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## Enhancing existing e-learning systems by single and group recommendations

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**Abstract:** The personalised recommendations are used routinely in today's e-learning systems especially in computer science and engineering domains. Students' personal characteristics that influence learning styles and collaboration, well accepted in education domain are generally omitted in the domain of recommendation. We propose a methodology for enhancing existing e-learning systems with personalised recommendations for learning groups (including groups formations based on the learning styles). For the evaluation we investigate computer science and engineering students' learning styles and distribution of personality characteristics in order to better understand their behaviour and needs in such a system. As an example usage of the proposed methodology we present an extension of existing e-learning system in the domain of programming by considering learning styles and group collaboration. As the result of proposed methodology, students reached statistically significant improvement of their knowledge level when learning in groups using proposed recommendation approach and groups formation (considering students' learning styles).

**Keywords:** learning styles; e-learning; group recommendation; collaborative learning; personalities; programming.

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## 1 Introduction

The extensive increase of MOOCs popularity has been observed in the recent years. More and more courses and disciplines are proposed to reflect the trend of modern education principles (Spector, 2014). The increasing trend of e-learning systems popularity in technical disciplines can be observed. This is true not only for student courses but for the professionals as well (Kilicay-Ergin and Laplante, 2013).

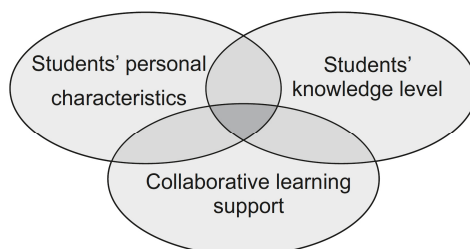
The collaborative support learning within e-learning systems can help to reduce some of the personality characteristics limitations of some students (e.g., introversion, diffidence) and to vitally involve them to the active learning process. Moreover, the personalised recommendations are often available for the students to help them in the learning process. Today, researches focus on improving recommendation approaches for single learners and designing methods to help him/her to achieve better results in possibly a shorter period of time (Michlík and Bieliková, 2010; Derntl and Hummel, 2005; Cakula and Sedleniece, 2005; Hwang et al., 2014). As the personalities of students differ, their activity and preferences are various. The most common and controversial representative of personality traits connected to the student is learning style. The students' learning styles are important to consider in the technical disciplines where various students' skills are needed, as they directly influence students' performance (Zywno, 2003; Litzinger et al., 2007; Montequín et al., 2013).

There exist several studies claiming that learning styles are not relevant characteristic and even more some researchers claim that nothing as learning styles exists (Dembo and Howard, 2007). In this paper, we do not support or destroy the myth of learning styles in the education. In fact, the opposite is true, we use students' learning styles as the one distinctive personality trait (which can be easily replaced by another). Learning styles serve only for extending capabilities of particular learning system and enable the students learning group formation. This is necessary for enhancing the e-learning system by single or group recommendation.

In today's e-learning systems, we can distinguish three major directions based on their main focus:

- 1 systems providing personalised recommendations for students (mainly based on students' knowledge level)
- 2 adaptive systems based on high-level students' characteristics (often considering personality characteristics or learning styles)
- 3 systems supporting active learning and collaboration.

In spite of the fact that each of these views is generally well-established principle in the standard education, and we can find their combination two by two, the complex combination (Figure 1 – dark area) is not used in today's e-learning systems.

**Figure 1** Different views on today's e-learning systems supporting a collaboration

Note: Not only students' knowledge level is considered, but their personalities play important role when a collaborative learning is performed.

Considering first direction, the positive effect of students' knowledge-based recommendations in e-learning has been massively shown in the literature (de Bra et al., 2003; Michlík and Bieliková, 2010; Šimko et al., 2010; Hammami and Mathkour, 2015; Debska and Kubacka, 2014). Optimal course material for study in these systems is usually chosen on the grounds of estimated learners' actual knowledge level on particular topic (considering various aspects, e.g., oblivion). Similarly, positive aspects of students' learning styles based adaptation of course materials have been reported in the literature (Felder and Silverman, 1988; Al-Dujaily et al., 2013; Dwivedi and Bharadwaj, 2013; Huang et al., 2011), but this aspect is very rarely reflected in today's e-learning systems that accommodate personalised recommendation.

Considering third direction we observe that despite the group learning in the standard education is well established and used (Díaz Redondo et al., 2014; Stahl et al., 2006; Williamson and Rowe, 2002), it is not considered much in today's e-learning systems. This can be partially explained by the basic shortcoming of standard group or collaborative learning – the need for the students of specific group to be present in one place. Another challenge of the group learning is how to provide a personalised recommendations for the whole group of students while there are users with various knowledge levels, attitudes and needs.

For this purpose, the group recommendation considering students' specific characteristics (from the learning style point of view) seems to be a promising approach, while the group recommendation combines single-user's preferences in order to choose items interesting for every group member. In such a learning group students can learn, discuss or solve a recommended task suitable for all group members. The group can be constructed ad-hoc from actually present students (educational system) or the learning style or other useful personality trait can be considered to create groups. Next, the group or collaborative learning (including the personalised recommendation) is performed.

The main stream of research suggests inclusion of diversity (e.g., cultural) within the groups to achieve better performance from the problem solving point of view (Thomas, 1999; Laughlin, 2011). The task of learning programming language, however, is not based on the problem solving principle. Moreover, from the heterogeneity point of view, the groups are formed only based on similar learning style (which affects only the recommended material type). Thanks to this, we are not restricting any other student's characteristic and the group diversity from other perspectives is maintained.

In this paper we investigate the learning styles and personality variance of students in order to identify suitable personality trait which can be use for the group formation. The main goal of this paper, however, is to enhance existing e-learning systems by

collaborative learning support and group recommendations in education process (Figure 1 – dark area). For this purpose, we propose a methodology to enhance general e-learning systems in order to provide recommendations boosted by students' learning styles and use these recommendations for active group learning. We employ learning styles and personality variance of students as an example of particular enhancement and describe it as a part of evaluation of our methodology. We evaluated our proposed approach in the domain of programming course.

## **2 Related work**

Three basic views in modern e-learning systems can be distinguished. Firstly, high level adaptation systems focus on course material, which is generally adapted to the learner's high level preferences and characteristics, e.g., learning styles. Secondly, the knowledge-based personalised systems monitor and predict learners' knowledge levels and thus personalise the course material from the optimal learning path for student point of view. Finally, e-learning systems providing collaborative support are often based on the 'question and answer' approach or on the generic discussion forums.

There are several approaches to the personalised recommendation in the adaptive e-learning systems. The research is mainly focused on the identification of students' preferences for the recommendation of appropriate learning resources (Goyal et al., 2012). For this purpose various recommendation methods are used – content-based approaches (e.g., de Bra et al., 2003; Šimko et al., 2010), collaborative methods (e.g., Wan et al., 2008), or their combinations (e.g., Zakrzewska, 2010; Bieliková et al., 2014; Chen et al., 2014).

The well-known system Adaptive Hypermedia Architecture (AHA!) (de Bra et al., 2003) provides content-based recommendations and an adaptive navigation to students in e-learning environment. It uses a layered user model that stores information about students' knowledge and his/her interaction and supports a knowledge spreading to related concepts. The user model is refreshed while interacting with the system and further used to the recommendation and navigation adaptation regarding to defined rules.

ALEF (Šimko et al., 2010) is another example of adaptive educational system developed and used at our university. Its domain model consists of learning materials and their metadata which are connected to each other. In Michlík and Bieliková (2010), the authors proposed an extension to this system with a personalised recommendation of learning objects for single-user considering limited time of the learning. Students' target knowledge of particular subject is set before the learning and learning objects are recommended in purpose to help the student to learn a defined set of concepts in a given time to a given level. When evaluating the objects suitable for the recommendation a thematic suitability of a learning object, a difficulty suitability and an object repetition suitability are taken into account.

Wan et al. (2008) in their approach multidimensional collaborative recommendation approach use learners' role-based multi-dimensional collaborative recommendation considering students' activity as a sequence of actions that a user makes while interacting with the system. They divide the students into two groups (roles) using Markov chain – beginners and advanced learners. These two roles together with explicit learning objects

ratings are the basis for recommendation, while a weight of rating of advanced learners is higher.

Chen et al. (2014) proposed hybrid recommender based on item-based collaborative filtering and sequential patterns. The collaborative part predicts relevant learning content based on similar students' rating, while the sequential pattern part mines the students' behaviour and discovers frequent patterns of clicks with minimal support. In the evaluation on the peer-to-peer basis, the proposed approach outperforms its components and the baseline respectively.

Adaptive e-learning systems model somehow student's knowledge, which is considered when the personalised recommendations are generated. On the opposite, student's learning styles are generally omitted when the personalisation (based on the students' knowledge) is available. Generally, learning styles are considered only to adapt the course material (Velázquez and Assar, 2007; Surjono, 2011; Mustafa and Sharif, 2011) and not in a combination to student's knowledge level. Mahnane et al. (2013) addressed this problem in their work, while proposed e-learning system includes a pedagogical sub module. This module considers student's learning and thinking styles as well and tries to adapt to students' characteristics.

From the e-learning system success point of view, recommending not only an appropriate learning material (from the students' learning style point of view), but simultaneously the 'best' learning object (from the students' actual knowledge level point of view) is critical.

When focusing on a collaborative learning, interesting fact was discovered by Hauger and Köck (2007) when comparing total of 13 e-learning systems. None of the systems which provide some level of a personalisation does not support a collaboration between students. This reveals huge gap between research theories, when the positive aspects of personalised education have been pointed out as well as the positive aspect of active group learning (North et al., 2000) but these are not used as a combination. Moreover, to our best knowledge current e-learning systems do not support the active group learning from the personalised approaches application point of view.

### **3 Learning styles application study**

The importance of the usage students' learning styles and corresponding teaching styles have been widely researched in the literature, while the positive aspects on the students' knowledge have been reported (Manochehr, 2006; Mustafa and Sharif, 2011; Hwang et al., 2012). Partially, the learning style can be considered as the one of the personality characteristics. From the learning style point of view every student can be characterised based on the four dimensions (Felder and Silverman, 1988):

- perception – sensory vs. intuitive
- input – visual vs. auditory
- processing – active vs. reflective
- understanding – sequential vs. global.

User modelling from the learning styles perspective is not trivial and covers various dimensions of how students process a new information. The following information on learning style description is summarised based on (Felder and Silverman, 1988).

Perception differentiates between a sensory and an intuitive way how the new information is captured by the students. The sensory perception is characterised by observing and capturing an information by the sense-perception. In the opposite, the intuitive perception is subconscious based on a speculation and an imagination.

Students with dominant sensory perception prefer known approaches and clear sequences. Moreover, ‘sensors’ prefer learning the facts and dislike surprises. In the opposite, students with dominant intuitive perception prefer an innovation, discovering relationships and are able to easily switch to new concepts.

Input refers to a way how the information is received. Students with the visual input preference, prefer an information presented by various figures, tables or graphs. Students with the auditory input preference, memorise a voice-based information or prefer a discussion of concepts.

Processing of the new information can be divided into two basic types: an active experimentation with a new information or deep analysis – reflection. The active experimentation refers to the discussion and testing of lessons learned, while the reflexive processing refers to the introspective observations (thinking quietly) of these information.

Generally, active students need some time to practical examination of a curriculum, prefer exercises to study texts and tend to prefer group learning, while reflexive students need time to thinking.

Understanding is the last dimension of learning styles. The sequential understanding is used in a standard education, while the continual sequence of concepts is presented to the students. On the contrary, the global understanding prefers the ‘big picture’ of the studied problem, which helps to understand lower parts.

The students with the sequential understanding prefer gradual exploring of a new information – step by step, logically following previous one. Students with the global understanding prefer ‘random’ learning without seeing connections, often producing novel approaches.

In order to provide an analysis of learning styles diversity of computer science and engineering students (and to explore the possibility to use learning style traits as the distinctive attributes for learning groups formation), we performed an experiment where the total of 276 students of bachelor study program informatics (years 2011–2013) were asked to complete the Felder and Silvermann learning styles questionnaire (Felder and Silverman, 1988). The main question we investigated was the variety of students’ learning styles in the domain of technical and informatics discipline and the possibility of the usage such information in the personalised recommendation process. In other words, we address these questions:

- What is the distribution of learning styles across the computer science students?
- What are the personality characteristics of these students?
- Are these characteristics diverse in order to use them in the recommendation generation process?

**Table 1** Diversity of student's learning styles (276 students of informatics study program)

	Perception				Input			Understanding		
	Sensory	Intuitive	Sensory/ intuitive	Visual	Auditory	Visual/ auditory	Sequential	Global	Sequential/ global	
Processing										
Active	42	5	42	42	0	27	24	14	51	
Reflexive	12	4	17	16	2	15	10	4	103	
Active/reflexive	67	14	73	94	4	56	27	24	19	
Sensory	N/A	N/A	N/A	89	1	31	35	10	86	
Intuitive	N/A	N/A	N/A	12	2	9	1	10	12	
Sensory/intuitive	N/A	N/A	N/A	71	3	58	25	22	85	
Visual	N/A	N/A	N/A	N/A	N/A	N/A	26	28	108	
Auditory	N/A	N/A	N/A	N/A	N/A	N/A	2	2	2	
Visual/auditory	N/A	N/A	N/A	N/A	N/A	N/A	23	12	63	

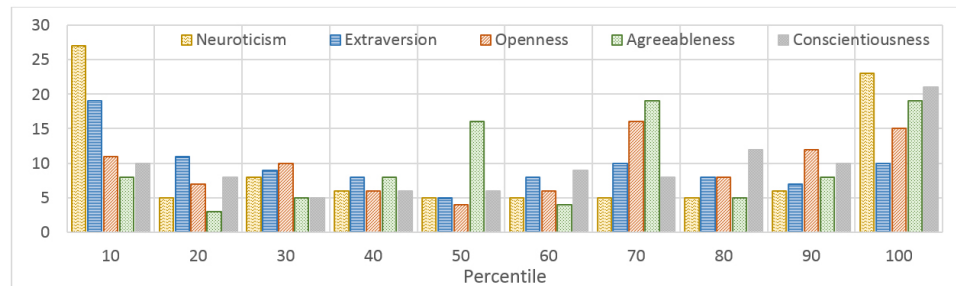
Note: N/A: refers to irrational combination.

As we can see (Table 1), students' learning styles are equally distributed across all available types except the intuitive perception and the auditory input. This is an expected result as technology oriented subjects are open (by the intuition) to the visual inputs and the sensory perception where the facts are formulated more clearly and formal as graphs, images, etc.

Not only students' learning styles are interesting from the teaching point of view. Students' personality characteristics also play an important role (Lu et al., 2013), especially when study groups are formed – e.g., an introvert student does not often prefer discussion. There are several studies which compare students' learning styles to the Big Five personality characteristics, while some recommendations for students learning process have been deduced (e.g., extrovert students prefer an auditory input) (Komaraju et al., 2011). In order to better understand possibilities of its usage, we also focus on the diversity of students personalities. Based on the Neurocriticism-Extroversion-Openness Five Factor Inventory by McCrae and Costa (2004), we compared obtained results to the Big Five personality model and investigated the distribution of computer science and engineering bachelor students as well.

As we can see (Figure 2), there are extremes from the diversity point of view – students are extrapolated as it seems students have very low or on the other side very high scores in the neuroticism dimension. From the extraversion point of view, we obtained expected results – introverts outbalance extroverts. Openness and agreeableness are distributed equally, while some increase in higher score can be observed. Finally, scores in the conscientiousness dimension are moved to the higher values. Obtained results indicate that there are a lot of strong introverts, while we can observe large group of emotionally stable and on the opposite labile students (neuroticism). As we can expect there is also strong group of efficient/well-organised students (conscientiousness).

**Figure 2** Histogram of Big Five personality percentile characteristics of computer science students (see online version for colours)



Notes: Results obtained based on the neurocriticism-extroversion-openness five factor inventory, population percentile computed for the Slovak republic.

When comparing correlation of learning styles and big five personality characteristics, we found statistical significant correlation between the extraversion and the active processing ( $\alpha = .05, p = .205, r = .44$ ), the extraversion and the reflexive processing ( $\alpha = .05, p = .205, r = -.35$ ), the openness and the sensory perception ( $\alpha = .05, p = .205, r = -.37$ ) and the openness and the auditory input ( $\alpha = .05, p = .205, r = .26$ ). Obtained results confirm general rules, and indicate the study correctness (e.g., the active learning style involves an active experimentation as discussing which is correlated to extraversion



students, etc.). We can conclude that our students' personalities and also their learning styles are diverse and thus the adaptation of e-learning for such students can be beneficial (can be used as the distinctive attribute for group formation or content adaptation).

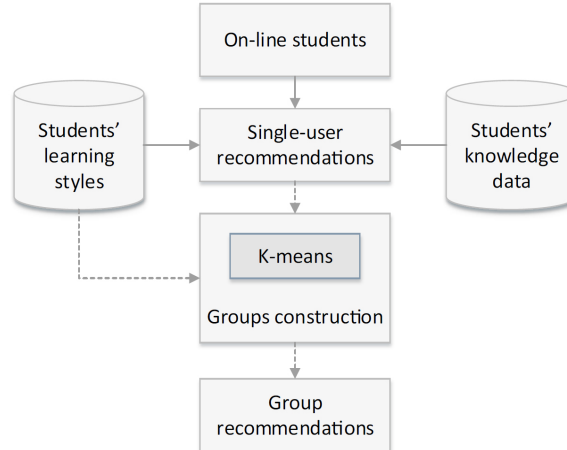
#### 4 Collaborative group learning support and learning styles

To bridge the gap between an active collaborative learning and the usage of students' learning styles in the e-learning we designed a group recommendation module which demonstrates the usage of the methodology for enhancing e-learning systems with students' learning styles and the collaborative support.

The proposed methodology consists of three stages (Figure 3):

- 1 modelling students' knowledge and their learning styles by various types of user models depending on the e-learning system
- 2 adjusting single-user personalised recommendations based on the relevance of learning objects according to students' learning styles (single-user recommendations are generated as defined in enhanced e-learning system)
- 3 supporting collaborative group learning by construction study groups based on the similar members' learning styles and construction of the group recommendations.

**Figure 3** Proposed enhancements for educational systems (see online version for colours)

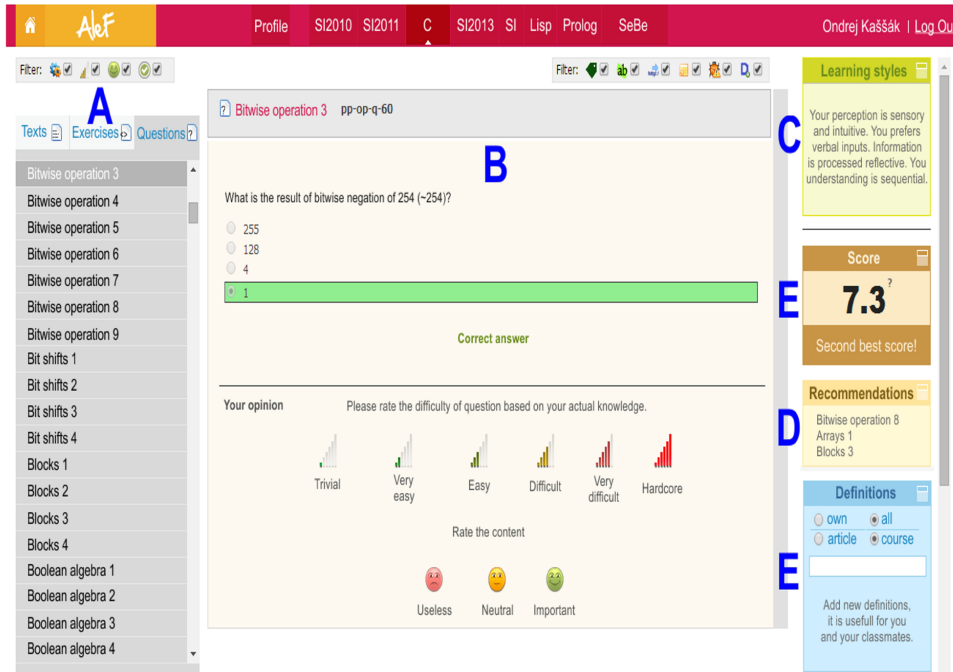


Notes: Based on students' learning styles, single-user recommendations are generated.

These single-user recommendations are aggregated in order to satisfy preferences of students, who are members of learning groups.

For the explanation of proposed methodology, we use the e-learning system ALEF in the domain of the programming learning at our faculty (Figure 4).

**Figure 4** Example of ALEF e-learning system screenshot (see online version for colours)



Notes: Student's knowledge is after interacting with a learning object stored in the user model automatically, while he/she can provide an additional information. A: menu providing several navigational styles based on the type of learning object. B: main content in the form of interactive examples. C: results of the student's learning style questionnaire. D: personalised recommendation for particular student. E: other functionality useful for current situation (course) and the student.

#### 4.1 User model

The starting point for recommendation in any form is a well formed user-model. In the case of the ALEF e-learning system, the user-model stores gathered information about the student's knowledge, interaction with the educational system and his/her explicit feedback. The recommendation is based on these characteristics. User-model for modelling user's knowledge is based on the computer-adaptive testing (Lincare, 2000), which has been extended with certainty factor to store the certainty that a student gains some knowledge (during the interaction with the system).

We have extended this model with learning styles of students developed by Felder and Silverman (1988), that describe a cognitive style in four dimensions: perception (sensing/intuitive), input (visual/verbal), processing (active/reflective) and understanding (sequential/global). To get the students' learning styles we incorporated an adaptive hierarchical questionnaire (Ortigosa et al., 2010) which introduces a new approach to predict students' learning styles by reducing the number of questions of original questionnaire presented by index of learning styles (from 11 to 4–6 questions per dimension). The decision trees (C4.5 algorithm) were constructed for every dimension by Ortigosa, which allow to react and reduce amount of question given to the subject in

order to determine his/her score. The student's learning style is then defined by a vector [equation (1)] of four values corresponding the four dimensions of learning styles in ranges from  $\langle 0, 1 \rangle$  and added to the student's user model.

$$\text{learning style}_{u \in \text{Users}} = \text{perception}_u, \text{input}_u, \text{processing}_u, \text{understanding}_u \quad (1)$$

#### 4.2 Single-user recommendation

First of all, we focus on enhancing standard – knowledge-based recommender with students' learning styles. Based on the users' knowledge modelled in the user model, the personalised recommendations of learning materials are generated for each student. Various approaches for the learning object (course material) relevance computation can be involved. Based on specific domain and course, the characteristic used in particular object relevance computation should be chosen, e.g.:

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for each  $o \in \text{Learning Objects}$  do
     $\text{rating}_{u \in \text{Users}, o} = \text{argmin}(c_1, c_2, \dots, c_n)$ 
end for

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where object characteristics  $c_1, c_2, \dots, c_n$  reflect important aspects of learning. In our experiments, we used the thematic relevance of learning object for specific student, the difficulty relevance and the relevance of repeating of specific learning object (Michlík and Bieliková, 2010). For every item the predicted rating is computed as the minimum of the item relevancies – thematic, difficulty and repetition relevance. Next, the set of objects and their predicted relevance (ratings) are ordered and Top-N relevant objects are recommended to the specific student.

We propose an enhanced approach, where object relevancies used in the e-learning system are adjusted in order to reflect student' learning styles.

*Adjusted learning object relevance based on the learning style* is computed as the relevance of the learning object  $o$  for specific user  $u$  (e.g., in ALEF system – thematic relevance, difficulty, prerequisite). The relevance is adjusted for every student and a learning object as an increase, a decrease or no change (some students are more tolerant to the difficulty, some prefer logical order, etc.) of the knowledge-based relevance (Table 2). In this manner, every student obtains most relevant learning objects, suitable for his/her knowledge level and learning style.

**Table 2** An example of the influence of the learning styles for the object relevance based on the psychology expert for the ALEF system

Relevance type	Increase	Decrease
Concept difficulty	Reflective processing	Active processing, global understanding
Prerequisite	Intuitive perception, global understanding	Sensory perception
Object difficulty	Active processing, sequential understanding	Reflexive processing

### 4.3 Recommendations to the group of students

The learning styles of students can be used not only in personalised recommendations, but we propose to use them also for the learning group construction and generating recommendations for such collaborative learning groups. The group formation plays an important role as the optimal student peer's result into beneficial collaboration (Magnisalis et al., 2011).

One of the standard problems of the e-learning in connection to the active group learning is the need for online students' presence (if the system supports online communication). As we want to motivate students to learn collaboratively, there is a need for the students to be online. In comparison to the standard collaborative learning, students do not have to be in one place, which extends the amount of students available.

To demonstrate the advantages of group recommendations and students' learning styles (we expect the students' knowledge improvement in comparison to the standard e-learning system) we propose to enhance the single-user recommendation in e-learning system by the group recommendation considering students' learning styles in order to minimise students' effort and to maximise the knowledge level obtained during the learning process (the students' learning style was used as one of the students' personality distinctive characteristics). We focused on an application of students' learning styles (obtained by a self-assessment questionnaire), which are used for the learning groups construction and to recommendation of the relevant content (based on the learning style characteristics).

Proposed approach consists of two basic steps:

- 1 create learning groups from actually online students (clustering based on the students' learning styles)<sup>1</sup>
- 2 aggregate single-user recommendations (generated as described in the section single-user recommendation) and provide the recommendation to the specific learning group.

First, the learning groups from the students actually present in the system are created. The process of the group construction and recommendation is based on an assumption that users with similar learning styles will achieve desired knowledge level more quickly in the comparison to users with various preferences.

After the groups are constructed, the second step – the aggregation of the single-user (every student of the learning group) recommendation is performed, in order to obtain one list of recommended items for the learning group. We propose to use the hybrid aggregation strategy because various homogeneity levels of groups can occur in the system (various knowledge levels or various learning styles). Based on the standard deviation of the recommendation for the group members is the aggregation strategy chosen as:

- minimal distance if the standard deviation is below defined level
- average value if the standard deviation is higher and includes defined level.

Parameter defining the level of the standard deviation can be set experimentally for the specific domain. In this manner, we obtain a list of recommended items for the particular

learning group, based on the single-user student recommendations enhanced by his/her learning style.

## 5 Evaluation

In order to investigate the effects of proposed e-learning enhancement methodology, we implemented proposed extensions to the e-learning system ALEF (Šimko et al., 2010). We focus on the single-user recommendations and the consideration of learning styles within the educational process. The group recommendation as the collaborative learning support tool was examined as well. We implemented proposed methodology as plugin extensions and performed several experiments. Because the educational system used for the evaluation does not include the audiovisual content, the input learning style was omitted during the evaluation.

### 5.1 Single-user recommendation boosted by learning styles

Firstly, we focus on the influence of learning style within the single-user recommendation. We were interested if the recommendations generated with the respect to the students' learning styles (adjusted with respect to Table 2) are preferred by the students more as the recommendation without the consideration of learning styles. For this purpose, we used the original single-user approach proposed in Michlík and Bieliková (2010) and our enhanced version (including consideration of the learning styles).

- *Hypothesis*: Enhanced learning styles recommendation approach is more preferred by students as recommendations provided without a learning style preference information.
- *Participants*: The total of 8 experts participated in this experiment, while experts had no information about used various recommendation approaches. All experts were PhD students teaching the course 'Programming language C' (male 23–25 years old).
- *Process*: For each participant, six recommendations generated by each method (six from the original and six from the learning styles enhanced approach) were mixed and presented in one list (12 items). Recommendations were generated for learning objects in the course 'Programming language C', while all experts were familiar with this language. Participants were asked to choose good recommendations (according to their best knowledge) in a particular situation. Moreover, the qualitative study – by interviewing experts was performed.
- *Results*: To compare the performance of both approaches (standard and learning styles boosted) we measured the ratio of clicks (the implicitly expressed feedback) for recommendations generated by each approach and randomly mixed. Proposed learning-styles boosted recommendations were chosen in 78% of clicks compared to the standard recommendation used in the ALEF e-learning system. The enhanced approach (considering the learning styles) thus outperformed the original approach. Moreover, every participant was asked to provide feedback after the experiments. Six out of eight experts reported that some of the recommendations were more

suitable for the actual needs – which are supported by the implicit feedback based on clicks. This is a promising result, as it indicates that learning styles improve the recommendation quality and the precision respectively.

## 5.2 *Group recommendation and learning styles*

We showed the positive aspects of application of students' learning styles to the personalised recommendation for students by enhancing the standard e-learning system. Next, we aim to evaluate the performance of the group recommendation for collaborative learning boosted by learning styles by performing a controlled live experiment.

- *Hypothesis:* Based on the results obtained from the single-user learning styles boosted recommendation we expect that – proposed group recommendation for the educational domain improves students' experience and knowledge level as when the standard single-user learning process (including recommendations) is performed.
- *Participants:* The total of 21 students of Informatics at our faculty was asked to learn the Lisp and Prolog language within the ALEF educational system. Participants were first-comers with both topics (20 males, 1 female, 12 in the second and 9 in the third year of bachelor degree).
- *Process:* Our contribution is based on employing group recommender to the e-learning system, we compared proposed approach to the well accepted collaborative filtering, which is often used in several systems. As we compared the performance of a single user learning to the proposed collaborative group learning, the experiment was split into two parts. Firstly, students had to learn alone – single-user recommendations were provided (computed by the enhanced approach considering learning styles, in which positive aspects were described in the experiment reported above). Next, these students were split into small groups (considering users' learning styles K-means algorithm was used to generate groups) and the group recommendation (boosted by learning styles) for the collaborative learning process was experienced. As we wanted to measure the knowledge impact of proposed enhancements, pre- and post-tests were performed in each part. The Prolog and Lisp language are generally not considered as equally difficult to learn. To avoid unnecessary bias, half of the students started with the Lisp and half with the Prolog language and in the next phase the groups were switched (Table 3). In this manner we created a controlled environment for the single and group collaborative learning respectively.
- *Results:* After the each part the pre- and post-test were evaluated and the knowledge increase was measured. As we can see (Table 4) during the group learning process (the group recommendations) students obtained higher knowledge level as when the single-user learning process was performed. Students in the group learning condition were able to communicate with other group members via a chat implemented in the system. The chat is an integral part of the group recommendation boosted learning – as the group recommendations without the possibility of the inter-group interaction are useless. As there are several reports in the literature, that anonymity increases the effectiveness of the groups (Jong et al., 2013), we wanted to encourage students to

communicate and to collaborate within the groups, and the anonymity within the chat was preserved.

**Table 3** Experiment settings and phases

<i>LISP</i>	<i>PROLOG</i>
Pre-test	Pre-test
Group A single learning	Group B single learning
Post-test	Post-test
Pre-test	Pre-test
Group B group learning	Group A group learning
Post-test	Post-test

**Table 4** The knowledge increase difference for the collaborative learning compared to the single-user learning

<i>Single-user</i>						<i>Group</i>					
<i>Lisp</i>			<i>Prolog</i>			<i>Lisp</i>			<i>Prolog</i>		
<i>Pre</i>	<i>Post</i>	<i>Delta</i>	<i>Pre</i>	<i>Post</i>	<i>Delta</i>	<i>Pre</i>	<i>Post</i>	<i>Delta</i>	<i>Pre</i>	<i>Post</i>	<i>Delta</i>
16%	60%	44%	14%	46%	32%	20%	81%	61%	7%	42%	35%
Average delta						Average delta					
38%						48%					

When comparing the total number of students' activity during the experiments (students' clicks on recommendations), students used generated recommendations approx. equally (347 clicks in the single-user recommendation, 321 clicks in the group recommendation).

In order to investigate statistical significance of the knowledge increase (based on the pre and post test results) we performed paired t-test. Obtained results are considered to be statistically significant ( $\alpha = 0.05$ ,  $p = 0.0347$ ,  $t = 2.2055$ ) and support our hypothesis that proposed group recommendation-based enhancement of the learning process considering students' learning styles improves the experience and knowledge level respectively.

As we pointed, there is no agreement of the learning style influence to the performance of students. In our study, we do not try to support or disprove such an evidence. From our point of view, grouping students based on some similar behaviour and preferences (e.g., learning styles, or other metric referring to their preferences during the learning process) helped us to form homogeneous groups, which were able to gain more knowledge during the same amount of time, thanks to the group recommendations.

Finally, students participated in the experiments were asked to provide remarks to the experiment (recommendations and learning approaches within e-learning system). The students indicated preference of the group-based learning, when some specific problem was discussed. When the standard and usual learning is performed by the students, they prefer to study alone. Proposed approach is thus beneficial where some exercises or questions are recommended. When 'only' some text is read by students, the main contribution of such an approach is ignored (the advantage of students with similar context or concept can be taken when asking for help – asked person has the context of the question which is not disturbing).

## **6 Conclusions**

There are plenty of e-learning systems used in various domains nowadays (Goyal et al., 2012), while all the time new systems are designed in order to cover new features and to improve students' experience (or the student's knowledge increase). Unlike this we propose novel methodology to enhance existing systems in order to support students' collaborative cooperation (including group recommendations). To support the collaborative cooperation within e-learning system, we proposed to create small ad-hoc study groups from online students. Next, the group recommendations are provided for such groups.

We showed that students' learning styles are evenly distributed across students, while some 'stereotypes' from personality characteristics (e.g., more introvert students) can be observed. We used students' personal characteristics (learning styles) as the distinctive attributes to create ad-hoc group and next to adjust weights of recommendations.

We proposed a methodology for enhancing existing e-learning systems by students' personal characteristics and the collaborative learning support with the group recommendations. To demonstrate proposed ideas we used layered user-model reflecting students' knowledge and enhanced it with students' learning styles. The learning styles are then used to prioritise students' preferences in the process of calculation the learning resources' suitability for the recommendation. We use a hybrid approach to aggregate single students' recommendations for group recommendation in order to support the collaborative learning.

As we showed in the Computer science and engineering domain, students' knowledge level was significantly improved by considering students' personal characteristics, e.g., learning styles. Moreover, the collaborative learning and group recommendations significantly improved the knowledge level, which students obtain during the learning process. This indicates that application of e-learning systems supporting collaborative learning is beneficial in such domains as programming education.

In our study, we have focused on the influence of group recommendation applied in the e-learning systems. As there is a need to generate study groups based on some similar behaviour or students' preferences, we used students' learning styles to generate study group (which can be easily replaced by other relevant characteristic). Because of this, we compared proposed approach to the standard and often-used collaborative filtering. It is clear, that the group-based recommendation in the e-learning system (when students are not physically present in one place) has to provide communication for these students (as the group interaction is one of the founding bricks of group recommenders). Because of these aspects, some of the knowledge improvement can be caused by students' communication, which in fact, supports our hypothesis that group recommendation (including within group communication) improved students' performance.

There are many possibilities for future research in this field, especially in exploring other properties of learning resources to be affected by students' personal characteristics, e.g., learning styles (including other domains as Computer science and Engineering students). Other possible extension to our approach is to enhance the group-creation process by taking into account not only students' learning styles but their personalities, preferences or learning process styles. Moreover, the long-term study (including repeated measures design) will help to explore group recommendation benefits on e-learning students' performance in more details.



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## Notes

- 1 Several group construction techniques can be involved with respect to the required groups size (two to four users).