# Increasing students' academic results in e-course using educational recommendation strategy

Martina Holenko Dlab, Nataša Hoić-Božić

***Abstract:*** *This paper presents research on implementing educational recommendation strategy, designed to provide personalization during moderated e-courses. Aimed at increasing students' academic results, the strategy includes recommendations that support students and groups while selecting between offered optional e-tivities, collaborators and Web 2.0 tools. In addition, advice regarding quantitative aspect of student's and group's contributions during e-tivities is provided. The strategy proved to be effective in a sense that students who received recommendations achieved better academic results in e-course.*

***Key words:*** *E-learning; Collaborative learning; Recommender Systems; ELARS, Web 2.0.*

## INTRODUCTION

Advances in the development of environments for e-learning were achieved by introduction of personalization mechanisms used to tailor the learning process to student's individual characteristics [4]. In recent years, changes in the field are influenced by so-called Web 2.0 [3] and e-learning 2.0 [6]. E-learning 2.0 promotes interaction between students that can be fostered by planning collaborative e-learning activities or e-tivities [15] such as discussions, collaborative writing, mental mapping, or blogging. Therefore, environments for e-learning 2.0 besides learning management systems (LMSs) usually contain Web 2.0 tools as well [3], [9]. These changes imply the need for new personalization mechanisms. To foster personalization within e-learning environments, recommender systems are increasingly used [5], [12].

The aim of the research described in this paper was to design educational recommendation strategy for personalization of collaborative e-tivities. The strategy contributes to the field of educational recommender systems by providing recommendations of items insufficiently present in the existing systems: optional e-tivities, collaborators, Web 2.0 tools and advice. Besides for individual students, recommendations are generated for groups of students as well. Characteristics that represent students and items are carefully chosen in order to enable recommendations in accordance with pedagogical criteria. Moreover, teachers are empowered to define the recommendation criteria according to the needs of specific e-tivity by modifying pre-defined recommendation rules. Proposed strategy was implemented within the E-Learning Activities Recommender System - ELARS [18] and evaluated using a comparative study. Results showed that students who received recommendations achieved better course results.

## RELATED WORK

Recommender systems support target user when accessing the items on the Web that are potentially useful or are in the scope of his/her interest [1]. Despite the present changes that affect e-learning, the most of existing educational recommender systems still emphasize knowledge transfer paradigm by recommending teaching materials (learning objects) or courses in general [7]. A smaller number of systems intended for moderated e-learning recommends a particular action. Their implementation in most cases includes support to the process of learning programming [14], [12]. Recent researches began to focus on the collaborative e-tivities [7], but not sufficiently. A domain independent approaches for recommending different actions are implemented within the TORMES system [16]. Other approaches include models for recommending learning peers [8] and for providing advice [2]. Target users in known systems are in the most cases individual students. Students are represented with preferences, learning styles, affective states, knowledge or communication level [16], [12]. In order to provide personalization within collaborative learning scenarios, recommender system should include a group model as well.

In the recommendation process, target user is presented with the item or a ranked list of items which are the most useful for him/her. Usefulness (utility) value is specified by the user or predicted. Prediction can be performed using a variety of input data and algorithms, but four main techniques can be identified. *Content-based recommendations* predict item's usefulness for the target user based on the usefulness of the similar items for him/her. Prediction can be based on utility values (*case-based*) or on user's characteristics (*attribute-based*). In *collaborative filtering*, items recommended to the target user are those with the highest utility for the similar users. The filtering presumes calculating similarity between the target user and other users (identification of nearest neighbors) and can be done in respect to users' characteristics (*attribute-based collaborative filtering*). *Knowledge-based recommendations* are generated based on expert's knowledge, represented with a set of "if...then..." rules (*constraint-based recommendations*). *Hybrid approaches* combine two or more mentioned techniques and often provide the most accurate recommendations [1], [13].

## ELARS RECOMMENDATION STRATEGY

During the recommendation process in ELARS (Fig. 1), recommendation algorithms are used to rank items (optional e-tivities, collaborators, Web 2.0 tools, advice) based on the calculated usefulness for target student or target group. Depending on the recommendation technique used, usefulness is calculated using data about items and/or students (groups) [11]. Students' (groups') characteristics are stored in the student and group model while activity model contains characteristic of the items, learning design definitions with adjustments of pedagogical rules, and other contextual information [10].

The reminder of this section brings description of items representations and recommendation algorithms for available types of items.

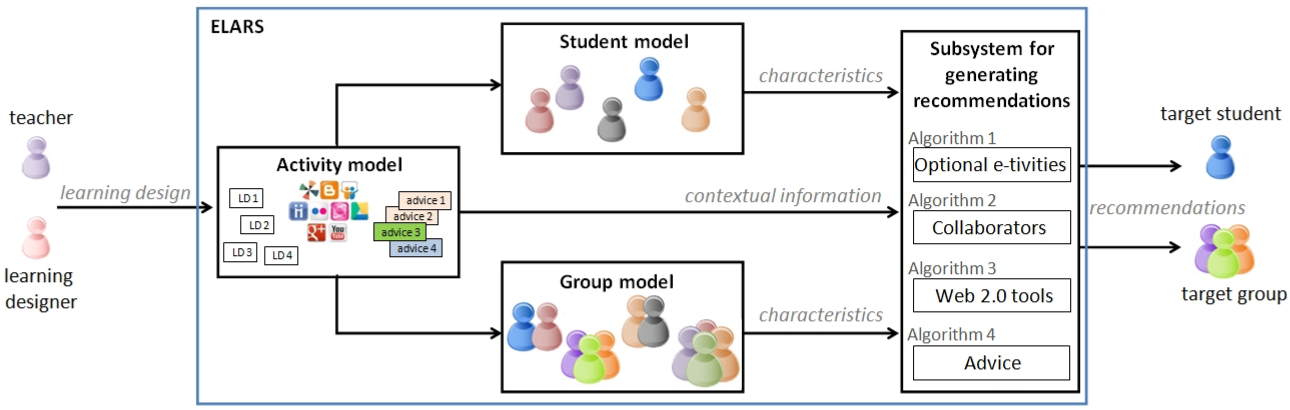


Figure 1 – Recommendation process in the ELARS system

### Optional e-tivities recommendations

Optional e-tivities recommendations support students and groups in choosing one of the offered optional e-tivities. Four groups of characteristics are used to represent users: *preferences of learning styles* according to VARK model (visual, aural, read/write, kinesthetic), preferences of Web 2.0 tools from e-learning environment, knowledge levels, and activity levels. At the beginning of the course, students solve standardized VARK questionnaire and enter results in the ELARS system. VARK model was selected as the most appropriate because it allows associating student's learning style preferences with characteristics of designed e-tivities in respect with its task and/or tool offered for its realization [17]. Students' *preferences regarding Web 2.0 tools* are also identified using a questionnaire in the ELARS system where students can specify how much they like a particular tool. *Knowledge level* is determined for every testing activity that the student participates in. It is calculated with respect to the accomplished results entered into the ELARS system. *Activity level* is assessed for every e-tivity that student or group participates in. It represents quantitative aspects of engagement and is calculated based on automatically collected activity data that is retrieved from Web 2.0 tools using APIs. All user's characteristics are represented as continuous variables with values ranging from -1 to 1 [10].

The representation of e-tivity includes VARK learning styles for which its task is appropriate for, optimal knowledge and activity level needed for solving the task (determined by the teacher), a list of Web 2.0 tools that are offered for realization of the e-tivity, and parameters that indicate whether the e-tivity is individual/group-based and optional/mandatory [10]. Using content-based recommendation technique [13], usefulness of the e-tivity *eLA* for the target student *s* is given as similarity of student's characteristics $s_i$ and matching characteristics of e-tivity $eLA_i$, $i=1,\dots,n$. The similarity is calculated based on weighted Manhattan distance [1], using formula (1). Usefulness of optional e-tivity for a group is determined in the same way, but group's characteristics are used in the calculation. To adjust the recommendation criterion, teacher chooses the set of characteristics relevant for realization of optional e-tivities and assigns them weights $w_i$.

$$sim_o(s, eLA) = \frac{1}{1 + \sum_{i=1}^{n} w_i |s_i - eLA_i|} \tag{1}$$

**Collaborators recommendations**

Collaborators recommendations support students in the selection of appropriate collaborators for group-based e-tivities. Potential collaborators are at the same time students so they are represented with a set of characteristics specified in the previous subsection. Usefulness of potential collaborator is calculated based on the similarity of his/her characteristics with the characteristics of the target student using an analogous procedure as in the case of optional e-tivities recommendations.

Besides the set of student's characteristic with weights, adjustments of recommendation criterion includes the way of grouping (heterogeneous or homogeneous groups) and minimal and maximal number of group members. If students should form homogenous groups, target student is advised to choose collaborators between the most similar students. In case students should form heterogeneous groups, the set of potential collaborators is decomposed to clusters using k-means algorithm and the target student is advised to choose *m* collaborators, each from different cluster (*m* equals the maximum number of group members).

**Tools recommendations**

Tools recommendations support students and groups in selecting one of the Web 2.0 tools offered for the realization of an e-tivity. Representation of Web 2.0 tool includes actions that can be perform with it (updates, comments, tagging, sharing), learning styles for which the tool is appropriate for, and whether the tool enables several students to work on the same content in the same time.

The recommendation algorithm is used to rank tools in accordance with students' preferences. Unknown preferences are predicted using a hybrid approach. The prediction of target student's preference for the target tool starts with the attribute-based collaborative filtering method [13]. The method relies on the set of $k$ the most similar students ($k$ nearest neighbours). Similarity between students is determined based on students' learning styles preferences, $s_i$ and $s'_i$, $i$=1,…,4, and calculated using formula (2). Calculation is based on cosine similarity [1], a commonly used metric for collaborative filtering. If there are at least $k$ students for which the target tool preference is known, the unknown tool preference for the target student is predicted based on neighbours' preferences. Otherwise, algorithm switches to content-based technique and predicts the unknown preference based on the target student's preferences for the tools similar to the target tool. In both cases, priority is given to the closest neighbours and normalization of preferences is performed in order to increase the prediction accuracy.

$$sim_t(s,s') = \frac{\sum_{i=1}^{4} s_i \cdot s'_i}{\sqrt{\sum_{i=1}^{4}(s_i)^2} \cdot \sqrt{\sum_{i=1}^{4}(s'_i)^2}} \quad (2)$$

**Providing advice**

Advice is used to motivate students and groups for active participation during e-tivities. Four different aspects of active participation are available in the predefined set. These are: participation with contributions, continuous participation, participation with various categories of contributions, and encouraging collaborators to participate [10]. Each piece of advice is represented with a symbol, a text, and a set of parameters that indicate to which aspect of active participation the piece of advice belongs to. The text includes explanation with variable parts (e-tivity name, due dates, intervals/categories without contributions, names of active collaborators, and similar) and recommended action. For example, a piece of advice goes like this: *There are members of yours group whose activity level is not satisfactory. These are: [not_active_collaborators]. In order to achieve a better group result, try to encourage your collaborators to engage to a greater extent*.

This type of recommendations is generated using knowledge-based (constraint-based) technique [1]. The usefulness of a piece of advice is set to 0 or 1 according to "if...then..." rules. All pieces of advice from the pre-defined set for which usefulness equals 1 are shown to student (group). Recommendation criterion in this case includes defining parameters for activity level calculation [10]: intervals and values that represent the teacher's expectations regarding types of contributions and continuity of participation.

**RESEARCH METHODOLOGY**

In order to evaluate effectiveness of recommendation strategy described above, comparative study was used. The e-course *Operational research 1*, designed for the graduate program in Computer Science major at the Department of Informatics, University of Rijeka, was chosen for the study. It is a blended learning course [9] so its learning design includes classical face-to-face teaching and online learning supported with Canvas Instructure LMS and Web 2.0 tools. Course participants were assigned to control (N=35) and experimental group (N=28). Students' success at the previous level of studies was considered as main factor that could affect the evaluation process. Therefore, average grades from undergraduate studies for students from the control and experimental groups were compared. It was determined that there was no difference between the observed groups. Course activities were in the case of experimental group personalized by the ELARS recommender system. Course points for students from the control and experimental groups were compared. In order to test the statistical difference between means of results, the Mann-Whitney U test for comparison of nonparametric independent samples was chosen. This choice was made based on D'Agostino-Pearson test for normality. The following hypothesis was tested: *Students who use the ELARS recommender system before and during e-tivities achieve better final results in e-courses*.

In addition, students' satisfaction with the system and received recommendations was examined using an anonymous online questionnaire. It consisted of set of statements with 5-point Likert scale of attitudes (1 – Strongly Disagree, 5 – Strongly Agree). From 28 participants in the experimental group, 23 (82.1%) filled the questionnaire.

**Course context and learning design**

Overall objective of the course *Operational research 1* is that students acquire fundamental knowledge about operational research with emphasis on methods for solving linear programming (LP) and transportation problems (TP). Course learning modules and their workflow are shown in Fig. 4. Within the modules Introduction to operational research, Linear programming, Duality, Post-optimality analysis and Transportation problem students attend face-to-face classes and use the LMS to examine corresponding materials and additional examples or solve tests for self-assessment. Achievement of learning outcomes is assessed using three paper-based tests with theoretical questions and/or practical tasks and computer laboratory exercise (Lab). In addition, three e-tivities are performed individually or in groups using Web 2.0 tools: Homework 1, Homework 2 and Revision. Course points can be collected in the following way: Test 1 (20 points), Test 2 (25 points), Test 3 (25 points), Lab (10 points), Homework 1 (10 points) and Homework 2 (10 points).

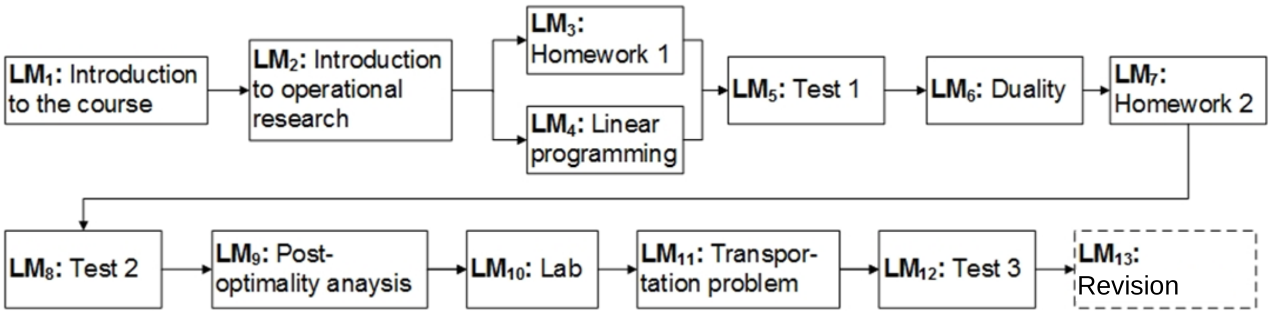


Figure 2. Course learning modules

Homework 1 and Homework 2 precede Test 1 and Test 2 and serve also as formative assessment. Revision activity is planned at the end of the course in order to allow students to repeat subject matter and collect up to 5 additional points for the course. The final grade is given on the basis of summation of all gathered points during the course according to the following scale: A - 90-100%, B - 80-69.9%, C - 70-59.9%, D - 60-49.9%. Students with less than 50 points fail and have to retake the course.

Students from the experimental group were using the ELARS system to receive recommendations so course learning design was supplemented with support and decision activities. Instead of one e-tivity, three e-tivities were offered in the $LM_7$ i $LM_{13}$.

As an example, Fig. 5 shows the workflow for $LM_7$ where students needed to choose between offered optional e-tivities in the ELARS. E-tivities were ranked according to learning styles preferences since they were designed to match read/write, visual or kinesthetic learning style. Depending on their choice, students solved practical task and presented their solutions using Wikispaces/Google Drive, Flickr/SlideShare or YouTube. Previously, they selected collaborators and/or tool within the decision activities. They also entered their user identities and feeds to enable the automatic collection of activity data from the chosen Web 2.0 tool. Collaborators recommendations were generated according to the activity levels for Homework 1 and students were encouraged to form heterogeneous groups with 3 or 4 members. Groups created publicly available content that served as additional learning material for others in the process of preparation for Test 2. During e-tivities, their collaboration and continuous participation was encouraged using advice while feedback regarding quality was provided by the teacher at the end of the e-tivity.

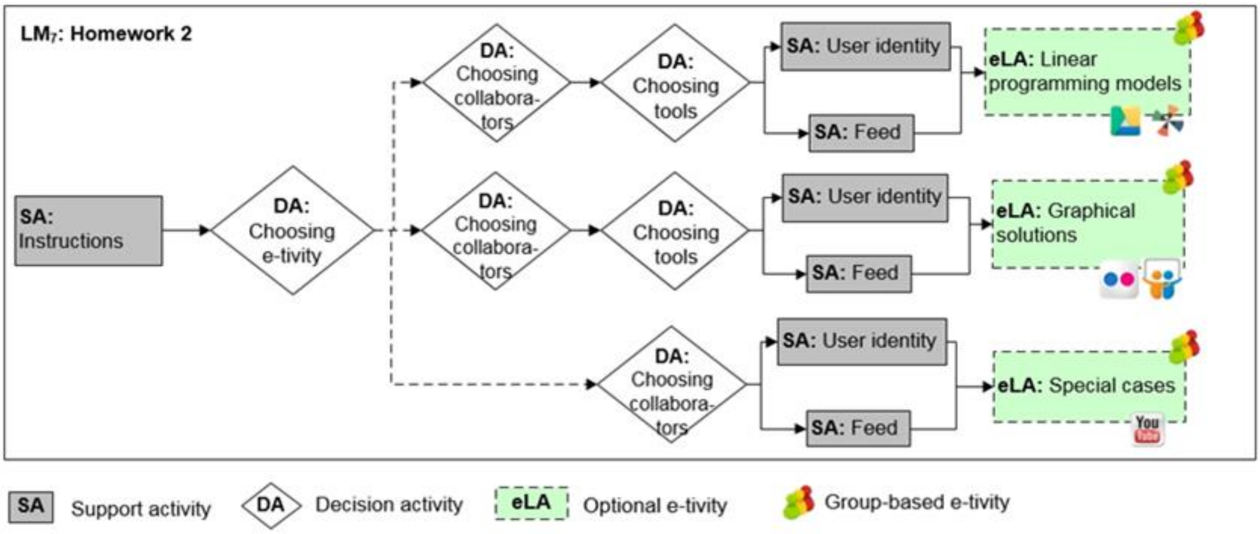


Figure 3. Example of learning module

## RESULTS AND DISCUSSION

### Academic results

Table 1 shows comparison of means for course grading components and final results for control and experimental group (in percentages). The Mann-Whitney U test revealed a statistically significant difference between means of the final results obtaining $p<0.05$ of significance. Therefore, the hypothesis was accepted and it was concluded that students who used the ELARS recommender system before and during e-tivities achieve better final result in e-courses. The mean value of final results for experimental group is near the threshold for grade B which shows high level of learning outcomes achievement.

In addition, statistically significant differences in means were observed for Test 1, Test 2 and Revision. Although the system was not used to directly support Test 1 and Test 2, preceding e-tivities designed to provide formative assessment were (Homework 1 and Homework 2). Significant difference between means was observed for Test 3 as well, but in the favour of the control group. Lower results for Test 3 in the case of the experimental group can be explained by the fact that students gathered the number of points that secured them passing grade before this activity. Students whose goal was not to get a better grade were not motivated to achieve higher results in Test 3.

Table 1 - Comparison of means (grading components and final results)

| Grading components | Homework 1 | Homework 2 | Test 1 | Test 2 | Test 3 | Lab | Revision | **Final result** |
|---|---|---|---|---|---|---|---|---|
| Control | 83 | 88.71 | 59.5 | 55.69 | 57.6 | 83 | 72.11 | **65.36** |
| Experimental | 91.79 | 96.16 | 81.77 | 78.38 | 53.07 | 74.5 | 95 | **77.9** |
| p | 0.7180 | 0.4799 | **0.0005** | **<0.0001** | **0.002** | 0.157 | **<0.0001** | **0.047** |

It should be noted that the experimental design of the study was not large enough to claim the effectiveness of the proposed recommendation strategy. However, the achieved results indicate great potential of this learning model in order to increase students' academic results in e-courses. Gained experiences serve as great starting point for feature research and indicate possible improvements. One of the most important insights that was observed is related to teachers' workload. Teachers did not need to remind students that a certain e-tivity started or encourage participation during the e-tivity. However, in order to assure that received advice correspond to the actual state of students' activity, the teachers had to remind students on deadlines for entering user identity and feed. Therefore, improvements to automate this process are needed in order to reduce teachers' workload, especially in the cases of a large number of students.

### Questionnaire results

Average results for the most important statements from the questionnaire are shown in the Table 2. Students are in general satisfied with the ELARS recommender system. They are satisfied with its interface and the way the recommendations are presented. The results shows that ELARS system was useful for students when they were supposed to choose between offered items and were satisfied with received recommendations. In addition, students stated that the system had a positive impact on their motivation for participation in e-tivities. These results indicate that the goals of the proposed recommendation strategy have been achieved.

Table 2 - Questionnaire statements and analysis of the results (N=23)

| Statement | 1 (%) | 2 (%) | 3 (%) | 4 (%) | 5 (%) | Mean | SD |
|---|---|---|---|---|---|---|---|
| You are satisfied with user interface of the ELARS system. | 0.0 | 13.0 | 17.4 | 52.2 | 17.4 | 3.74 | 0.92 |
| You are satisfied with the way the recommendations are presented. | 0.0 | 0.0 | 39.1 | 39.1 | 21.7 | 3.83 | 0.78 |
| ELARS is useful for choosing collaborators for e-tivities. | 0.0 | 17.4 | 34.8 | 13.0 | 34.8 | 3.65 | 1.15 |
| ELARS is useful for choosing tools for e-tivities. | 0.0 | 8.7 | 26.1 | 30.4 | 34.8 | 3.91 | 1.00 |
| ELARS is useful for choosing optional e-tivities. | 0.0 | 4.3 | 21.7 | 47.8 | 26.1 | 3.96 | 0.82 |
| ELARS is useful for providing advice and to get insight to activity levels of your collaborators and other groups. | 0.0 | 0.0 | 30.4 | 43.5 | 26.1 | 3.96 | 0.77 |
| You are satisfied with the recommendations received from ELARS. | 0 | 13.0 | 26.1 | 39.1 | 21.7 | 3.70 | 0.97 |
| The use of ELARS positively affected the level of your motivation for realization of e-tivities. | 4.3 | 8.7 | 17.4 | 39.1 | 30.4 | 3.83 | 1.11 |

## CONCLUSIONS AND FUTURE WORK

In this paper the research on evaluating effectiveness of novel recommendation strategy for personalization of e-learning was presented. According to the results, the strategy proved to be effective since students who received recommendations achieved better results in the e-course. The results of the questionnaire showed that students find it useful for e-tivities and are satisfied with received recommendations. By recommending optional e-tivities, collaborators, Web 2.0 tools, and advice, the focus of personalization was moved from learning objects to actions before and during collaborative e-tivities. The prerequisite for personalization using proposed strategy is a certain level of flexibility arising from the course learning design. This includes enabling students to group themselves, planning e-tivities that can be realized with different Web 2.0 tools or optional e-tivities among students (groups) will choose one. The recommendation process takes into account different student's (group's) characteristics and contains variable pedagogical rules which can be modified by the teacher according to the needs of certain e-tivity.

Further development of the ELARS systems will include support to teachers in the process of learning design definition. Teachers will be provided with a set of design templates that will serve as examples of good practice in order to support them in defining course activities and their workflows. Teacher's workload will also be reduced by automatic reminders of deadlines. Reminders will be implemented for support and decision activities since these activities are important for providing personalization in the ELARS.

## ACKNOWLEDGMENT

The research has been conducted under the project "E-learning Recommender System" (reference number 13.13.1.3.05) supported by University of Rijeka (Croatia).

## REFERENCES

[1] Adomavicius, G. and A. Tuzhilin, "Toward the next generation of recommender

systems: a survey of the state-of-the-art and possible extensions," *IEEE Trans. Knowl. Data Eng.*, vol. 17, no. 6, pp. 734–749, 2005.
[2] Anaya, A., M. Luque, and T. García-Saiz, "Recommender system in collaborative learning environment using an influence diagram," *Expert Syst. Appl.*, vol. 40, no. 18, pp. 7193–7202, 2013.
[3] Anderson, P., "What is Web 2.0? Ideas, technologies and implications for education," *Technology*, vol. 60, no. 1, pp. 1–64, 2007.
[4] Brusilovsky, P. and N. Henze, "Open Corpus Adaptive Educational Hypermedia," in *The Adaptive Web: Methods and Strategies of Web Personalization*, P. Brusilovsky, A. Kobsa, and W. Neidl, Eds. Springer-Verlag, 2007, pp. 671–696.
[5] Bustos-López, M. and R. V.-R. G. Alor-Hernández, "An Architecture for Developing Educational Recommender Systems," *Res. Comput. Sci.*, vol. 106, pp. 17–26, 2015.
[6] Downes, S., "E-learning 2.0," *eLearn*, vol. 2005, no. 10, p. 1, 2005.
[7] Drachsler, H., K. Verbert, O. C. Santos, and N. Manouselis, "Panorama of recommender systems to support learning," in *Recommender Systems Handbook*, 2015, pp. 421–451.
[8] Hassan, M. and M. Hamada, "Recommending Learning Peers for Collaborative Learning Through Social Network Sites," in *IEEE ISMS, Intelligent Systems, Modeling and and Simulation Simulation*, 2016, pp. 60–63.
[9] Hoic-Bozic, N., M. Holenko Dlab, and V. Mornar, "Recommender System and Web 2.0 Tools to Enhance a Blended Learning Model," *IEEE Trans. Educ.*, vol. 59, no. 1, pp. 39–44, Feb. 2016.
[10] Holenko Dlab, M., "Recommender system for activities in computer- supported collaborative learning." Ph.D. dissertation (in Croatian), Faculty of Electrical Engineering and Computing, University of Zagreb, Zagreb, Croatia, 2014.
[11] Holenko Dlab, M., N. Hoic-Bozic, and J. Mezak, "Personalizing E-Learning 2.0 Using Recommendations," in *Methodologies and Intelligent Systems for TEL (mis4TEL 2014), Advances in Intelligent Systems and Computing*, 2014, pp. 27–35.
[12] Klašnja-Milićević, A., M. Ivanović, and A. Nanopoulos, "Recommender systems in e-learning environments: a survey of the state-of-the-art and possible extensions," *Artif. Intell. Rev.*, vol. 44, no. 4, pp. 571–604, Sep. 2015.
[13] Manouselis, N., H. Drachsler, R. Vuorikari, H. Hummel, and R. Koper, "Recommender Systems in Technology Enhanced Learning," in *Recommender Systems Handbook*, Boston, MA: Springer US, 2011, pp. 387–415.
[14] Michlík, P. and M. Bieliková, "Exercises recommending for limited time learning," *Procedia Comput. Sci.*, vol. 1, no. 2, pp. 2821–2828, 2010.
[15] Salmon, G., *E-tivities: the key to active online learning*. Psychology Press, 2002.
[16] Santos, O. C., J. G. Boticario, and Á. Manjarrés-Riesco, "An approach for an affective educational recommendation model," in *Recommender Systems for …*, Springer New York, 2014, pp. 123–143.
[17] Zuckweiler, K. and Q. Cao, "Combining learning styles and technology acceptance: new perspectives on online business education," *Int. J. Inf. Oper. Manag. Educ.*, vol. 3, no. 2, pp. 81–92, 2009.
[18] "ELARS Home page - DEMO," 2015. [Online]. Available: http://elars.uniri.hr/elarsdemo. [Accessed: 01-Jan-2016].

## ABOUT THE AUTHORS

Martina Holenko Dlab, PhD, Department of Informatics, University of Rijeka, Phone: +385 51 584 708, E-mail: mholenko@inf.uniri.hr.

Prof. Natasa Hoić-Božić, PhD, Department of Informatics, University of Rijeka, Phone: +385 51 584 707, E-mail: natasah@inf.uniri.hr.