is, on the one hand, a component-based one, and a ETAS-M-based on the other. In the model, the evaluation criteria are performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC) and influence of the pedagogical paradigm (IPP). IPP is proposed by ETAS-M (Poelmans et al. 2009) instead of the social influence (SI) criteria in the UTAUT.

It's more convenient in comparison with the purely components-based model presented by Kurilovas and Zilinskiene (2012), because it is based only on the evaluation of acceptance and use of a UoL made by the users, and it fully reflects their needs and points of view. Additionally, this kind of model does not require any specific high-level expertise from the experts-evaluators for evaluating UoL alternatives in conjunction with the internal quality criteria of the components. The proposed UoL acceptance and use evaluation model is presented in Figure No. 3.

After creating the UoL acceptance and use evaluation model, one should apply some evaluation method in order to evaluate a particular UoL.

The proposed UoL evaluation method is based on Figure No. 3 and could be expressed by the Formula (1):

$$f(x) = \left(\frac{\sum_{i=1}^{n} SI_i}{n}\right)\left(\sum_{j=1}^{m} \alpha_j f_j(x)\right), \quad (1)$$

where $i$ is the learning component (LO, LA or LE), $n$=3, $SI_i$ is the Suitability Index of the corresponding learning component $i$ to a particular student, is the weight of criterion $j$, and $f_j(x)$ is the value of criterion $j$, $m$=4 (PE, FE, FC and IPP).

Thus, in order to identify the numerical value of the UoL evaluation function, one should (1) multiply the values of all the

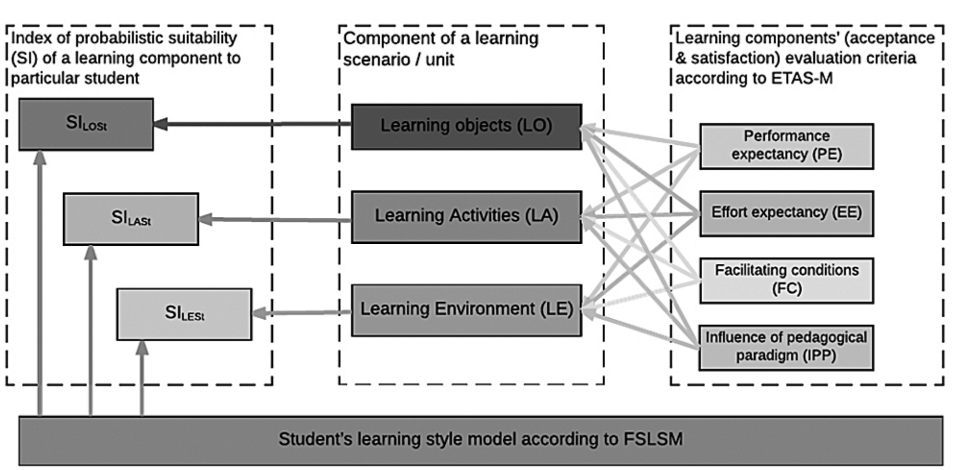


*Fig. No. 3.* ***The proposed UoL acceptance and use evaluation model.***

ETAS-M-based evaluation criteria by their weights, (2) add these numbers together and identify the sum, (3) multiply all these sums by the probabilistic suitability indexes of the corresponding learning components and (4) identify the total sum. The higher the numerical value of *f(x)*, the better is the UoL for a particular learner.

## 4. Implementing the Methodology Using Different Weights of the Evaluation Criteria

In Formula (1), the weights $\alpha_j$ of the evaluation criteria $j$, $j$=1, … , 4 could be equal or not. It depends on evaluators' points of view concerning the importance of the evaluation criteria.

In the case when evaluation criteria seem of equal importance for the evaluators, according to Kurilovas and Zilnskiene (2012): $\sum_{i=1}^{m} a_i = 1,\ a_i > 0$, all the weights of evaluation criteria are $\alpha_j$ =0.25.

In this case, it's very easy to calculate the values of *f(x)* in Formula (1).

Let us imagine that for a particular student $ST_1$, whose profile is described by Table No. 1, a recommender system had recommended the most suitable learning units $UoL_1$ and $UoL_2$ consisting of the aggregated learning comp onents (LO, LA and LE), $i$=1,..,3 having the highest suitability indexes for the student $ST_1$.

Further, let us imagine that the values of $f_j(x)$ of the evaluation criteria $j$=1,…,4 (i.e. PE, EE, FC and IPP), in using trapezoidal fuzzy numbers (Jasute et al. 2016), are respectively

$UoL_2$: (1.000 0.800 0.800 0.500)

$UoL_2$: (0.900 0.900 0.700 0.600)

In the case when all the weights are equal:

$UoL_1\left(\sum_{j=1}^{m} \alpha_j f_j(x)\right)$ = 0.25*1.000 + + 0.25*0.800 + 0.25*0.800 + 0.25* *0.500 = 0.775

$UoL_2\left(\sum_{j=1}^{m} \alpha_j f_j(x)\right)$ = 0.25*0.900 + + 0.25*0.900 + 0.25*0.700 + 0.25* *0.600 = 0.775

In the when the weights are different (e.g., the weights of PE=IPP=0.3; FE=FC=0.2):

$UoL_1\left(\sum_{j=1}^{m} \alpha_j f_j(x)\right)$ = 0.3*1.000 + + 0.2*0.800 + 0.2*0.800 + 0.3* *0.500 = 0.77

$UoL_2\left(\sum_{j=1}^{m} \alpha_j f_j(x)\right)$ = 0.3*1.000 + + 0.2*0.800 + 0.2*0.800 + 0.3* * 0.500 = 0.77

Further, in order to identify the probabilistic suitability indexes of learning components, a quite simple and convenient expert evaluation method, based on the application of trapezoidal fuzzy numbers, could be selected to identify which of the learning components (LOs, LAs and LEs) are suitable to the student learning styles in accordance with the FSLSM.

For this purpose, we have selected the example of learning activities based on the application of augmented reality and social media. The following question was formulated for the experts: "What do you think is the suitability level of learning activities based on the application of augmented reality and social media for the Felder-Silverman learning styles (excellent, good, fair, poor or bad)?"

9 external experts have filled in the questionnaire by selecting one of the linguistic variables. The results were as follows:

*Table No. 2.* ***Expert evaluation results.***

| *LSt* | | *SEN* | *INT* | | *VIS* | *VER* | | *ACT* | *REF* | | *SEQ* | *GLO* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Value | | 0.73 | 0.76 | | 0.92 | 0.59 | | 0.86 | 0.46 | | 0.68 | 0.77 |

In Table No. 2, the experts have expressed their opinion on the suitability of social media and augmented reality-based learning activities to all FSLSM-based learning styles of any hypothetic students.

The expert evaluation results, presented in Table No. 2, have shown that learning activities based on the application of augmented reality and social media are (1) most suitable for Visual (value 0.92) and Activist (value 0.86) learners, and that they are (2) most unsuitable for Verbal (value 0.59) and Reflective (value 0.46) learners.

If we would multiply the probabilistic values (PR) of particular students' learning styles according to Table No. 1 by the suitability values (V) of learning activities and learning styles in accordance with Table No. 2, we would obtain the probabilistic values SI of suitability of the particular learning activities for a given student that would be all in accord with Formula 2:

$$SI_{ACT} = PR_{ACT} * V_{ACT} \tag{2}$$

This is the example of the Active learning style of the particular student $ST_1$. In the same way, we could calculate the probabilistic suitability indexes of all learning styles of the particular student, based on the results seen in Table No. 1:

$SI_{SEN} = 0.64 * 0.73 = 0.47$; $SI_{INT} =$
$= 0.36 * 0.76 = 0.27$

$SI_{VIS} = 0.82 * 0.92 = 0.75$; $SI_{VER} =$
$= 0.18 * 0.59 = 0.11$

$SI_{ACT} = 0.73 * 0.86 = 0.63$; $SI_{REF} =$
$= 0.27 * 0.46 = 0.12$

$SI_{SEQ} = 0.45 * 0.68 = 0.31$; $SI_{GLO} =$
$= 0.55 * 0.77 = 0.42$

Finally, the average $SI_{ST1} = 0.385$

In the same way, we could easily calculate the suitability indexes for LOs and LEs, e.g., $SI_{ST1}$ for LOs in $Uol_1$ could be equal, for example, to 0.500, and $SI_{ST1}$ for LEs in $Uol_1$ could be equal, for example, to 0.600:

$SI_{ST1}$ for LOs in $Uol_1 = 0.500$;
$SI_{ST1}$ for LAs in $Uol_1 = 0.385$; and
$SI_{ST1}$ for LEs in $Uol_1 = 0.600$

The average $SI_{ST1}$ for $Uol_1 = 0.495$

Thus, $f(x) = \left(\frac{\sum_{i=1}^{n} SI_i}{n}\right)\left(\sum_{j=1}^{m} \alpha_j f_j(x)\right) =$
$= 0.495 * 0.775 = 0.384$

In the case when the evaluation criteria seem to be of unequal importance for the evaluators, one should apply another MCDM method, e.g., the TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution).

In this case,

$$f(x) = \left(\frac{\sum_{i=1}^{n} SI_i}{n}\right) \cdot$$
$$\cdot\left(\frac{\sqrt{\sum_{j=1}^{m}(\alpha_j(\tilde{r}_{ij}-\tilde{r}_{ij}^{-}))^2}}{\sqrt{\sum_{j=1}^{m}(\alpha_j(\tilde{r}_{ij}-\tilde{r}_{ij}^{+}))^2}+\sqrt{\sum_{j=1}^{m}(\alpha_j(\tilde{r}_{ij}-\tilde{r}_{ij}^{-}))^2}}\right),$$
$$\tilde{r}_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{n} r_{ij}^2}}. \tag{3}$$

$\tilde{r}_{ij}^{-}\left(\tilde{r}_{ij}^{+}\right)$ – the worst (best) value of normalized $j$ criteria to the alternative.

Since the influence of the criteria on the evaluation outcomes is different, the vector of the criteria value that determines the importance of criteria is stipulated (Kurilovas and Vinogradova 2016). The TOPSIS method allows us to explicitly interpret the absolute evaluation of the alternative as well as its deviation magnitude from the average attained at the best and the worst alternatives (Hwang and Yoon 1981). Moreover, empirical experience suggests that the TOPSIS method provides the most stable results when the input data is oscillating (Podviezko and Podvezko 2014).

Values of the cumulative criterion $\left(\sum_{j=1}^{m} \alpha_j f_j(x)\right)$ of the TOPSIS method fall in the interval of its possible values [0,1]. The cumulative criterion $\left(\sum_{j=1}^{m} \alpha_j f_j(x)\right)$ takes the value 1 for the best alternative, for which the best values of criteria are chosen, and takes the value 0 for the worst alternative, for which the worst values of criteria are chosen.

The most important advantage of the method for choosing it for the absolute evaluation is that by taking all criteria values, the averages of corresponding best and worst values, the resulting cumulative criterion of the method TOPSIS $\left(\sum_{j=1}^{m} \alpha_j f_j(x)\right)$ takes the value 0.5 (Podviezko and Podvezko 2014).

In the case when the weights are equal:

Thus,

$$f_{UoL_1}(x) = \left(\frac{\sum_{i=1}^{n} SI_i}{n}\right)\left(\sum_{j=1}^{m} \alpha_j f_j(x)\right) =$$

= 0.495 * 0.4400 = 0.2178

and

$$f_{UoL_2}(x) = \left(\frac{\sum_{i=1}^{n} SI_i}{n}\right)\left(\sum_{j=1}^{m} \alpha_j f_j(x)\right) =$$

= 0.495 * 0.5600 = 0.2772

In the case when the weights are different, e.g., $\alpha_j$ = (0.3, 0.2, 0.2, 0.3):

Thus,

$$f_{UoL_1}(x) = \left(\frac{\sum_{i=1}^{n} SI_i}{n}\right)\left(\sum_{j=1}^{m} \alpha_j f_j(x)\right) =$$

= 0.495 * 0.4108 = 0.2033

and

$$f_{UoL_2}(x) = \left(\frac{\sum_{i=1}^{n} SI_i}{n}\right)\left(\sum_{j=1}^{m} \alpha_j f_j(x)\right) =$$

= 0.495 * 0.5892 = 0.2917

The final results are as follows:

| *Methods* | *Equal* | | *Different* | |
|---|---|---|---|---|
| | *Additive utility function* | *TOPSIS* | *Additive utility function* | *TOPSIS* |
| $UoL_1$ | 0.775 | 0.2178 | 0.77 | 0.2033 |
| $UoL_2$ | 0.775 | 0.2772 | 0.77 | 0.2917 |

The ranging of the final results is as follows:

| *Methods* | *Equal* | | *Different* | |
|---|---|---|---|---|
| | *Additive utility function* | *TOPSIS* | *Additive utility function* | *TOPSIS* |
| $UoL_1$ | 1–2 | 1 | 1–2 | 1 |
| $UoL_2$ | 1–2 | 2 | 1–2 | 2 |

The evaluation results of the methodology have shown that the TOPSIS method gives more precise evaluation results in comparison with the simple experts' utility function in the formula (1). Therefore, we could conclude that the TOPSIS formula (3) could be successfully used in formula (1) instead of the experts' additive utility function. The values of the TOPSIS or the experts' additive utility function in formula (1) show acceptance and use of the UoL technology, and the average probabilistic suitability index in formula (1) shows the suitability of the UoL for a particular student.

## Conclusion

In the paper, the authors propose certain personalized learning units/scenarios for the acceptance, use and suitability of a particular student model, which is based on MCDA criteria identification principles, a learning component-based evaluation model and the Educational Technology Acceptance & Satisfaction Model (ETAS-M), which is, on its own behalf, based on the UTAUT model. The personalization of UoL components and the whole UoL should be guaranteed by the correct identifying and corresponding probabilistic suitability indexes.

The proposed model is component-based, on the one hand, and a ETAS-M-based on the other. It's more convenient, in comparison with a purely components-based model, because it is based only on the evaluation of the suitability of UoLs and how it is used by the users, and it fully reflects their needs and points of view. Additionally, this kind of model does not require specific high-level technological expertise from the experts-evaluators.

On the other hand, the proposed model is better than the pure ETAS-M/UTAUT-based model because of its flexibility, as it takes into consideration the corresponding suitability indexes of all learning components of a UoL, i.e., the proposed model reflects the suitability of a given UoL to particular students.

Finally, in the paper, a personalized UoLs evaluation method was proposed by the formula (1).

The examples have shown that the TOPSIS method could also be successfully used in the formula (1) to identify the values of the acceptance and usage of a UoL.

The proposed methodology is feasible to be applied in real-life pedagogical situations in educational institutions. In order to easily create and evaluate personalised UoLs, educational institutions should establish FSLSM-based student profiles, use high quality vocabularies of learning components and have enough expertise to identify corresponding suitability indexes.

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**APIE PERSONALIZUOTŲ MOKOMŲJŲ MODULIŲ PRIIMTINUMO, NAUDOJAMUMO IR TINKAMUMO VERTINIMO METODOLOGIJĄ**

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S a n t r a u k a

Straipsnio tikslas yra pristatyti personalizuotų mokomųjų modulių / scenarijų priimtinumo, naudojamumo ir tinkamumo konkretiems besimokantiesiems metodologiją (t. y. modelį ir metodą). Mokomaisiais moduliais / scenarijais čia vadinamos mokomųjų komponentų (mokomųjų objektų, mokomųjų veiklų ir mokomosios aplinkos) metodologinės sekos. Aukštos kokybės mokomieji moduliai turi būti sudaryti iš mokomųjų komponentų, kurie yra optimizuoti konkrečių besimokančių asmenų atžvilgiu pagal jų asmeninius poreikius, t. y. mokymosi stilius. Straipsnyje optimizuoti mokomieji moduliai reiškia mokomuosius modulius, sudarytus iš komponentų, kurie turi aukščiausius tikimybinius tinkamumo rodiklius konkrečių besimokančiųjų atžvilgiu pagal Felderio ir Silverman mokymosi stilių modelį. Straipsnyje pateikta personalizuotų mokomųjų modulių vertinimo metodologija yra grindžiama (1) daigiakriterių sprendimų analizėje gerai žinomais vertinimo kriterijų identifikavimo principais; (2) edukacinių technologijų priimtinumo ir pasitenkinimo modeliu (ETAS-M), grįstu gerai žinomu vieningos technologijų priimtinumo ir naudojamumo teorijos (UTAUT) modeliu, ir (3) tikimybiniais tinkamumo rodikliais mokomųjų komponentų tinkamumui konkretiems besimokantiesiems identifikuoti pagal jų mokymosi stilius. Straipsnyje pristatyta personalizuotų mokomųjų modulių priimtinumo, naudojamumo ir tinkamumo vertinimo metodologija yra absoliučiai nauja mokslo literatūroje, pateikta ir metodologijos įgyvendinimo pavyzdžių, naudojant skirtingus vertinimo kriterijų svorius. Ši metodologija yra taikytina realiose gyvenimo situacijose, kai mokytojai turi padėti mokiniams kurti ir taikyti mokomuosius modulius, kurie yra tinkamiausi pagal jų poreikius, ir tuo būdu pagerinti švietimo kokybę ir efektyvumą.

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