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A recommender agent based on learning styles for better virtual collaborative learning experiences

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ABSTRACT

Almost unlimited access to educational information plethora came with a drawback: finding meaningful material is not a straightforward task anymore. Based on a survey related to how students find additional bibliographical resources for university courses, we concluded there is a strong need for recommended learning materials, for specialized online search and for personalized learning tools. As a result, we developed an educational collaborative filtering recommender agent, with an integrated learning style finder. The agent produces two types of recommendations: suggestions and shortcuts for learning materials and learning tools, helping the learner to better navigate through educational resources. Shortcuts are created taking into account only the user's profile, while suggestions are created using the choices made by the learners with similar learning styles. The learning style finder assigns to each user a profile model, taking into account an index of learning styles, as well as patterns discovered in the virtual behavior of the user. The current study presents the agent itself, as well as its integration to a virtual collaborative learning environment and its success and limitations, based on users' feedback.

1. Introduction

Technology boost has enabled new education paradigms, such as: student-centered learning, situated cognition, communities of practice, distributed cognition, everyday cognition, and constructivism in general (Brown, 2005). Education does no longer mean only knowledge transfer, from teachers/tutors to students, but means community, working in groups, doing projects, sharing ideas with peers, being challenged, learning to support personal goals (Prensky, 2007; Zhang, de Pablos, & Xu, 2014; Zhang, de Pablos, & Zhang, 2012; Zhang, de Pablos, & Zhu, 2012). As a consequence of the emergence of the new learning paradigms and in order to cater the "neomillennial learning styles" of students (Liu, Cheok, Mei-Ling, & Theng, 2007), new forms of learning and education have appeared: the continuous education, the competences-oriented education, education at work, the online education, the collaborative education. Computer supported collaborative learning (CSCL) is among the most challenging new learning forms, as its value and its limits are still under research (Chikh & Berkani, 2010; Mukama, 2010; Othman, Othman, & Hussain, 2013). In CSCL, several students with different ways of thinking, feeling, and acting "work together to solve problems or build knowledge supported by specifically designed software" (Prinsen, Volman, & Terwel, 2007). CSCL is well-known for the fact that it provides educational opportunities for students with "low anxiety, high problem solving efficacy" and "time management problems in their learning strategies" (Solimeno, Mebane, Tomai, & Francescato, 2008), while loneliness and demotivations are among the main causes of failure in e-learning (Tobarra, Roblez-Gomez, Ros, Hernandez, & Caminero, 2014). Thus collaborative e-learning through virtual communities, wikis, forums, chat rooms, virtual worlds provided successful examples of virtual learning experiences (Zhang, Liu, de Pablos, & She, 2014; Zhang, Ma, Wu, de Pablos, & Wang, 2014; Zhang, Zhang, de Pablos, & Sun, 2014; Zhang et al., 2014). A growing body of research has demonstrated that personalization is essential in virtual collaborative learning experiences, if they aim to fulfill their full potential in nowadays education (Ashman, Brailsford, &

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Brusilovsky, 2009; Bodea, Dascalu, & Lytras, 2012; Dascalu, Bodea, Lytras, de Pablos, & Burlacu, 2014; Dragoi, Rosu, Pavaloiu, & Draghici, 2013; Hsu, Chen, Huang, & Huang, 2012; Mamat & Yusof, 2013; Stefan, Gheorghiu, Moldoveanu, & Moldoveanu, 2013). Starting from this premise, we propose in this study a personalization method of a virtual collaborative learning environment, represented by an e-learning community, through collaborative filtering recommendations.

The paper is structured as follows: after the introductory part (Section 1), Section 2 presents an extensive state of the art in the personalization of virtual learning environments domain, through educational recommendations and consideration of learner profiles in general and learning styles associated with those profiles in particular. Section 3 describes the proposed recommendation method. Section 4 presents the collaborative learning environment U-learn, in which the recommendation method was deployed. Section 5 reveals the preliminary results and discussions of our research. Conclusions are drawn in Section 6.

2. Personalizing virtual collaborative learning experiences

According to Ashman et al. (2009), personalization means identifying the most suitable information to the users' needs, taking into account a user model. In the particular case of e-learning, personalization could mean fostering a particular learning behavior so that the learners to achieve their goals. Personalized e-learning environments implement several challenging concepts: one-to-one/many-to-one learning and self-directed learning. While traditional e-learning environments implement the one-to-many learning concept (one tutor-multiple learners), personalized e-learning environments use one-to-one or many-to-one concept (one or several tutors for the same learner). In traditional e-learning environments, the learning units, their sequence, their content is established by the tutor, while in personalized e-learning environments they are chosen by the learner (self-directed learning) (Kurilovas, Kubilinskiene, & Dagiene, 2014).

Ashman et al. (2009) make an interesting debate upon the pros and cons of exploiting personalization technology in web-based learning: they notice that its use determines its value. Comparing with e-commerce personalization, e-learning personalization is still experimental, with less market penetration. Before exemplifying the benefits brought by personalization, one should take into account that it might be a threat to security and data privacy and not very reliable, as personalization algorithms might be prone to errors. Ashman et al. (2009) argue that people are complex and impossible to be sketched in a profile, which, in the end, is approximate. Offering personalized recommendations in a virtual environment can be detrimental to people, as in real life knowledge is not synthesized, but has to be discovered. Despite the cons of personalization, we think that learning should be a highly personal experience, thus personalizing virtual learning environments (VLE) would have great pedagogic benefits. Studies have demonstrated that learners participating in personalized learning environments are more motivated and more willing to spend time in the educational context than other students (Brusilovsky, Sosnovsky, & Yudelson, 2009; Weber & Brusilovsky, 2001). Last, but not least, personalization can be a support technology for people struggling with finding out the needed piece of information from the huge volume of Internet data which is, unfortunately, of variable quality.

2.1. Improving learning experiences through educational recommendations

Under the pressure of increasing the education effectiveness, most of the educational systems became learner-centered (Geven, 2010; Semple, 2000). A research on the adoption of learning-centered approach, made in several small colleges and universities (Weimer, 2002), indicates that the adoption of learner-centered paradigm is not initially welcomed by all students, some of them preferring a passive learning environment. But, in the end, almost all the students found the learner-centered experience as being superior to traditional ones, as a consequence of their ownership of the learning experience. Comparing the learner-centered with the traditional teacher-centered systems, Huba and Freed (2000) point out that the teacher' role changed from an information giver and primary evaluator to a coach, facilitator and contributor, providing relevant educational recommendations to students. Allan (2004) also considers that teacher should engage students in their learning, assisting students to master their learning objectives. Learning can mainly be achieved not based on delivery of information but on a real engagement of students, based on efficient indications/recommendations.

One of the most powerful vehicles for providing educational recommendations is the feedback provided by teachers to the students. Feedback, and especially formative feedback, is considered as being critical for improving knowledge and skill acquisition and increase the motivation for learning (Hattie & Timperley, 2007; Shute, 2007). According to Shute (2007), the formative feedback represents information communicated to the learner that is intended to modify the learner's thinking or behavior for the purpose of improving learning. The following six type of educational indications/recommendations are identified: attribute-related (information addressing central attributes of the target concept or skill being studied), topic-contingent (information relating to the target topic currently being studied), response-contingent (focusing on the learner's specific response; it may describe why the answer is wrong and why the correct answer is correct; this does not use formal error analysis), hints/cues/prompts (guiding the learner in the right direction, e.g., strategic hint on what to do next or a worked example or demonstration; it avoids explicitly presenting the correct answer), bugs/misconceptions (information requiring error analysis and diagnosis; this is information about the learner's specific errors or misconceptions, e.g., what is wrong and why), and tutoring recommendations (the most elaborated information, a combination of previous ones).

Hattie and Timperley (2007) introduce a model of feedback based on three major questions: "Where am I going?", "What progress is being made toward the goal?" and "Where to next?" (which correspond to feed-up, feed-back, and feed-forward educational recommendations) and four levels at which the feedback operates: the level of task performance, the level of process of understanding how to do a task, the regulatory or meta-cognitive process level, and/or the self or personal level (unrelated to the specifics of the task). Across these levels, the educational recommendations could have different effectiveness in reducing the gap between current and desired understandings.

Educational recommendations are not all the time effective, as they are not always accepted by the students – they can be modified or rejected instead. Educational recommendations can significantly improve learning processes and outcomes, only if they are properly designed and correctly delivered.

Research on technology-assisted education indicates that technology can support key practices of student-centered learning, such as assessing individual students' strengths and needs, flexible scheduling and effective educational recommendations (Moeller & Reitzes, 2011).

When debating upon educational recommendations mediated by technology, mentioning recommender systems is mandatory. A recommender agent gives the user suitable resources and guidance in a large space of possible options (Burke, 2002), thus increasing the visibility of proper e-learning resources (Zhang, de

Pablos, & Zhou, 2013; Zhang, Vogel, & Zhou, 2012). The main beneficiaries of recommender systems are individuals who lack sufficient subjective personal experience in a specific field or they do not have the competence or sometimes the time to evaluate the potentially overwhelming number of alternative items that are available online. Example of recommenders' capabilities in education are: give proper knowledge to proper members in collaborative team contexts, by respecting role, tasks, members' level of knowledge; assist students to plan their semester schedule, by checking courses that comply with constraint regulation and with students' preferences; give books recommendations; give learning tools recommendations (Bodea et al., 2012; Capuano, Gaeta, Ritrovato, & Salerno, 2014). Examples of successful educational recommendation systems are Willow, PAcMan, Protus. Willow provides recommendations in a non-intrusive way through the dialogue metaphor: the system suggests a set of recommendation, but afterwards the learner can provide feedback which influences the future recommendations (Santos, Boticario, & Perez-Marin, 2014). PAcMan (Personal Activity Manager) allows users to manage their online resources and tools according to a very simple model of learning activities; acts both as a personal learning environment (PLE) and as a recommender system (Modritscher, 2010). Protus is a learning style-based recommendation system for learning Java (Klasnja-Milicevic, Vesin, Ivanovic, & Budimac, 2011).

Recommendations are a common technique of personalizing VLE, but they are not straightforward: several algorithms should be applied to obtain meaningful educational recommendations. Data mining techniques use the gathered information about the learner behavior (e.g. navigation history) to produce recommendations. These techniques are suitable to recommend the sequence of learning materials (i.e. learning path) rather than the learning materials itself. Content-based algorithms make recommendations taking into account the ratings of the users, the description of the items that have been rated and the description of items to be recommended. These algorithms are usually used for recommending bibliographical materials (Adomavicius & Tuzhilin, 2005). Collaborative-filtering algorithms are suitable for recommendations in collaborative educational contexts. Materials, tools, links can be recommended based on identification of learners with similar profiles/behaviors and extrapolation from their preferences (Schafer, Frankowski, Herlocker, & Sen, 2007). In order to address the sparsity and overspecialization problems that are the drawbacks of collaborative filtering and content-based filtering, respectively, hybrid approached of recommendations were also developed (Burke, 2002).

2.2. Impact of learning styles to the success of online learning environments

If recommendations are a personalization technique, the user model is the foundation of personalization, "the heart of all automated personalization systems" (Ashman et al., 2009): it can be either persistent across sessions, or session-dependent, either filled in voluntarily by the user, or inferred from behavioral data within the application. For e-learning, it mainly contains personal details about learners, previous knowledge, learning experience, education, learning goals, learning style. The challenge for each e-learning researcher/developer is to establish the optimal structure of the learner model for one's application. In our research, we focused on the personalization of e-learning experience according to one's learning style (LS), as learning styles are considered one of the most important factors influencing e-learning and personal academic competence (Shaw, 2012).

According to Kurilovas et al. (2014), "learning styles are strategies, or regular mental behaviors, habitually applied by an individual to learning, particularly deliberate educational learning, and built on her/his underlying potentials". There are several models used to categorize people taking into account their LS (Ocepek, Bosnic, Serbec, & Rugelj, 2013), e.g. Kolb's learning style model (KLS), Rancourt's learning style model (RLS), Hemispheric dominance and learning styles model (HLS), VAK learning style model (VLS). KLS is based on four modes (abstract conceptualization, concrete experience, active experimentation and reflective observation) and on grouping people taking into account different combinations of dominant modes in: assimilator, converger, accommodator and diverger. RLS is based on psycho-epistemological models, which assigns to people one of the following styles: rational, empirical or noetic. HLS proposes the following learning styles: right-hemispheric, left-hemispheric and integrated learning style, while VLS proposes: visual learning style, aural learning style and kinesthetic learning style. A LS can be determined either using a standard questionnaire, which depends on the chosen LS model (e.g. for KLS, the Learning Style Inventory is used; for RLS, a Knowledge Accessing Models Inventory is used), either discovering the student's LS from his/her behavior within the learning system (e.g. students choosing the same learning sequence have the same LS). Although the first method is time-consuming for the student, it is safer and less prone to errors than the second one.

Numerous studies analyzed the correlation between LS and various aspects of learning scenarios (Hsu et al., 2012; Klasnja-Milicevic et al., 2011; Latham, Crockett, McLean, & Edmonds, 2012; Vesin, Ivanovic, Klasnja-Milicevic, & Budimac, 2012). Kurilovas et al. (2014) established interconnections between LS and preferred learning activities, learning object types and relevant teaching/learning methods. Shaw (2012) investigated the relationship between LS (Assimilator/Converger/Accommodator/Diverger), participation types (Replier/Asker/Watcher/No activity) and learning performance in a collaborative online learning environment (online forum) for programing languages: he used KLS and Social Learning Theory to define students' characteristics. Klasnja-Milicevic et al. (2011) developed a recommendation module of a Java programming tutoring system – Protus, which recognizes different patterns of LS and learners' habits through testing the LS of learners and makes educational content recommendations. The same group of researchers developed Protus 2.0, based again on the principle of learning style identification for course personalization, but inserting this time Semantic web technologies (Vesin et al., 2012). Latham et al. (2012) describe Oscar, a conversational intelligent tutoring system to learn SQL, which can automatically predict learning styles: "Oscar's pedagogical aim is to provide the learner with the most appropriate learning material for their learning style to promote a more effective learning experience and a deeper understanding of the topic. The results of all these efforts to personalize virtual learning environments based on users' LS sustain that undoubtedly there is an impact of correlating LS and learning scenarios on learning performance and learners' satisfaction.

3. A recommender agent based on learning styles

Students often need to choose additional bibliographical resources for university courses. Unfortunately, they do not always listen to their professors and prefer a quick web search. We concluded that there is a strong need for recommended learning materials, for specialized online search and for personalized learning tools, suitable for each student's profile. According to the findings from previous section, LS is a driving force in modeling learner's profile and in building useful recommendations. We developed a recommender agent based on LS and, for validating it, we included it in a virtual learning environment, U-learn. Further, we present the rationale of our agent, as well as its features.

3.1. Rationale

In order to be as accurate as possible in terms of requirements for the proposed agent we have built a survey using the online tool Qualtrics (www.qualtrics.com). The survey has been completed by 35 people with diverse educational backgrounds ranging from business, technical to law, communication and marketing degrees. Our respondents had bachelor/master degree or they were young professionals, as usually these are the persons who embraced more easily technology-based forms of education. Among the questions we put, there were: "How do you usually access bibliographical materials?", "What are the main problems when using internet in order to search for bibliographical resources?", "Do you think you will use a recommender system for bibliographical resources?", "How satisfied you are about the learning tools currently available?" The most important findings are summarized below:

- People usually access information via the Google web browser, because it provides very clear information but for specific purposes they also use a specialized website where they know they can find information easier or they want to narrow it down.
- When looking for resources on the internet the vast majority of people think that the most important problems are that they do not find targeted/specific information and that usually it took them some time to reach to the desired piece of information.
- The most important characteristics for a learning tool are that is should be reliable, easy to use, and easy to access and it should have the ability to provide personalized information: many parts of the application should be customizable.
- Almost all people who were questioned were permanently looking for new learning tools and resources as there are a lot of information available and there is a need for personalized learning.

Based on our respondents' feedback, we have built the functional and non-functional requirements of our recommender agent. Consequently, in order for our agent to bring improvements and novelties to the e-learning process, it should take into account:

- Personalized profile: The agent should be able to offer to the user details about him (e.g. his learning style and what are the implications that his learning style has on his way of learning).
- Aggregated information: The user should be able to access information from a database; he should be able to add information to the database but also should have the possibility to access other Internet links from the application.
- Computed learning style: The agent should be able to compute the learning style according to a predefined methodology and also provide information to the user about how and what to improve to his learning.
- Collaborative recommendations: The agent should be able to make smart educational recommendations to the user, exploiting the benefits of an e-learning community.

Taking into account several criteria that are relevant for e-learning environments, we decided that the agent should be integrated in an application with an easy-to-use interface. Because this application aims to be a support tool for people from a wide range of ages and educational backgrounds, the application has to be intuitive. More than that, as the application will be a tool to facilitate the learning process, it has to be easy to walk through, without raising any issues. One of the most important problems that people have nowadays in accessing relevant information and in learning is that they do not have all the information that they need at their fingerprints. One does not want to go to the library to get a big book and then come home and try to search through it. For this problem the application will have a search bar so that everybody can browse through keywords into the educational material database.

3.2. Features

The recommended agent exploits the user profile. The user profile is saved into a learner preference tree model and it has two parts: the static one and the dynamic one. The static part is either self-built or extracted from an e-learning system/social network, using customized connectors (via FBGraph API): interest, education and country are provided by each user. The dynamic part refers to the user LS: it is initialized via a questionnaire (Soloman & Felder, 1996) and then updated, taking into account one's behavior within the e-learning environment (e.g. if the user actively participates in the collaborative e-learning process, by sharing constantly/scarcely new tools and educational articles).

The recommended agent offers two types of recommendations: shortcuts and suggestions. Shortcuts recommend learning materials (local and from web) and learning tools taking into account only the static part of the user profile: more exactly, the educational interests declared when starting using the recommender. Suggestions make more complex recommendations, based on the learning style of the user and based on the materials and tools considered useful by other users with the same learning style: an adaptation of the item-based collaborative-filtering recommendation algorithm featured in the "Mahout in Action" book was implemented (Owen, Anil, Dunning, & Friedman, 2011).

3.2.1. Description of the recommendation algorithm

The item-based collaborative filtering recommendation is totally based on user-item ranking/score (e.g., a user rated a learning tool with 3 stars, or a user "likes" an article). When one computes the similarity between items (in our case tools, articles), one has to know only all users' history of ratings. So the similarity between items is computed based on the ratings instead of the metadata of item content. The algorithm steps are the following:

- A user chooses the educational tools/articles he likes from the available ones in the local database; if he considers that the provided tools/articles are not satisfactory, then he is free to add more tools/articles: an initial matrix of items' preferences is built.
- An inverted matrix is computed based on which users have chosen which tools.
- The Jaccard Similarity is computed for every tool hence it will form a matrix that is symmetric on the diagonal. The Jaccard Similarity, also known as the Jaccard index/coefficient, is a statistic used in order to compare the similarity and diversity of sample sets (Similarity measures, 2010). The Jaccard coefficient is defined as the size of the intersection divided by the size of the union of the sample sets and measures the similarity between finite sample sets, as in formula (1).

$$JaccardSimilarity(A,B) = \frac{|A \cap B|}{|A \cup B|} \tag{1}$$

  where A and B are 2 sets.
- The final score for each tool/article is calculated by summing the Jaccard Similarities between it and other tools/articles.
- Recommendation contains the tools/articles with highest scores.

For exemplification, suppose we want to recommend tools for User 3 from U-learn database. We have the following users and their likes in our educational context (initial matrix):

- User 1 likes: Tool1, Tool4, Tool5.
- User 2 likes: Tool2, Tool4.
- User 3 likes: Tool1, Tool4, Tool2.
- User 4 likes: Tool2, Tool5.
- User 5 likes: Tool3.

Then an inverted matrix is computed based on which users have chosen which tools:

- Tool 1: User 1, User 3.
- Tool 2: User 2, User 3, User 4.
- Tool 3: User 5.
- Tool 4: User 1, User 2, User 3.
- Tool 5: User 1, User 4.

The Jaccard Similarity is computed for every tool hence it will form a matrix that is symmetric on the diagonal. For the considered example, the similarity matrix is available in Table 1.

Hence the recommendation for user 3 consists in Tool3 and Tool5, with the below scores:

Score(Tool3) = similarity (1,3) + similarity(4,3) + similarity(2,3).
Score (Tool5) = similarity(1,5) + similarity(4,5) + similarity(2,5).

3.2.2. Index of learning styles

The algorithm described in the previous section is applied within the users having the same LS available in the database. So, before the recommendation algorithm, the users have to be classified into LS groups. For that, we used The Index of Learning Styles (ILS), which is an on-line instrument to assess learners' preferences on four dimensions: active/reflective, sensing/intuitive, visual/verbal, and sequential/global (Soloman & Felder, 1996). The ILS is used mainly by individuals who wish to find out their learning style profile and by people in the teaching industry who can use it for teaching, advising or even to further research. The ILS is a free, 44-item questionnaire that asks the respondent to choose one of two endings to a sentence that focuses on some aspect of learning. Scoring is 1, 3, 5, 7, 9, and 11, with 1 and 3 showing a balance along the spectrum, 5 and 7 showing a moderate preference for one end of the spectrum, and 9 and 11 a strong preference for one end or the other. According to Soloman and Felder (1996), active learners like trying something out, doing it, and seeing if it works, particularly in groups. Reflective learners want to think it through first, take notes in class, and work alone. Intuitions like discovering possibilities, grasping new concepts, and working with abstractions. Visual learners want to see pictures, diagrams, flow charts, films, and demonstrations. Verbal learners like hearing and discussing information, taping lectures, and explaining themselves. Sequential learners like to move step-by-step through the material, progress logically to the solution to a problem. Global learners want to see the big picture, take in information randomly before putting it all together, and work intuitively.

The recommender agent proposes an integration of ILS. The main reason behind this integration is that being a learning environment, one of the first things that a learner must find out is his LS. Our agent takes into account all the 8 categories of styles. After completing the general and required questionnaire for LS, for each user his own learning style is computed. However the recommendation is based only on 4 dimensions and that is because the other 4 are complementary hence once cannot be visual and verbal at the same time.

Table 1
Example of Jaccard Similarity matrix.

	Tool1	Tool2	Tool3	Tool4	Tool5
Tool1	1	0.25	0	0.66	0.33
Tool2	0.25	1	0	0.5	0.25
Tool3	0	0	1	0	0
Tool4	0.66	0.5	0	1	0.25
Tool5	0.33	0.25	0	0.25	1

4. U-learn – a virtual collaborative learning environment using the proposed recommender agent

U-learn is a web based application designed using JAVA technologies in NetBeans IDE and can be access via any browser. More than that, it is a collaborative learning environment, in which the users can share useful learning objects ("any digital resource that can be reused to support learning", according to Kurilovas et al. (2014)) and learning tools. When referring to the integration of educational recommender agent described in Section 3 within the application, U-learn application has two main functionalities: it associates a learning style to each user and based on the learning style it is able to recommend specific bibliographical materials (articles) and educational tools to the users.

4.1. Technological choices

Several technologies, but mainly based on Java Web, were combined during the development of U-learn. The architecture of U-learn goes hand in hand with the technological choices we made. In terms of architecture, we implemented a Model-View-Controller (MVC) model, exploiting the Java Server Faces (JSF) benefits.

The presentation layer of the U-learn application contains the web application pages which are Java pages accessible through a browser. In the back end there are java beans which communicate with a database. The most important requirement in order to run the application is the client browser as the whole learning process is interfaced through it. While it is compatible with Google Chrome, Mozilla Firefox, Safari, Opera and Internet Explorer 9, Internet Explorer 6 or less is problematic. Several elements such as <div> tags or unreferenced CSS make it hard to visualize correctly. Mozilla Firefox is the best client for the platform as it was the main testing option during development and also Firefox Driver is used for the web search functionality.

All the information gathered from the users must be saved into the application in order to be retrieved later on. For that, a MySQL database was used. The Apache Derby has been used in order to make possible the database connectivity, as it is also compliant with the JAVA standards.

The server component of U-learn is of Java Web Application type comprised of JSF web pages and Entity Java Beans (EJB) with which the data from the database can be manipulated. Java Web Applications have the advantage that they can be configured with many application servers (Apache Tomcat, GlassFish, WebSphere). In our case, the web application is configured with GlassFish, open – source application server. GlassFish is well known for integrating portable and scalable enterprise applications with legacy technologies. In order to give the application the capability to validate and parse XML documents, the Java API for XML Processing has been used. In order to include rich GUI elements, PrimeFaces, an open source JSF component suite, was integrated. Another technology we used was Selenium, a suite of tools that is used for web browser automation across many platforms.

4.2. Functionalities

There are 5 parts accessible to the user via a navigation bar below the header: View Articles, Add Article, View Tools, Add Tools, Suggestion and Shortcuts (see Fig. 1). There are also two sections/buttons facilitating the access to the home page all the time and to quick web search according to one's learning goals.

Each tool will contain the following information: title, link, type and description. A list of registered tools is available in Fig. 2. Each user will be able to add new tools and to browse through existent ones. The tools' type can be selected from a drop-down list containing the available types or a new type can be proposed. The same functionalities are available for bibliographical materials: each article contains the title, the content, the authors, the keywords and a link if the content is not text or is too big.

The user can find recommendation of learning tools or articles registered in the application database according to his learning style by clicking on "Suggestion". He can find recommendations of learning tools and articles registered in the application database according to his declared educational interests by clicking on "Shortcut" (see Fig. 1). If none of these recommendations satisfy him, a web search is integrated in the application, implemented with Selenium Web Driver.

In order to have access to the U-learn recommendations, a user must login/register. Each user will have to create an account into the database so his profile to be persistent between sessions. An error message will appear if the user is already in the database or if the login credentials are not correct. The login is possible via Facebook account also, so social network integration is supported. After creating an account, each user will have to complete a profile, in several steps:

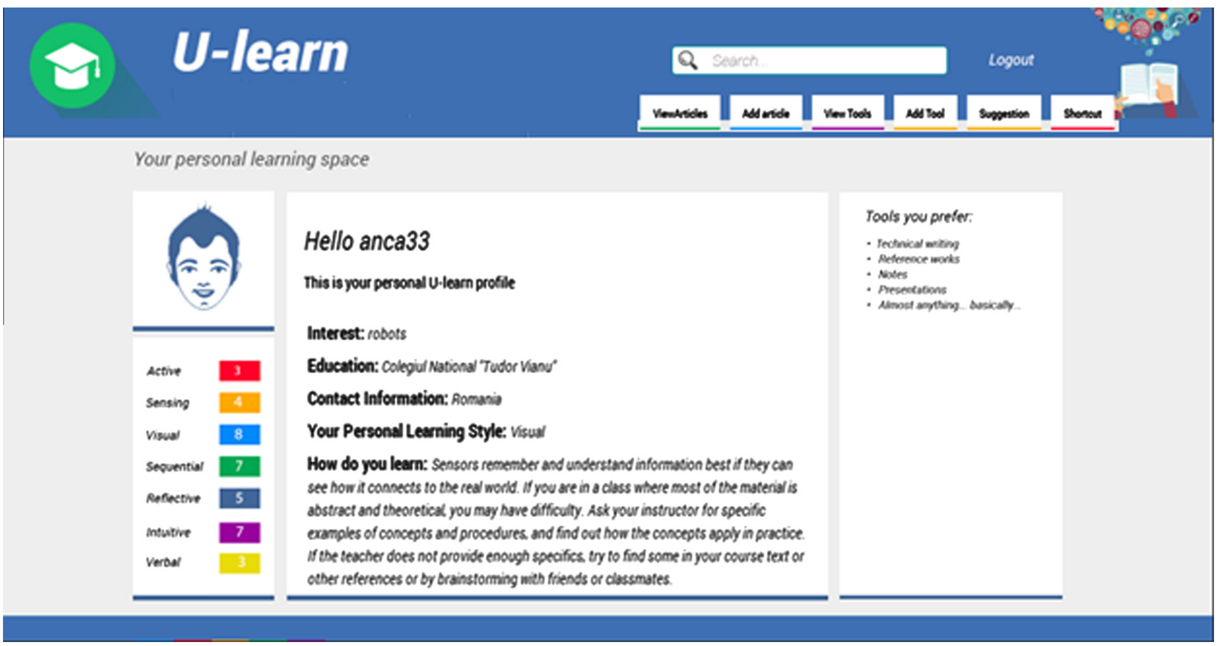

Fig. 1. U-learn application.

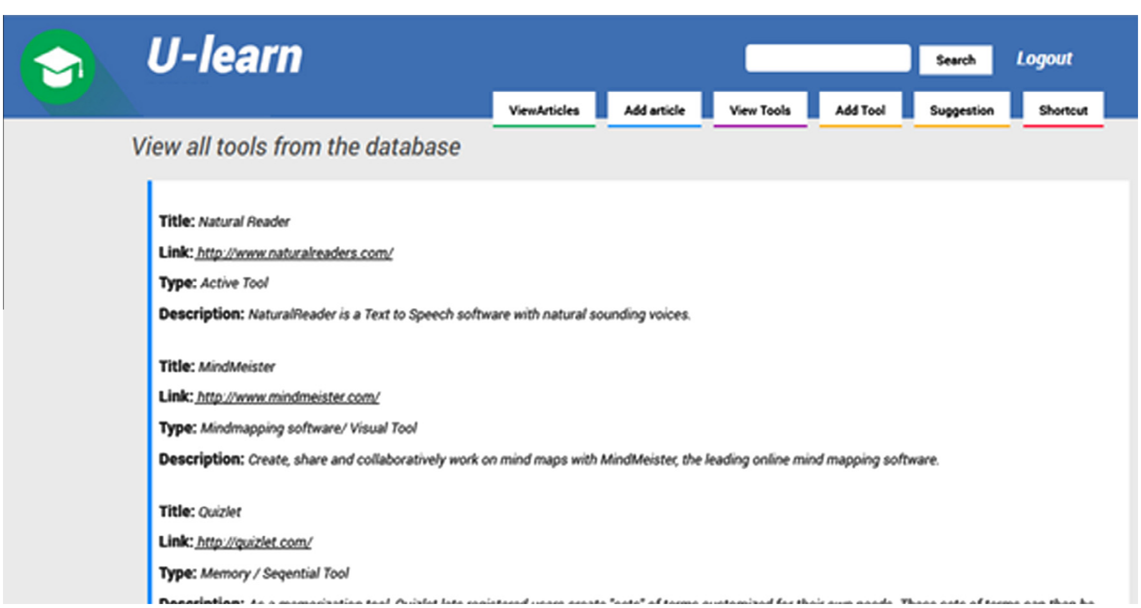

Fig. 2. Educational tools' description in U-learn application.

- First step consists in providing information about his area of interest, education and country. This step will appear only once when the user has registered for the first time, as the requested profile information is static.
- Secondly, the user will have to choose from 5 randomly selected learning tools from the database the ones that he thinks are most useful to him. He will be able to see the description for the tool and also a link to the proposed tool. This screen will appear also just once as the user should provide consistent data to the application so that the recommendations will be computed correctly.
- Next, the LS finder will be activated: the Learning Styles Questionnaire developed according to (Soloman & Felder, 1996) will be displayed, as in Fig. 3. The application allows completing the questionnaire only once, as then the LS is dynamically adjusted. There are 44 questions and each has two answer possibilities, at the end the user has to press submit and the LS is associated. Then the user can see his complete profile, with the score that he has from the questionnaire, the learning style and the interpretation. He will be able to see also the chosen educational tools.

As XML technologies are used when creating/searching for articles and tools, the recommendation module can be used as a stand-alone agent within other e-learning applications, if integration rules are respected: format of user profiles, of tools and articles description.

4.3. Integration scenario of the recommender agent in U-learn

The activity diagram in Fig. 4 best describes a normal scenario for a simple user on the U-learn platform. The user decides to create a new account on our system and begins his e-Learning journey. Firstly, the user creates a new account by filling out a form (login/register). Then he is asked to provide even more information about himself that will appear also on the personal profile page. Then he is asked to answer the LS questionnaire. This questionnaire has no right or wrong answers. The user has to choose for each of the 44 questions either answer A or B. He is then asked to self-asses himself by choosing one or more tools from 5 randomly selected tools from the database. Then the user is prompted to the main page where he has all the information that he has

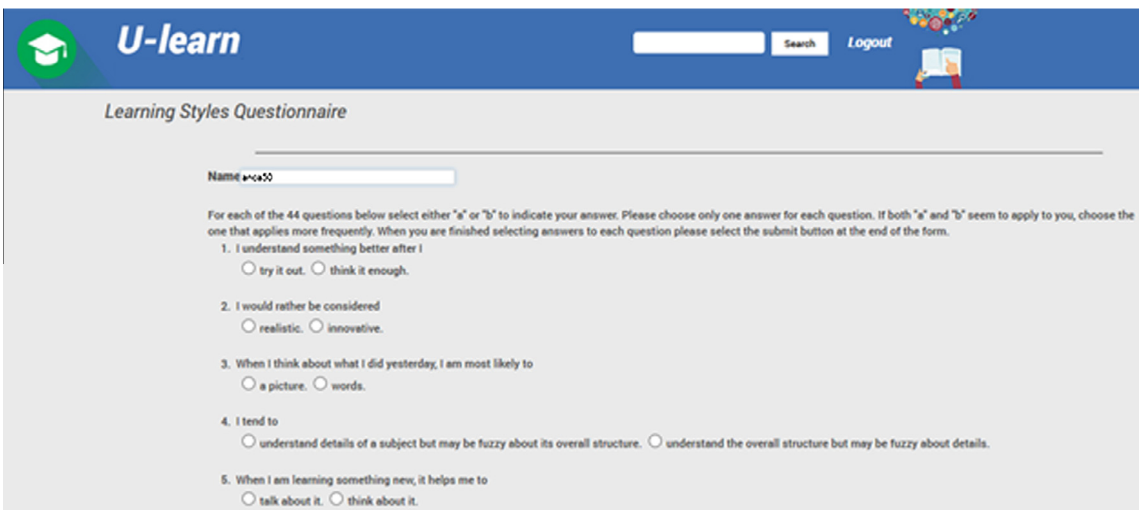

Fig. 3. Learning Style Questionnaire included in U-learn application.

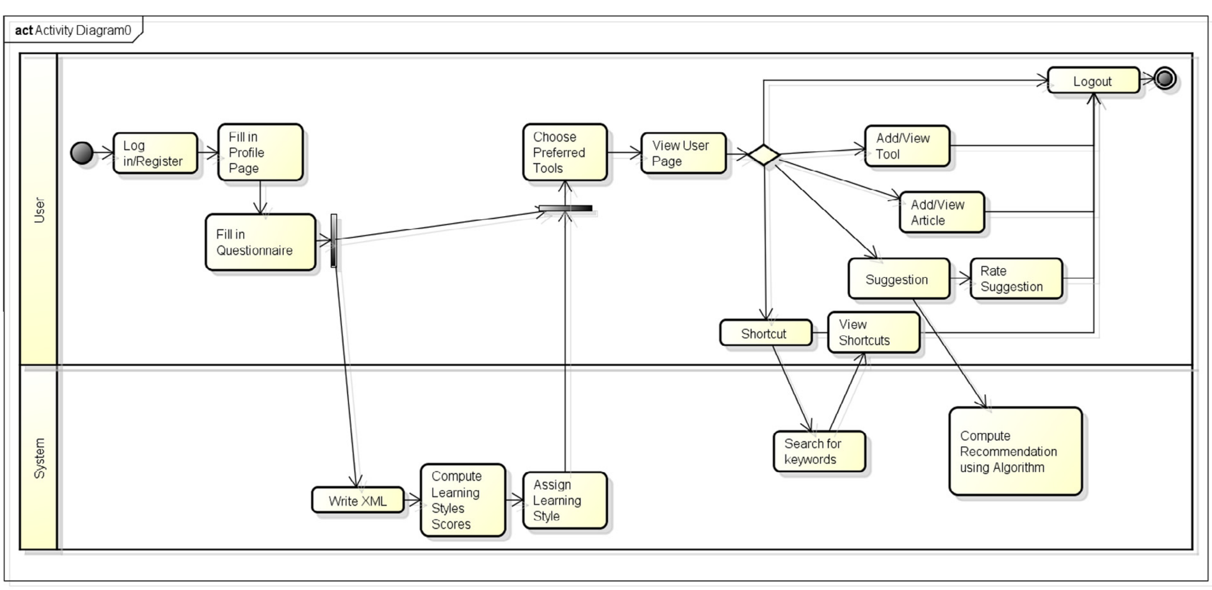

Fig. 4. Recommendation scenario in U-learn application.

provided aggregated into one single page, he can now see his learning style and also find out the scores and how he should tackle learning based on his learning style. He then proceeds to the Suggestion tab where he finds out yet other tools/articles that he can use for his learning. The user can search articles/tools into the U-learn database by the interest that he has previously provided when registered. For that, he has to access the Shortcut tab or he can use the search bar. He can then improve the database by adding more tools and more articles, hoping that the other members of the e-learning community will do the same. Finally he can also search online after the interest that he has provided. When he is no longer interested in working with the application he can hit logout and leave the application.

The success of recommendation algorithm within U-learn is based on the participatory behavior of all U-learn users. As one can see in the sequence diagram from Fig. 5, satisfying recommendations cannot be obtained without sharing articles and educational tools with the other participants of the virtual learning

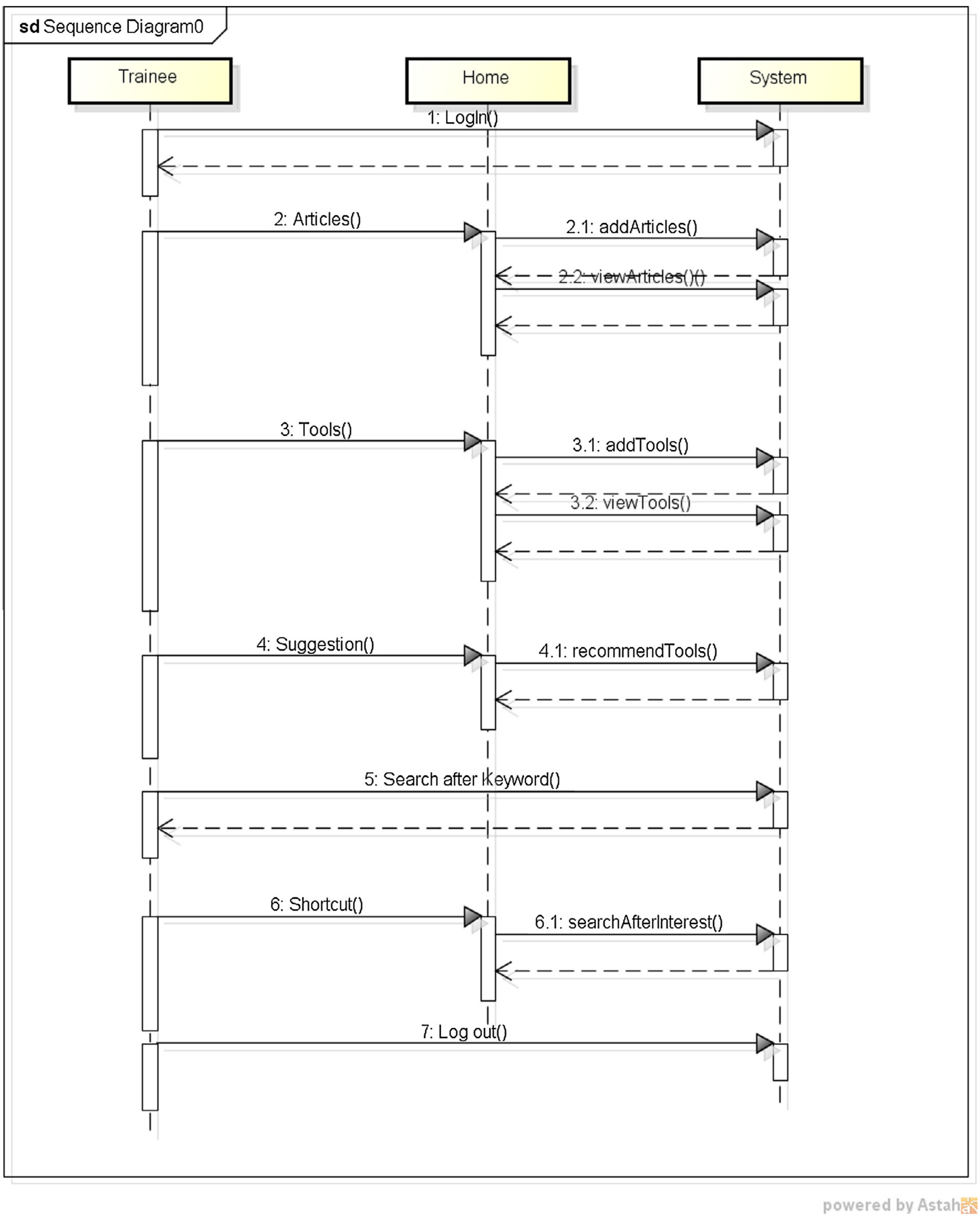

Fig. 5. Typical workflow in U-learn application.

environment, so collaboration is a mandatory ingredient in our scenarios.

5. Results and discussions

The purpose of this section is to illustrate the application areas that have been validated by the users and to extract the areas that can be improved further on. The e-learning platform has been already tested by a group of 25 students at the Faculty of Engineering in Foreign Languages, at the University POLITEHNICA of Bucharest, and its efficiency and effectiveness were proved.

In order to be able to validate the proposed application, we have designed a feedback form to find out opinions related to: easiness of access, easiness of use, learning style accuracy, usefulness/applicability, recommendation accuracy. The form has only 4 questions as we do not want to be a burden to the users of the application. Firstly, the users are asked to rate statements related to the following: “The application is easy to use”, “The application has a good user interface”, “The application is useful” (see Fig. 6). Most of our respondents (90%) said they were happy and very happy when using U-learn, mainly thanks to the provided educational recommendations.

Secondly, our users were asked if they would recommend U-learn application to friends. As seen in Fig. 7, 88% of them answered positively (Very Likely, Likely, Somewhat likely), the rest being undecided. Then, our respondents were asked if they would use the application in the future: according to Fig. 8, 77% answered positively, 22% were undecided, while only 11% answered negatively. Still, because even these respondents would recommend it to others, we were satisfied with the results.

When asked about suggestions for future development, our respondents proposed several improvements: an enhanced social dimension and multiplatform integration, to extend the tool by transforming it into a web aggregator for curation of information and data from all the tools and materials that the user is interested in.

Because the implemented algorithm belongs to the collaborative filtering recommendation algorithms’ family, there are several drawbacks to it which are further discussed. For all the educational tools there has to be at least one person having each learning style that has chosen that tool as preferred one. This is because the algorithm is based on some mathematical computations and it is not possible to do mathematical computations taking into account the NULL value. There has to be a critical number of people that are registered into the database for the algorithm to offer valuable results, but the algorithm is able to improve and it gets better when the number of users grows. Because the algorithm is based on a mathematical formula and not on machine learning, it computes a value for the recommendation for every item, no matter the value. Hence, in order to address this problem we have added a threshold value that a recommendation has to score above in order to be shown to the user: this threshold value was established experimentally. Other two issues we had to address were the sparsity problem and the cold-start problem, typical issues for collaborative filtering recommendations. The sparsity problem affects collaborative filtering algorithms regardless of their success in many application domains, applicability and quality. This problem is caused by the insufficient information for identification of similar users. In order to deal with the sparsity problem, U-learn users are not only classified according to their preferences, but the algorithm runs separately for users having the same learning style. In this way, the sparsity problem is attenuated. The cold-start problem is related to the insufficient number of users during the first stages of application deployment. It was the most difficult problem

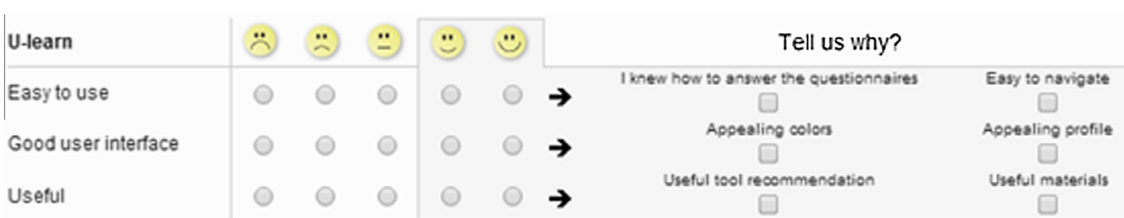

Fig. 6. Sample of validation question for U-learn application (made with Qualtrics tool).

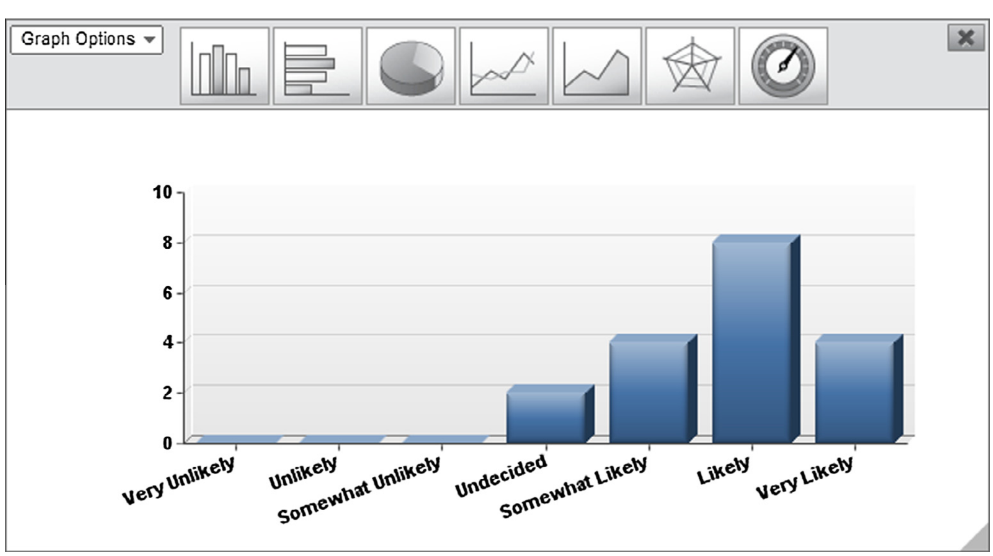

Fig. 7. Answers for “ How likely is that you will recommend a friend to use U-learn application?” (obtained with Qualtrics tool).

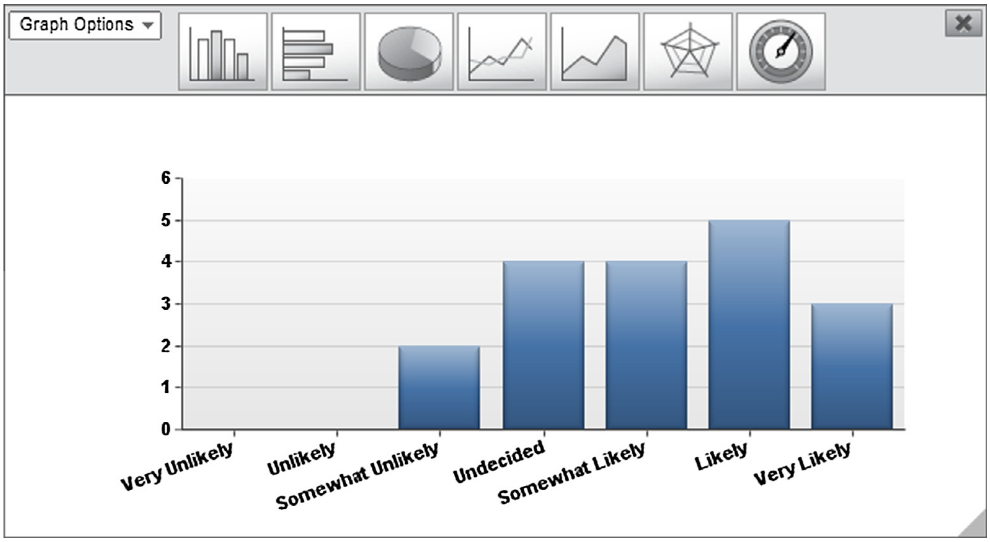

Fig. 8. Answers for "How likely is that you will use U-learn application in the future?" (obtained with Qualtrics tool).

that we have encountered during the development, as the system needs a significant base of real respondents to the LS questionnaire. A number of 30 people ranging from different background have been taking part in the pilot part of the project, when the results were not very concluding. For the algorithm to compute accurately, we had to use surrogate users. However this accuracy increased once more users were in the database. We consider that a number of 60 users is enough to obtain meaningful recommendations. Although there are limitations of our algorithm, due to the positive feedback received by our first users, we are determined to optimize it in the future.

6. Conclusions

In today's society the presence of e-learning services is no longer a novelty, but personalizing them in a meaningful way is still a challenge. In this paper we propose to accomplish this through a recommender agent based on learning styles, which offers suggestions of educational bibliographic materials and tools, with the purpose of helping learners to accomplish their goals.

When making recommendations, we started from the premise that learners with the same learning style would perform better using the same learning tools/materials. In order to validate our hypothesis, we included the recommender agent within a virtual collaborative learning environment, U-learn and we received positive feedback from our users. The same hypothesis was made and validated by other researches: "the achievement scores of students in online courses whose learning styles were matched with particular types of instruction were higher than those of students whose learning styles were not matched" (Shaw, 2012). Although there are other systems recommending educational materials, as far as we know, none recommends learning tools, as we do.

Future tests are needed to prove the usefulness of the recommender agent itself: we consider that the precision and recall metrics are the most suitable in this case. For the moment, the test users stated that recommendations enhance indeed their engagement in the learning process and their willingness to share their knowledge with the other community members. As future work, we want to extend the social network connectors to extract data from several environments (not only Facebook) and also we want to establish a template service for other users who want to implement web services to link their e-learning applications with our recommender agent. Research has shown that ILS is different depending on the background of the learner (Soloman & Felder, 1996): we plan to combine the LS profile and the education information provided in the static profile of the user and, in this way, to optimize the recommendations.

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