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**RESEARCH ON MULTIPLE CRITERIA
DECISION MAKING METHODS AND
ITS APPLICATION FOR EVALUATING
THE QUALITY OF PERSONALISED
LEARNING SCENARIOS**

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Abstract

The main aim of the report is to analyse and propose a novel probabilistic model to evaluate the quality of personalised learning units (scenarios), i.e. their suitability to particular students according to their learning styles. In the report: first, systematic literature review on scientific methods and techniques on evaluating the quality of personalised learning units (scenarios) and other learning components is performed, and second – an original research methodology and some examples of evaluating the quality and suitability of learning units to particular students' needs is presented. Expert evaluation method based on multiple criteria decision making approach is applied in the report. Students' learning styles are analysed according to Felder-Silverman learning styles model. Students' learning styles are necessary to create learning units that should be optimal for particular learners. These learning units should consist of suitable learning components (learning objects, learning methods and activities, virtual learning environments: learning tools, apps etc.) optimal to particular students according to their learning styles. Original probabilistic model is presented and applied to establish not only students' learning styles but also probabilistic suitability of inquiry-based learning activities to students' learning styles. An example of personalised learning unit based on original intelligent software agent is presented in more detail. Examples of the expert evaluation of the quality of learning units and suitability to students' learning styles are also presented in the report.

Keywords: learning personalisation, evaluation, personalised learning, learning styles, probabilistic model, learning units, intelligent technologies

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Introduction

The aim of the report is two-fold: first, to perform systematic literature review on scientific methods and techniques on evaluating the quality of personalised learning units and, second, to analyse and propose a novel probabilistic model to evaluate the quality of personalised learning units.

Learning personalisation became very important and popular topic in scientific literature during last years (e.g. [1], [2], [3], [4], [5], [6], [7], [8], [9]). Therefore, research topic of evaluating the quality of personalised learning components (i.e., learning objects, learning methods and activities, technologies and apps learning paths and environments) has become highly demanded, and there are some relevant methods and techniques proposed in the area (e.g. [10], [11], [12], [13], [14]).

Since the overall aim of the report is to create and evaluate the quality of a probabilistic model for a whole personalised learning units / scenarios consisting of suitable learning components optimal to particular students according to his/her profile/model, several formulas and tables are proposed further for some components of the learning units / scenarios.

Systematic Review

In order to identify existing scientific methods and techniques on evaluating the quality of personalised learning paths (scenarios), basic systematic literature review method devised by Kitchenham [15] has been used. The following research questions have been raised to perform systematic literature review under this method:

- 1 Question: What methods and techniques on evaluating the quality of personalised learning exist in scientific literature?
- 2 Question: What methods and techniques of multiple criteria decision making in education exist in scientific literature?

Systematic literature review was performed on 13 May 2016 in Thomson Reuters Web of Science database. Search history is presented in Figure 1.

We see that during the last years (2014-2016), 121 papers were found on the topic “learning AND personalised AND quality”, including 75 articles, and 30 papers were found on the topic “multiple criteria decision making AND education”, including 23 articles.

After applying systematic review methodology [15], on the last stage 11 suitable articles were identified to further detailed analysis on the topic “learning AND personalised AND quality”, and 3 – on the topic “multiple criteria decision making AND education”. Thus, 14 articles have left for further analysis.

Set	Results		Save History	Open Saved History
# 7	23	TS=(multiple criteria decision making AND education) Refined by: DOCUMENT TYPES: (ARTICLE) Timespan=2014-2016 Search language=Auto		
# 6	30	TS=(multiple criteria decision making AND education) Timespan=2014-2016 Search language=English		
# 4	75	TS=(learning AND personalised AND quality) Refined by: DOCUMENT TYPES: (ARTICLE) Timespan=2014-2016 Search language=Auto		
# 3	121	TS=(learning AND personalised AND quality) Timespan=2014-2016 Search language=English		

Figure 1. Search history in Thomson Reuters Web of Science database

The analysis results are as follow:

Lin et al. [16] argue that an important issue in personalised learning is to provide learners with customised learning according to their learning characteristics. Their paper focused attention on scheming learning map. The learning goal can be achieved via different pathways based on alternative materials, which have the relationships of prerequisite, dependence, and sequence. Owing to distinct learner characteristics, different learning materials with various forms have distinct effects on learners, such as learning performance (benefit objective), learning time (cost objective), and so forth. Accordingly, scheming learning map is the trade-off multiple objectives optimisation. Hence, this paper first proposed an innovative approach based on enhanced genetic algorithm with Technique for Order Preference by Similarity to Ideal Solution, to facilitate the search for the near-optimal solution of learning map. Moreover, a web-based learning management system based on the proposed approach was developed to help instructors facilitate the customised learning itineraries for learners.

Fernandez and Delgado [17] think that, in the context of the European Higher Education Area, the traditional tutoring concept has to evolve to become a more complete and personalised learning instrument. Several aspects must be covered by tutoring services, which can be grouped into three: academic or assistance to the student in the teaching-learning processes, curricular or guidance in the choice of their academic and professional itinerary, and personal or support regarding their integral development. In the paper, after factor analysis with factor rotation, three dimensions of security/confidence, personal interest/motivation and utility for the academic subjects were identified. According to [17], the parallelism between these dimensions with the personal, curricular and academic tutoring dimensions that the student-centred learning supports, confirms the need for implementation of this new model of tutoring.

In Yang and Ju [18] study, the authors design a resource evolution support system called learning cell system. Two key issues – the intelligent control of content evolution and the dynamic semantic associations between resources – are addressed by combining technologies of semantics, trust evaluation, rule-based reasoning, and association rule mining. The operating effect of this system shows that it can control content evolution and effectively build semantic associations among resources.

In Limongelli et al. [19], the authors tackle the aim of providing the teacher with social collaboration tools, to support the process of course construction. Such a process comprises several distinct steps, from concept mapping, through selection of suitable learning material, to the final stages of delivery in a LMS. The authors argue that it is a heavy process, through which teachers have to spend a lot of time to build or to retrieve the right learning material from local databases or from specialised repositories on the web. The authors address the topic of modelling the teacher. The model they define aims to give teachers a personalised support, encompassing consideration for their own pedagogy, teaching styles, and teaching experience during course creation.

Saleem et al. [20] propose a decision strategy based service ranking model. Considering that different users follow different strategies in different contexts at different times, the authors apply a machine learning algorithm to learn a personalised ranking model for individual users based on how they select services in the past. The authors have implemented and tested the proposed approach, and their experiment results show the effectiveness of the approach.

Martinez-Cruz et al. [21] claim that in the literature one can find countless approaches for generating personalised recommendations and all of them make use of different users' and/or items' features. In this sense, building accurate profiles plays an essential role in this context making the system's success depend to a large extent on the ability of the learned profiles to represent the user's preferences and needs. The authors argue that an ontology works very well to characterise the users profiles involved in the process of generating recommendations. In [21], the authors develop an ontology to characterise the trust between users using the fuzzy linguistic modelling, so that in the recommendation generation process they do not take into account users with similar ratings history but users in which each user can trust. [21] presents the ontology and provides a method to aggregate the trust information captured in the trust-ontology and to update the user profiles based on the feedback.

Lu et al. [22] argue that a recommender system aims to provide users with personalised online product or service recommendations to handle the increasing online information overload problem and improve customer relationship management. According to [22], researchers and managers recognise that recommender systems offer great opportunities and challenges for education and other domains, with more recent successful developments of recommender systems for real-world applications becoming apparent. This paper therefore reviews up-to-date application developments of recommender systems, clusters their applications into eight main categories including e-learning, and summarises the related recommendation techniques used in each category.

Bajenaru and Smeureanu [23] proposed model particularity consists in implementation of domain specific ontologies using Protege environment using a personal methodology according to the student's knowledge profile. The settling of the students' profile is based on processing their entry data to allow the training process personalisation, automatically generated by the intelligent system. In [23], the student's profile is identified by integrating a static and a dynamic model. Due to this methodology, students will be able to receive the learning material by an e-learning system, according to their level of knowledge, preferences and interests: a personalised model driven approach.

Kosir et al. [24] consider that user profiling represents an important initial step in personalising web services and in building recommendation systems. In [24], the authors propose a hybrid method that combines time-decay and profile correction using prototype profiles. The additional profile correction step considers the interests of similar users and expands the interest scores beyond the concepts detected in the user's past actions, which facilitates faster profile adaptation to the user's new interests. Experiments revealed that it is crucial to build the user's profile using a large number of events from his/her past and to update the profile regularly.

According to Schuwer and Kusters [25], one of the claims the OER movement makes is that availability of open digital learning materials improves the quality of education. The promise is the ability to offer educational programs that take into account specific demands of the learner. The authors consider that advanced IT support for both the modelling of the learning materials and services and a configurator to be used by a learner are necessary conditions for this approach.

With the aim of developing an evaluation method to evaluate creative products in science and technology class, Lu et al. [26] study constructed a set of criteria with data collected from teachers and students. The analytic hierarchy process (AHP), a multiple criteria decision-making tool for single rater, was selected for the purpose of weighting and evaluating students' products. However, the traditional AHP used one rater's pair-wise comparisons; its subjectivity and complexity limit its applications in school. For solving this problem, the [26] study developed an advanced technique, called direct-rating AHP (DR-AHP), to extend the applicability of the traditional AHP. The DR-AHP is used to obtain weights or preferences for criteria/alternatives by a process of directly ranking criteria/alternatives by single/multi rater(s), checking consistency, and developing a rank vector matrix. The results of the study showed its superiority in objectivity and efficiency over traditional ways of evaluation. The results also demonstrate how the AHP and DR-AHP are capable of helping evaluators systematically construct criteria and/or to evaluate students' creative products for classroom instruction as well as during many other activities.

Renzulli and Gaesser [27] consider that research over the past several decades supports an expanded system for gifted student identification. Most researchers and practitioners agree that isolated IQ or achievement score is no longer enough. In [27], the authors discuss the critical issue of having a cohesive relationship between the identification process and education programming for high ability students. The authors claim that conception or definition issue should be consistent with the types of services for which students are being identified.

In Wu et al. [28] study, the multiple criteria decision-making approach was adopted to construct an objective and effective analytical model of critical factors influencing college students' creativity. The fuzzy Delphi method was first employed to screen the critical influential factors (criteria/sub-criteria) categorised by four dimensions: "Individual qualities," "Family background," "School element," and "Community", which are synthesised from the literature review and in consultation with experts from relevant fields in Taiwan. Then, the fuzzy analytic hierarchy process (FAHP) method was applied in [28] to calculate the relative weights of the selected critical criteria/sub-criteria that impact creativity for college students. The authors claim that the prioritised weights analysed by the proposed model can not only serve as a useful self-assessment tool for college students to better understand key influential factors on their own creative abilities for developing their potential creativity, but also can provide an important reference for educational units and/or interested parties in policy making and strategies to help effectively promote college students' creativity development.

Findings of the Systematic Review

Although there are several studies conducted that identified some methods and techniques to creating or identifying different personalised learning components (mainly, learning objects), there is no sound methodology to creating the whole personalised learning units / scenarios.

On the other hand, some multiple criteria decision making approaches to evaluating the quality of different learning components exist, but there is still no psychologically, pedagogically, mathematically, and technologically sound methodology to creating and evaluating the whole personalised learning units, and research in this area should be further developed.

A Novel Probabilistic Method to Create and Evaluate the Quality and Suitability of Learning Scenarios to Particular Student's Needs

According to [29], learning software and all learning process should be personalised according to the main characteristics/needs of the learners. Learners have different needs and characteristics i.e. prior knowledge, intellectual level, interests, goals, cognitive traits (working memory capacity, inductive reasoning ability, and associative learning skills), learning behavioural type (according to his / her self-regulation level), and, finally, learning styles.

According to [30], future high-quality and effective education means personalisation plus intelligence. Learning personalisation means creating and implementing personalised learning units / scenarios based on recommender system suitable for particular learners according to their personal needs (i.e. learning styles). Educational intelligence means application of intelligent (smart) technologies and methods enabling personalised learning to improve learning quality and efficiency [30].

In personalised learning, first of all, integrated learner profile / model should be implemented, based on e.g. Felder & Silverman learning styles model (FSLSM) [31]. Dedicated psychological questionnaires (e.g. Soloman and Felder's Index of Learning Styles questionnaire [32]) should be applied here. After that, one should integrate the rest features in the learner profile (knowledge, interests, goals, cognitive traits, learning behavioural type etc.).

After that, ontologies-based personalised recommender system should be created to suggest learning components (learning objects, activities and methods, platforms/environments, tools, apps etc.) suitable to particular learners according to their profiles [29], [30].

Thus, personalised learning units / scenarios could be created for particular learners. A number of intelligent technologies should be applied to implement this approach, e.g. ontologies, recommender systems, intelligent agents, decision support systems to evaluate quality and suitability of the learning components, personal learning environments etc. [30].

In order to propose psychologically, pedagogically, mathematically, and technologically sound methodology to creating and evaluating the whole personalised learning unit / scenario, several approaches, concepts and methods are applied in the paper as follows.

They are:

- The concept of learning unit / scenario developed in [33], [34],
- Learning personalisation method based on application of intelligent technologies [30],
- A stochastic approach for automatic and dynamic modelling of students' learning styles proposed in [35],
- Personalised learning objects' recommendation method presented in [29] and [36], and
- Personalised learning activities recommendation method proposed in [37].

According to [34], learning activities (LAs) are one of the core structural elements of the 'learning workflow' model for learning design. They form the link between the roles and the learning objects (LOs) and services in the learning environment. The activities describe a role they have to undertake within a specified environment composed of LOs and services. Activities take place in a so-called 'environment', which is a structured collection of LOs, services, and sub-environments. LO is referred here as any digital resource that can be reused to support learning [34]. Virtual Learning Environment (VLE) is referred here as a single piece of software, accessed via standard Web browser, which provides an integrated online learning environment [34].

Therefore, we can conclude that learning unit / scenario could consist of learning activities, learning objects and learning environment referred here as services package. This kind of services package in e-learning theory is commonly known as VLE. Thus, we can divide learning unit / scenario into three components, namely LAs, LOs and VLE [34].

Kurilovas and Zilnskiene [33], [34] argue that, from technological point of view, one can divide the learning software (in our case LOs, LAs and VLE) quality criteria into ‘internal quality’ and ‘quality in use’ criteria. ‘Internal quality’ is a descriptive characteristic that describes the quality of software independently from any particular context of its use, while ‘quality in use’ is evaluative characteristic of software obtained by making a judgment based on the criteria that determine the worthiness of software for a particular project or user [33].

LOs and VLE quality criteria (incl. personalisation) and evaluation methods are quite widely analysed in scientific literature (e.g. [12], [36], [38]). LA quality criteria and personalisation features are conversely analysed insufficiently.

According to [33], LA quality criteria are ‘conformance with learning goal’, ‘interoperability and flexibility’, ‘feedback and appropriate assessment’ (‘internal quality’ criteria) as well as ‘ease of use’, ‘active engagement of learners in learning’, ‘facilitation of interaction and collaboration’, ‘employment of multiple teaching/learning methods’, and ‘incorporation of learners backgrounds, experiences and expectations’ (‘quality in use’ criteria).

In this report, Felder-Silverman learning styles model (FSLSM) [31] is applied to create and evaluate personalised LS. FSLSM is known as the most suitable for engineering education and e-learning. FSLSM classifies students according to where they fit on 4 scales pertaining to the ways they receive and process information (dimensions) as follows:

- (1) By Information type: Sensory (SEN) – concrete, practical, oriented towards facts and procedures vs Intuitive (INT) – conceptual, innovative, oriented towards facts and meaning;
- (2) By Sensory channel: Visual (VIS) – prefer visual representations of presented material – pictures, diagrams, flow charts vs Verbal (VER) – prefer written and spoken explanations;
- (3) By Information processing: Active (ACT) – learn by trying things out, working with others vs Reflective (REF) – learn by thinking things through, working alone, and
- (4) By Understanding: Sequential (SEQ) – linear, orderly, learn in small incremental steps vs Global (GLO) – holistic, systems thinkers, learn in large leaps [31].

Probabilistic model of learning styles according to FSLSM is presented in [35]. It is based on the results of filling in Solomon and Felder Index of Learning Styles questionnaire [32] by students. Before starting any learning activities, every student should fill in this questionnaire consisting of 44 questions, 11 questions for each of 4 aforementioned FSLSM dimensions (i.e. ways the students receive and process information). Students’ preferences are considered as probabilities in the four-dimensional FSLSM.

Due to the probabilistic nature of learning style in the FSLSM, Dorca et al. [35] approach is based on probabilistic learning styles combinations. Each learning styles combination is a 4-tuple composed by one preference from each FSLSM dimension. Students’ probable learning styles are stored in student profile / model as values of the

interval [0,1]. Those values represent probabilities of preference in each of FLSM dimension. Therefore, students' learning styles are stored as probability distributions considering each learning FLSM dimension. Considering this kind of model, students' learning styles (LS) are stored in their profiles / models according to Definition 1:

Definition 1:

$LS = \{(PR_{SEN} = x; PR_{INT} = 1 - x), (PR_{VIS} = y; PR_{VER} = 1 - y), (PR_{ACT} = z; PR_{REF} = 1 - z), (PR_{SEQ} = v, PR_{GLO} = 1 - v)\}$, where

PR_{SEN} is the probability of the student's preference for the Sensory LS; PR_{INT} is the probability of the student's preference for the Intuitive LS;

PR_{VIS} is the probability of the student's preference for the Visual LS; PR_{VER} is the probability of the student's preference for the Verbal LS;

PR_{ACT} is the probability of the student's preference for the Active LS; PR_{REF} is the probability of the student's preference for the Reflective LS; and

PR_{SEQ} is the probability of the student's preference for the Sequential LS; and PR_{GLO} is the probability of the student's preference for the Global LS.

Consequently, $PR_{SEN} + PR_{INT} = 1$; $PR_{VIS} + PR_{VER} = 1$; $PR_{ACT} + PR_{REF} = 1$; $PR_{SEQ} + PR_{GLO} = 1$. Calculations of probabilities should be done according to Formula 1:

$$PR_i = \frac{A_i}{11} \quad (1)$$

The Formula (1) divides by 11 the number of favourable answers to LS (A_i), considering that Index of Learning Styles [32] has 11 questions for each FLSM dimension, totalling 44 questions. In (1), i represent a LS in FLSM dimension, and A_i represent the number of favourable answers to a LS. PR_i is a probability of preference to a learning style by the student in a FLSM dimension, according to aforementioned Definition 1.

An example would be if a student answers 7 questions favourable to the Sensory LS, and 4 questions favourable to the Intuitive LS: $PR_{SEN} = 7 / 11 = 0.64$, and $PR_{INT} = 4 / 11 = 0.36$, and further on to all dimensions of FLSM. Thus, one could obtain e.g. the following LS initially stored in his/her student profile / model:

Table 1. Example of LS initially stored in the student profile / model

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

Since the aim is not only to present probabilistic model to establish students' learning styles but also to create probabilistic model of suitability of learning components of

the learning units to particular students' according their learning styles, inquiry-based learning (IBL) activity is used as an example.

Inquiry-based learning activity and sub-activities are presented in [37] based on [39]. According to [37], [39], IBL activity consists of a number of sub-activities as follows: A1: Orienting and asking questions; A2: Hypothesis generation; A3: Planning; A4: Investigation; A5: Analysis and interpretation; A6: Model exploration and creation; A7: Conclusion and evaluation; A8: Communication and justifying; A9: Prediction; and A10: Discover relationships.

According to [37] research methodology, in order to interrelate FSLSM and IBL activities, a special questionnaire was created for Lithuanian teachers-experts in the area. The questionnaire was created using FSLSM [31] and IBL activities and sub-activities vocabulary according to [39]. The experts have been asked to fill in the questionnaire in terms of establishing suitability of proposed IBL activities and sub-activities to students' learning styles according to FSLSM. The level of suitability have been proposed to express in linguistic variables 'bad', 'poor', 'fair', 'good' and 'excellent'. After teachers experts had filled in the questionnaire, the authors have mapped linguistic variables into non-fuzzy values using trapezoidal fuzzy numbers as presented in [13].

In [37], suitability of IBL activities and sub-activities to FSLSM is presented in Table 3. IBL activities are divided into sub-activities, and all those sub-activities are evaluated by the experts in terms of their suitability to students' learning styles. Expert evaluation method based on multiple criteria decision making approach is applied here. Suitability ratings obtained (see [37] Table 3) mean the aggregated level of suitability of particular IBL sub-activities to particular learning style. If one should multiply these suitability ratings by probabilities of particular students' learning styles according to Table 1, he/she should obtain probabilistic ratings/values of suitability of particular IBL sub-activities to particular student's learning style according to Formula 2:

$$PRV_{ACT} = PR_{ACT} * V_{ACT} \quad (2)$$

This Formula should be applied for each IBL sub-activity analysed in [37], where PRV_{ACT} means probabilistic value (level) of suitability of particular IBL sub-activity to particular student according to his/her preference to Activist learning style, PR_{ACT} means probabilistic value of the student's preference to Activist learning style (e.g. 0.73 according to Table 1), and V_{ACT} means the value of suitability of particular IBL sub-activity to Activist learning style (according to [37] Table 3).

Accordingly, one could calculate all probabilistic values (PRVs) of suitability of all IBL sub-activities to all students according whose data is stored in the student profile/model. In all cases, one should obtain PRVs as values of the interval [0,1].

Thus, according to Formula (2),

$PRV_{ACT} = 0.73 * 0.86 = 0.63$ for IBL sub-activity A1.1 (Observe phenomena),
 $PRV_{GLO} = 0.55 * 0.79 = 0.43$ for IBL sub-activity A2.1 (Select and complete hypotheses),

$PRV_{VIS} = 0.82 * 0.88 = 0.72$ for IBL sub-activity A3.2 (Equipment and actions),
 $PRV_{INT} = 0.36 * 0.86 = 0.31$ for IBL sub-activity A4.1 (Explore) etc.

The higher PRV the higher is the student's preference to particular IBL sub-activity, and vice versa.

Accordingly, PRVs mean the index of particular learning component's suitability to particular student. These suitability indexes should be included in the recommender system, and all learning components should be linked to particular students according to their suitability indexes. The higher suitability index the better the learning component fits particular student's needs. Thus, optimal learning unit (i.e. learning unit of the highest quality) for particular student means a methodological sequence of learning components (LAs, LOs to be learnt and VLE) having the highest suitability indexes. The level of students' competences, i.e. knowledge / understanding, skills and attitudes / values directly depends on the level of application of optimal learning units / scenarios in real pedagogical practice.

Since the overall aim of the research is to create a probabilistic model for a whole personalised learning unit / scenario consisting of suitable learning components (LOs, LAs and VLE) optimal to particular students according to his/her profile / model, one should apply Formula 1, appropriate Table 1, and Formula 2 for all components of the learning paths/scenarios.

Thus, pedagogically and technologically sound vocabularies/standards for learning components, such as IEEE LOM [40] for learning objects and [39] for leaning activities such as IBL should be prepared and stored in the recommender system. Furthermore, collective intelligence of experts and students (see e.g. top-down vs bottom-up evaluation approach [12]) should be used to evaluate suitability of learning components to particular learner needs (like in [37]).

Finally, evaluation of created learning units / scenarios should be performed by applying multiple criteria decision making models and methods as proposed e.g. in [12], [33], [34].

Conclusion

Future high-quality and effective education means personalisation plus intelligence. Learning personalisation means creating and implementing personalised learning paths/scenarios based on recommender system suitable for particular learners according to their personal needs (i.e. learning styles). Educational intelligence means application of intelligent (smart) technologies and methods enabling personalised learning to improve learning quality and efficiency. In personalised learning, first of all, integrated learner profile / model should be implemented. After that, it's necessary to integrate the rest features in the learner profile (knowledge, interests, goals, cognitive traits, learning behavioural type etc.). After that, ontologies-based personalised recommender system should be created to suggest learning components (learning objects, activities and methods, platforms/environments, tools, apps etc.) suitable to particular learners according to their profiles / models.

Thus, personalised learning units / scenarios could be created for particular learners according to their profiles. A number of intelligent technologies should be applied to implement this approach, e.g. ontologies, recommender systems, intelligent agents, decision support systems to evaluate quality and suitability of the learning components, personal learning environments etc.

In the report, probabilistic model for a whole personalised learning unit / scenario consisting of suitable learning components optimal to particular students according to their profiles is proposed. The model is based on students' probabilistic learning styles and expert evaluation of suitability of different learning components to students' learning styles.

Thus, the indexes of particular learning component's suitability to particular students could be calculated. All learning components in the recommender system should be linked to particular students according to their suitability indexes. The higher suitability index the better the learning component fits particular student's needs. The optimal learning unit (i.e. learning unit of the highest quality) for particular student means a methodological sequence of learning components (LAs, LOs to be learnt and VLE) having the highest suitability indexes. The level of students' competences, i.e. knowledge / understanding, skills and attitudes / values directly depends on the level of application of optimal learning units / scenarios in real pedagogical practice.

For this purpose, pedagogically and technologically sound vocabularies / standards for learning components should be created and stored in the recommender system. Furthermore, collective intelligence of experts and students should be used to evaluate suitability of learning components to particular learner needs.

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