On Suitability Index to Create Optimal Personalised Learning Packages

Eugenijus Kurilovas[1,2(✉)], Julija Kurilova[1], and Tomas Andruskevic[3]

[1] Vilnius University Institute of Mathematics and Informatics, Vilnius, Lithuania
jevgenij.kurilov@mii.vu.lt, saragosa21@gmail.com

[2] Vilnius Gediminas Technical University, Vilnius, Lithuania
jevgenij.kurilov@vgtu.lt

[3] Vilnius University Faculty of Mathematics and Informatics, Vilnius, Lithuania
tomas.andruskevic@mif.vu.lt

Abstract. The paper aims to present a novel probabilistic method to creating personalised learning packages. The method is based on learning components' suitability to students needs according to their learning styles. In the paper, the authors use Felder-Silverman Learning Styles Model and an example of Inquiry Based Learning (IBL) method. Expert evaluation method based on trapezoidal fuzzy numbers is applied in the research to obtain numerical values of suitability of learning styles and learning activities. Personalised learning packages should consist of learning components (learning objects, learning activities and learning environments) that are optimal (i.e. the most suitable) to particular students according to their learning styles. "Optimal" means "having the highest suitability index". Original probabilistic method is applied to establish not only students' learning styles but also probabilistic suitability of learning activities to students' learning styles. An example of personalised learning package using IBL activities is presented in more detail.

Keywords: Learning styles · Learning packages · Probabilistic method · Suitability index · Expert evaluation

1 Introduction

The aim of the paper is to present a novel probabilistic method to creating personalised learning packages. The method is based on learning components' suitability to students needs according to their learning styles (LS). Expert evaluation method based on application of trapezoidal fuzzy numbers is applied in the paper. Personalised learning packages should consist of smaller learning components (learning objects, learning activities and environments) that should be optimal (i.e. the most suitable) to particular students according to their LS.

The main research question of the paper is whether there is a methodology to create optimal personalised learning packages, and, if so, what should this methodology be based on. The answer is that such methodology should be based on analysis of learning components' suitability indexes to students' personal needs.

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Suitability Index presented in the paper is the main value used to establish the preference list of learning components according to their suitability level to students' LS. It is based on probabilistic model of students' LS and ratings (values) of learning components' suitability to particular students according to their LS.

The rest of the paper is organised as follows: related research is presented in the following Section, research methodology is presented in Sect. 3, Sect. 4 presents research results, and Sect. 5 concludes the paper.

2 Related Research

2.1 Learning Personalisation

Learning personalisation became very popular topic in scientific literature during the last years [2, 6, 14, 21, 25, 26, 36, 38, 39]. Research topic on creating full learning packages (units) and smaller learning components that should be optimal (i.e. the most suitable) to particular students based on expert evaluation techniques has also become highly demanded, and there are some relevant methods and techniques proposed in the area [19, 20, 27, 37].

The overview of literature shows that there has not been a concrete definition of personalisation so far. The main idea is to reach an abstract common goal: to provide users with what they want or need without expecting them to ask for it explicitly [29]. From the educational point of view, personalisation attempts to provide for an individual tailored products, services, information, etc. A more technical standpoint to personalisation is linked with the modelling of Web objects (products and pages) and subjects (users), their categorisation, organising them to achieve the desired personalisation. According to Sampson [31], personalisation provides training programmes that are customised to individual learners, based on an analysis of the learners' objectives, current status of skills/knowledge, LS preferences, as well as constant monitoring of progress. The concept of personalised learning becomes increasingly popular. It advocates that instruction should not be restricted by time, place or any other barriers, and should be tailored to the continuously modified individual learner's requirements, abilities, preferences, background knowledge, interests, skills, etc. The personalised learning concept signifies a radical departure in educational theory and technology, from "traditional" interactive learning environments to personalised learning environments.

According to [32], some of the most prominent characteristics of this shift can be summarised as follows: (1) while "traditional" learning environments adopt the one-to-many learning mode, personalised learning environments are based on the one-to-one or many-to-one learning concept (i.e. one, or many tutors for one learner); (2) traditional learning environments usually pose a number of constraints in relation to the learning setting; personalised learning environments, on the other hand, facilitate learning independent of time, location etc.; (3) traditional learning environments are usually being designed for the "average learner"; while, in personalised learning environments, the learning material and sequencing, learning style, learning media etc., depend on the individual learner's characteristics, i.e. background, interests, skills, preferences etc.; (4) in traditional learning environments, the curriculum, learning units etc., are determined by the tutor, while in personalised learning settings, they are based on the learner's requirements (self-directed learning).

2.2 The Educational Perspective

According to [34], the concept of personalised learning builds mainly on the cognitive and constructivist theories of learning. Instructional principles of cognitive theories argue for active involvement by learners, emphasis on the structure and organisation of knowledge, and linking new knowledge to learner's prior cognitive structures. Constructivist instructional theory, on the other hand, implies that instructional designers determine which instructional methods and strategies will help learners to actively explore topics and advance their thinking. Learners are encouraged to develop their own understanding of knowledge [22].

Several research efforts have been devoted in the identification of the dimensions of individual differences. One of the most prominent research areas in this context concerns the learning styles and learning differences theory, which implies that how much individuals learn has more to do with whether the educational experience is geared towards their particular style of learning. LS are strategies, or regular mental behaviours, habitually applied by an individual to learning, particularly deliberate educational learning, and built on her/his underlying potentials. Learners are different from each other, and teaching should respond by creating different instruction for different kinds of learning. Learners also differ from each other in more subject-specific aptitudes of learning, e.g. some being better at verbal than numerical things, others vice versa [22].

There are numerous methodologies and tools that attempt to categorise learners according to differences in learning and cognitive styles. The most well-known of these efforts include Felder and Silverman LS Model [7]; Multiple Intelligences [8]; Grasha-Riechmann Student LS Scales [9]; Honey & Mumford LS [10]; the Myers-Briggs Type Indicator [15]; Kolb LS Theory [16]; and Auditory, Visual, Tactile/Kinaesthetic LS [33]. According to [32], in order for these methodologies and tools to be effectively applied, we need to be able to (1) accurately classify each learner according to a selected taxonomy of individual differences, and (2) determine which are the characteristics of the learning environment that are appropriate for this category of learners.

2.3 The Technological Perspective

Several notions are used to define personalised virtual learning environments.

According to [32], intelligent learning environments are capable of automatically adapting to the individual learner, and therefore constitute the most promising technological approach towards the realisation of the personalised learning concept. An intelligent learning environment is capable of automatically, dynamically, and continuously adapting to the learning context, which is defined by the learner characteristics, the type of educational material being exchanged etc.

According to [3], Adaptive Educational Hypermedia is a relatively new direction of research within the area of adaptive and user model-based educational applications

Adaptive Educational Hypermedia systems build a model of the individual user/learner, and apply it for adaptation to that user.

There are several works performed in the area. They are presented in [22], e.g. research on Intelligent Adaptive Learning Environments, on adaptivity features to a regular learning management system to support creation of advanced eLessons, and on diagnosing students' LS in an educational hypermedia system.

2.4 Application of Expert Evaluation Techniques in Education

With the aim of developing an evaluation method to evaluate creative products in science and technology class, Lu et al. [28] 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 [28] 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.

Renzulli and Gaesser [30] 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. [40] 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 [40] to calculate the relative weights of the selected critical criteria/sub-criteria that impact creativity for college students.

In this paper, a novel research methodology is proposed to personalise learning.

3 Research Methodology

According to [22], 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 [24], future high-quality and effective education means personalisation plus intelligence. Learning personalisation means creating and implementing personalised learning packages (units) based on recommender system suitable for particular learners according to their personal needs. Educational intelligence means application of intelligent (smart) technologies and methods enabling personalised learning to improve learning quality and efficiency.

According to [13], (a) pedagogical change is necessary to improve learning outcomes for students, and (b) the main success factors in implementing personalised learning packages are: (1) identification of students' LS; (2) identification and application of suitable learning activities, methods, learning objects, tools and apps according to students' LS; and (3) use of proper sets and sequences of learning methods while implementing learning packages.

In personalised learning, first of all, integrated learner profile/model should be implemented, based on e.g. Felder & Silverman Learning Styles Model (FSLSM) [7]. Dedicated psychological questionnaires (e.g. Soloman and Felder's Index of LS questionnaire [35]) 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, environments, tools, apps etc.) suitable to particular learners according to their profiles [22, 24].

Thus, personalised learning packages could be created for particular learners. A number of intelligent (smart) 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. [24].

In order to propose psychologically, pedagogically, mathematically, and technologically sound methodology to creating and evaluating the whole personalised learning package, several approaches, concepts and methods are applied in the paper as follows. They are: (1) the concept of learning package/unit developed in [17, 18]; (2) learning personalisation method based on application of intelligent technologies [24]; (3) a stochastic approach for automatic and dynamic modelling of students' learning styles proposed in [4]; (4) personalised learning objects' recommendation method [5, 22], and (5) personalised learning activities recommendation method based on expert evaluation techniques proposed in [12].

4 Research Results

4.1 Probabilistic Model of Learning Styles

According to [17], 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 [17]. 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 [17]. Therefore, we can conclude that learning package (unit) could consist of LAs, LOs 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 the whole learning package/ unit into three components, namely LAs, LOs and VLE [17].

Kurilovas and Zilnskiene [17, 18] 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 [18].

LOs and VLE quality criteria (incl. personalisation) and evaluation methods are quite widely analysed in scientific literature [5, 20, 23]. Conversely, LA quality criteria and personalisation features are analysed insufficiently.

In this paper, Felder-Silverman LS Model (FSLSM) [7] 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:

- By Information type: Sensory (SEN) vs Intuitive (INT);
- By Sensory channel: Visual (VIS) vs Verbal (VER);
- By Information processing: Active (ACT) vs Reflective (REF), and
- By Understanding: Sequential (SEQ) vs Global (GLO).

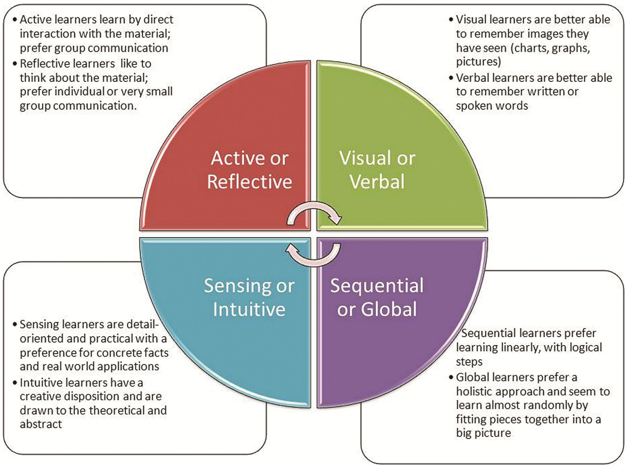

Fig. 1. FSLSM dimensions.

Probabilistic model of learning styles according to FSLSM is presented in [4]. It is based on the results of filling in Soloman and Felder Index of LS questionnaire [35] by students. 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 (Fig. 1).

Due to the probabilistic nature of LS in the FSLSM, Dorca et al. [4] approach is based on probabilistic LS combinations. Each LS combination is a 4-tuple composed by one preference from each FSLSM dimension. Students' probable LS are stored in student profile/model as values of the interval [0,1]. Those values represent probabilities of preference in each of FSLSM dimension. Therefore, students' LS are stored as probability distributions considering each FSLSM learning dimension. Considering this kind of model, students' LS are stored in their profiles/models according to Definition 1:

Definition 1: LS = $\{(\mathrm{PR}_{SEN} = x; \mathrm{PR}_{INT} = 1 - x), (\mathrm{PR}_{VIS} = y; \mathrm{PR}_{VER} = 1 - y), (\mathrm{PR}_{ACT} = z; \mathrm{PR}_{REF} = 1 - z), (\mathrm{PR}_{SEQ} = v, \mathrm{PR}_{\mathrm{GLO}} = 1 - v)\}$, 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, $\mathrm{PR}_{SEN} + \mathrm{PR}_{INT} = 1$; $\mathrm{PR}_{VIS} + \mathrm{PR}_{VER} = 1$; $\mathrm{PR}_{ACT} + \mathrm{PR}_{REF} = 1$; $\mathrm{PR}_{SEQ} + \mathrm{PR}_{GLO} = 1$. Calculations of probabilities should be done according to Formula 1:

$$PR_i = \frac{A_i}{11} \tag{1}$$

The Formula (1) divides by 11 the number of favourable answers to LS (A_i), considering that Index of LS [35] has 11 questions for each FSLSM dimension, totalling 44 questions. In (1), i represent a LS in FSLSM dimension, and A_i represent the number of favourable answers to a LS. PR_i is a probability of preference to a LS by the student in a FSLSM 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: $\mathrm{PR}_{SEN} = 7 / 11 = 0.64$, and $\mathrm{PRI}_{INT} = 4/11 = 0.36$, and further on to all dimensions of FSLSM. 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

4.2 Learning Activities and Learning Styles Suitability Index

Since the aim of the paper is not only to present probabilistic model to establish students' LS but also to create probabilistic method to obtain suitability of learning components of the learning packages to particular students' according their LS, Inquiry-Based Learning (IBL) activity is used as an example.

IBL activity and sub-activities are presented in [12] based on [1]. According to [1, 12], 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 [12] 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 [7] and IBL activities and sub-activities vocabulary according to [1]. The experts have been asked to fill in the questionnaire in terms of establishing suitability of proposed IBL activities and sub-activities to students' LS 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 [19]. In [12], the Table of suitability of IBL activities and sub-activities to FSLSM is presented. IBL activities are divided into sub-activities, and all those sub-activities are evaluated by the experts in terms of their suitability to students' LS. Expert evaluation method is applied here. Suitability ratings obtained in [12] 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' LS according to Table 1, he/she should obtain probabilistic ratings/values of suitability of particular IBL sub-activities to particular student's (i.e. Active) LS according to Formula 2:

$$\mathrm{PRV}_{ACT} = \mathrm{PR}_{ACT} * \mathrm{V}_{ACT} \tag{2}$$

This Formula should be applied for each IBL sub-activity analysed in [12], where PRV_{ACT} means probabilistic value (level) of suitability of particular IBL sub-activity to particular student according to his/her preference to Activist LS, PR_{ACT} means probabilistic value of the student's preference to Activist LS (e.g. 0.73 according to Table 1), and V_{ACT} means the value of suitability of particular IBL sub-activity to Activist LS (according to [12]).

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 indexes 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 those Suitability Indexes. The higher Suitability Index the better the learning component fits particular student's needs.

Thus, optimal learning package (i.e. learning package 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 packages in real pedagogical practice.

Thus, in order to create a probabilistic model for a whole personalised learning package consisting of suitable learning components optimal to particular students according to their profiles, one should apply Formula 1, appropriate Table 1, and Formula 2 for all aforementioned components of the learning packages.

Thus, pedagogically and technologically sound vocabularies/standards for learning components, such as IEEE LOM [11] for LOs and [1] for LAs such as IBL or Problem-Based Learning [22] 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 [20]) should be used to evaluate suitability of learning components to particular learner needs [12].

Finally, evaluation of created learning packages should be performed by applying multiple criteria decision making methods as proposed e.g. in [17, 18, 20].

5 Conclusion

Future high-quality and effective education means personalisation plus intelligence. Learning personalisation means creating and implementing personalised learning packages based on recommender system suitable for particular learners according to their personal needs. 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, ontologies-based personalised recommender system should be created to suggest learning components suitable to particular learners according to their profiles. Thus, personalised learning packages could be created for particular learners according to their profiles. A number of intelligent (smart) technologies should be applied to implement this approach, e.g. ontologies, recommender systems, intelligent agents, expert evaluation techniques etc.

In the paper, probabilistic method to create the whole personalised learning packages consisting of suitable learning components optimal to particular students according to their learning styles is proposed. The method 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. The main limitation of the paper is that the only example of the learning components, i.e. inquiry-based learning activities, was analysed in terms of its suitability to learners.

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 package (i.e. learning package of the highest quality) for particular student means a methodological sequence of learning components with 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 packages in real pedagogical practice.

For this purpose, pedagogically and technologically sound vocabularies of 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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