Personalized recommendation strategies for eLearning: An AHP approach

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eLearning has become a key adjunct to both, education in general and the business world; it is becoming an important tool to allow the flexibility and quality requested by such a kind of learning process. One of recent challenges in eLearning industry is personalized learning (PL), aimed on meeting the needs and aspirations of each individual learner. A PL can be considered as a facility for an individual to access, combine, configure and manage digital resources (knowledge assets and services) related to their present learning needs and interests. The role of teachers in PL is also enhanced, since they should monitor learners’ progress, make dynamic coherence between educational goals and students’ achievements, and provide all needed recourses accordingly. The variety of PL systems are already developed, the most attempts of learner personalization are focused on the level of knowledge, background and hyperspace experience, preferences and interests, or even learning styles and achievements. It still does not fully address the issue of intelligent personalized recommendations stimulated by the huge wealth of opportunities for collaboration and communication offered by semantic technologies and intelligent reasoning techniques.

In this paper, focusing on the well-known Analytical Hierarchical Process (AHP) method, we propose a framework for addressing different kinds of learners’ preferences in PL, integration with historical data and experiences, and making recommendations and personalization accordingly. Firstly, we are focused on making analyses of relevant kinds of preferences defined by both, learners and teachers over learning process in general (including indicators of progress, learning styles, pedagogic approach, etc.), learning resources and learners’ interests and goals. Also, relevant historical data should be recognized with appropriate retrieving methods and potential web resources if applicable. Finally, semantic structure should be proposed as conceptual framework enabling integration of all gathered data and application of AHP algorithm for processing. The final output of this paper is integrated approach for representing and reasoning over preferences in PL, with effective order decision outcomes in a way that it makes personalized recommendations over available resources, services and dynamic actions.

Keywords: Recommendations, AHP algorithm, learning environment, personalized learning


Introduction

Current learning practices are often based on individual use of diverse learning systems, tools, and services. One of the major problems with this “fragmented” approach is in its lack of means for enabling integration and data exchange about activities that learners perform within individual learning systems/tools and learning artifacts they produce during those activities. Paradigm of Personal Learning Environments (PLEs) allows a
learner to interact with diverse systems, tools, and services to access content, assess his/her knowledge, collaborate with other learners (Attwell, 2007). It helps a learner build his/her Personal Knowledge Network encompassing diverse kinds of learning resources that include not only digital resources but also other individuals as potential collaborators, tutors, advisers, etc.

Tobin (Tobin 2000), for example, states: “All learning is self-directed ... The leader may not have control over what is taught, but the learner always has control over what is learned”. Thus, one of the core issues in learning is the personalization of the learning experience and further, personalization of learning resources (Stankovic, 2008). By personalization we mean the ability of the learner to learn and specify the way she/he deems fit (Stankovic, 2008). Attwell (2007) stresses that central to learning is “placing control of learning in the hands of learners themselves and providing learners with the skills and competences to manage their own learning”. Jafari notes that learners “need to have a system that is centered on what they want and need, (Jafari, McGee and Carmean, 2006). This requires a system that is adaptive and responsive”. It is also written “management by the learner is often key to learning”, (Jafari, McGee and Carmean, 2006).

In a learning environment each individual learner has different characteristics, motivation and success, which all together indubitably should dictate the learning process (Chatti et al., 2010). Earlier in the literature, there is recognized a need to move away from the ‘one size fits all’ paradigm and to offer learner’s personalized earning experience (Ognjanovic and Sendelj, 2012). In meanwhile, a variety of extensions is developed, which define the development of adaptive systems and the most of the attempts in this area are based on their adaptation to user’s level of knowledge (Jovanovic et al., 2009) (Jovanovic, Knight et al., 2007). Other leader features taken into account are background, hyperspace experience (Ognjanovic and Sendelj, 2012), preferences and interests, or even learning styles and their effects on learning achievements (Zimmerman, 2002). In recent years, the crucial element of modeling adaptive systems is based around acquiring and representation of user’s knowledge. It still does not address the far more natural problem of collaboration between students and personalization of that environment. In real life scenarios, each learner has a variety of selection criteria and requirements over them for selection of preferable learner for collaboration and cooperation (Ognjanovic, Gasevic and Bagheri, 2013) (Ognjanovic and Sendelj, 2012).

E-learning requires tools that support participants as both, learners and users, (Smulders 2002). E-learners interact in a complex space which includes the tools, their peers and their e-tutors. Dillenbourg and colleagues (Dillenbourg, Järvelä and Fischer 2009) suggested that there is a need to explore this interactional space in order to better understand e-learning. Contextual information from the interactions can improve e-learners' awareness, organizational and learning activities. Therefore tools need to support e-learners by exposing the contextual information within the interactional space.

All mentioned PLE concepts lead to definition and analyses of learner’s preferences and their further fulfillment, (Jafari, McGee and Carmean, 2006). On the other side, user preferences may be so complex and hard for interpretation (Jovanovic, Gasevic et al., 2009), which means that implementation of service for specification of preferences, may result with service with difficulties for use. For example, in traditional classroom, in case of a student who did not successfully master the previous lectures and there is more time for exam preparation, teacher will dedicate to student the basic concepts with additional practical exercises. On the other side, if student made a lower total score with a group of exercises/questions with master results, teacher will try to improve it implicitly, with additional learning materials, etc. All these good practices from traditional classrooms should be, if it is possible, transformed and integrated in e-learning environment.

Special attention should be put on available historical data (representing attitudes, previous behavior and experiences in learning environment) since they contain wealth of data and information which implicitly (mostly often by sharing experience, social
networks, etc.) influence and dictate (Babad, Darley and Kaplowitz, 1999) current learning practices and behaviors.

This paper is mainly focused on the analyzes how the well-known algorithms from different fields, such as operational research, artificial intelligence, data mining, etc., can be adopted in order to present and process different kinds of requirements in learning environment, which results would define the PLE adopted to each individual student.

The paper is organized as follows: the following section presents well-known and widely used recommendation strategies in the literature. The next section presents the recommendation strategy in PLE by introducing different scenarios. Then we discuss the plan for future work, and finally conclude the paper with directions related to implementation issues, and related work discussion.

Recommendation strategies

In this section we give comprehensive analyses of different recommendation strategies that are well known and widely used in different areas, such as operational research, data bases, etc. In our previous research (Ognjanovic, Gasevic and Bagheri, 2013) we showed that there is no general best fitting recommendation strategy, i.e. each domain of application should be separately analysed, and appropriate approach selected.

There is a variety of formalisms and methods developed for addressing different preference structures with different scales of input and output information and with different semantics. According to (Turski, 2008), input and output preference information can be qualitative, quantitative and/or verbal. Moreover, different types of scales can be used for specifying preference information, namely: ordinal scales, which define ordering between options; interval scales, where numerical grades are defined up to an affine transformation, and ratio scales, where grades are defined up to a multiplicative factor (Domshlak, H"ullermeier and Kaci, 2011). Most of the current approaches collect independent preferences, under the mutual preference independence (MPI) hypothesis (Keeny and Raiffa, 1976), which means that a user's preference for an options independent of the other options (Yu et al., 2010). However, the MPI hypothesis is not always true in practice (Stirling et al., 2007). People often express conditional preferences - they can state their preference for a particular option only when some the state of another option is determined (Yu et al., 2010). In fact, conditional preferences appear to be more natural to human thinking (Yu et al., 2010).

While there have been considerable amounts of research dedicated to managing conditional user preferences, there have been less attention paid to methods for representing and resolving preferences with qualitative initial input with an established numerical interpretation. The practical application of such a framework could be found in different fields and real-life problems. Suppose that a student with a limited budget wants to buy a new laptop. Price and performance are two criteria with the same importance for her, but they are both more important than additional accessories. For her, a laptop with low price is preferred over medium or high prices; but, in case of finding a laptop with a high performance, medium price could be also acceptable to her. Also she is thinking that given extra money to buy accessories, a printer is a more preferred device than a webcam; unless she decides to buy a high performance laptop in case she will buy a webcam to go with it. When visiting the electronics shop website, she finds over twenty different laptops and wants to quantitatively measure the suitability of each of them based on her preferences and finally choose the most appropriate one based on her preferences. This above example sets the basis for our research objective: the formulation of a prioritization technique, which captures conditional preferences, prioritizes the set of alternatives (options) according to ratio output scale and allows different sorts of preferences which
include partially complete and incomplete definitions with the possibility of inducing cycles.

Quantitative preferences

As we previously mentioned, in the literature, there is a lot of different qualitative and quantitative prioritization techniques with different types of scales of input and output data. All of them are with different characteristics often developed basically for addressing group of preferences for especial importance in the considering field. In this section we list methods and formalisms from different fields the most related to quantitative tradeoffs and conditionally defined preferences (Ognjanovic, Gasevic, and Bagheri, 2013):

- AHP as proposed by Saaty (1980) is a widely adopted multi-criteria decision making method that can assist in organizing and analyzing complex decisions (Büyüközkan, Çifçi, and Güleryüz, 2011; Čen and Wang, 2010). AHP enables decision making parties to deal with both tangible and intangible options and to monitor the degree of consistency in the judgments of the involved parties (Roper-Low, 1990). As a well-accepted method (Roper-Low, 1990), AHP has been used extensively in many important decision making domains such as forecasting, quality management, business process management, quality function deployment, and performance management (Büyüközkan, Çifçi and Güleryüz, 2011; Čen and Wang, 2010; Forman and Gass, 2001). The structured technique has also been applied in education (Liberatore and Nydick, 1997; Liu'an, Xiaomei and Lin, 2012; Yüksel, 2012). For example, AHP has been used for the analysis of teaching quality (Liu'an, Xiaomei and Lin, 2012) and evaluation of educational effectiveness (Yüksel, 2012), based on hierarchical models of influencing criteria.

In order to use the AHP, stakeholders’ first need to determine the relative importance of each of the available criteria (i.e., concerns and qualifier tags) compared to the others. Relative importance is typically defined with odd numbers ranging from 1 (equal importance) to 9 (extreme importance of one over the other). That is, in the concern prioritization step, the relative importance of each concern \( \{c_1, \ldots, c_n\} \) with respect to the others is defined by the stakeholders. The concerns are compared in a pair-wise way, and the relative priorities \( \{r_{c1}, \ldots, r_{cn}\} \) are calculated for each of them, defining their ranks. The ranking of available options (i.e., course in our case) are then formed. The options (i.e., courses) \( \{o_1, \ldots, o_n\} \) available to the students are also associated with qualifier tags, \( o_j = <q_{t1}^j, \ldots, q_{tm}^j> \), \( 1 \leq j \leq n \).

During the course ranking process, in order to find the actual priority and importance of the available courses, the relative importance of the qualifier tags is computed by performing the AHP, assigning them \( \{r_{q1}^1, \ldots, r_{q1}^{QT1}, \ldots, r_{q1}^m, \ldots, r_{q1}^{QT1}, \ldots, r_{mq}^{QT1}\} \), which are the ranks of qualifier tags of the \( t^{1}, \ldots, n^{th} \) concern, respectively.

Afterwards, the rank of each course is determined based on the ranks of the qualifier tags that are associated with the courses. That is \( 1 \leq j \leq n \ r(<q_{t1}, \ldots, q_{tm}>)= f(r_{c1} \times r_{q1}^t, \ldots, r_{cm} \times r_{qm}^t, \ 1 \leq j \leq n \), where \( f \) is a predefined function (i.e., minimum, maximum, or mean). The goal of this stage is to assign higher ranks to the courses which are related to more important concerns from the students’ viewpoint.

- TOPSIS (technique for order preference by similarity to an ideal solution) method is an example of a family of methods based on quantitative measurements (based on categorization of Larichev (Turski, 2008). There are many algorithms belonging to this category, such as SAW, LINMAP, CORPAS, but their characteristics do not differ to much base on issues presented in table below. This method considers three types of attributes/criteria: qualitative, quantitative and cost attributes and transforms various
attribute dimensions into non-dimensional attributes, which allows comparisons across criteria. The basic principle of TOPSIS method (Hwang and Yoon, 1981) is that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. The best ideal and negative ideal solutions are found based on statically defined preferences, i.e. the best price is the lowest one, the best quality is the highest one etc. which presents the limit of its use for addressing different sorts of preferences.

- An example of comparative preference methods based on pair wise comparison of alternatives is ELECTRE family of methods developed in mid-sixties which had a strong impact on the Operational research community (Figueira, Mousseau and Roy, 2005). Two important concepts underscore the ELECTRE approach are thresholds and outranking. In contrast to the traditional approach, ELECTRE introduces the concept of an indifference threshold, and the preference relationships are redefined as follows: preferred, indifferent, and cannot be compared. The whole family of methods is developed in order to support heterogeneity of scales, interpretation of outranking relation as a fuzzy relation and situations when relative importance coefficients of criteria are not completely defined. These methods are well known for decision optimization in the case of decisions taken in circumstances of certainty and, as in TOPSIS methods, preferences are statically defined which is the main mason for impossibility of its application in the domain addressed by this paper.

- Also related, the Bubble sort technique has been used to rank order the preference statements. Bubble sort is in essence very similar to AHP with the slight difference that preference comparisons are made to determine which preference has a higher priority, but not to what extent. It is clear that Bubble sort suffers from similar issues to AHP, e.g., the large number of required comparisons. There have been proposals to reduce the number of required comparisons in comparison-based techniques, which are generally referred to as incomplete pair-wise comparison methods. These techniques are based on some local and/or global stopping rule, which determines when further comparison will not reveal more useful information with regards to the prioritization of the options. Such techniques can be beneficial if used along with techniques such as AHP, S-AHP, and Bubble sort.

- Additionally, Hierarchical Cumulative Voting (HCV) has been used to prioritize preferences where top vote-getter preferences are prioritized higher than the others (Brafman and Domshlak, 2002). One of the drawbacks of this approach is that as the number of preferences (options) increases, it becomes very hard for the stakeholders (voters) to select the best voting tactic, which would reveal their preferences about the highest priority preferences. In addition, HCV assumes that it is possible to hierarchically divide the objects of interest into different levels but does not contain any mechanism for doing so (Karlsson, Olsson, and Ryan, 1997). If we would like to extend HCV for both conditional and unconditional situations, the first solution would be to divide conditional and unconditional options in two different groups. Although in such a case it may happen that we have only one unconditional option (or even none) and a large number of conditional options which means that we have a new problem of properly dividing the options into groups. On the contrary, if all of the options are in one block, there is a problem of compensation which is well known for this method.

**Qualitative preferences**

On the other hand, numerous studies have specifically examined conditional preferences and different sorts of preferences with conditionality.

The CP-net (Boutilier, 2003) is formalism for compactly expressing conditional preferences in multivariate problems. It is a qualitative graphical representation of preferences that reflects conditional dependence and independence of preference statements under a ceteris paribus (all else being equal) interpretation. Its extension, TCP-
nets (tradeoffs-enhanced CP-nets) capture both information about conditional independence and information about conditional relative importance. Thus, they provide a Richter framework for representing user preferences, allowing stronger conclusions to be drawn, yet remain committed to the use of intuitive, qualitative information as their source. CP-nets/TCP-nets are general framework for addressing conditionality in preferences.

Few extensions are recently done:

- In (Wilson, 2011) TCP-nets are extended to more general cp-theory in order to express preferences of a lexicographic kind. It is kind of preferences where user wants to express much stronger statements such as those of the form: x is preferred to x’ irrespective of the values of other variables, where the variable x is the most important variable, and, for example, x’ represents a value that should be avoided if at all possible. It is also shown that CP-nets and TCP-nets cannot be used for this stronger kind of preference statement and the Cp-theory is based on ‘swapping sequences’, which is a natural generalization of flip-ping sequences in CP-nets and TCP-nets. All these theories have limitation on its focus on acyclicity which is a strong restriction, limiting their potential applicability. Based on some limitations, dominance testing takes polynomial time which is advantage of these theories.

- Conditional Outcome Preference Network (COP-network) is one more example of users’ preferences presentation with directed graph. Additionally to other methods, this method develops a utility function to predict all known utilities but it suffers of the same things.

- There is another variant of the TCP-net, known as UCP-nets (Boutilier, Bacchus and Brafman, 2001) that capture quantitative preferences and relative importance information using utility functions. They combine the theory of CP-nets and GAI-nets (generalized additive decomposable utility functions). They have a limitation, as they do not make any assumption on the kind of interactions between attributes that need to be prioritized (Boutilier, Bacchus and Brafman, 2001)

- There is a work different to one proposed in (McGeachie and Doyle 2011), where TCP-nets theory is analyzed as a model for representing and reasoning with quantitative (Mukhtar, Belaïd and Bernard, 2009). Preferences and constraints are specified qualitatively and then mapped on to a quantitative utility model. Despite the advantages of TCP-nets, they do not allow for quantitatively comparing each pair of criteria within TCP-nets, i.e., it is possible to compare them only in the form: “if two options have the same final ranking I prefer one which has a higher value of one criterion over the other” as shown in (Mukhtar, Belaïd and Bernard, 2009). This form of comparison might be considered to be conditional as well, but it can cause cycles as previously mentioned by short example in the introduction.

- The most related to our work is recently done extension of CP-nets with (McGeachie and Doyle, 2011) quantitative trade-offs statements. The extension is made by concepts from elementary geometry and usage of additive linear value function which corresponds to user’s preference relations (Brafman, Domshlak, and Kogan, 2004) and representation of tradeoff statements as constraints on the partial derivatives of the value function. They have demonstrated that for each acyclic CPnet additive value function can represent all forms of preferences (Brafman and Domshlak, 2002). Unfortunately, it also suffers of cycles induced by conditionally defined preferences as CP-nets/ TCP-nets. Also, priority statements specific for TCP-nets are not completely addressed and that novel representation raises many new questions for further research, especially about interaction with ceteris paribus preference statements (McGeachie and Doyle, 2011). This method proposes the transformation of the set of preferences into the system of linear inequalities, and in generally, that system should
not have a solution. In that case it should be so useful to recognize the subset of preferences causing the inconsistency.

Conditional preferences and other kinds of preferences

CS-AHP (Conditional Stratified Analytic Hierarchy Process) adopts Analytical Hierarchy Process (AHP) technique (Ognjanovic, Gasevic and Bagheri, 2013) for different kinds of preferences using the two-level hierarchy hierarchical structure of concerns and qualifier tags. Concerns are a set of quality characteristics that represent the important matters of interest to the-for learners such as fields of professional specialization, spoken languages or preferred message response time.

Qualifier tags represent the possible enumerations values for each concern. Once the relative importance is set between all pairs of concerns, the AHP performs a tuned pairwise comparison of the learners’ requirements. The outcome of the procedure are ranks \( (r_1, \ldots, r_n) \), which provide values from the \([0,1]\) interval over the set of available options by performing two main steps: i) the set of concerns and their qualifier tags are locally ranked, let annotate with and \( \{r^1_{qt_1}, \ldots, r^n_{qt_1|QT_1}\} \), \( \ldots \), \( \{r^n_{qt_1}, \ldots, r^n_{qt_1|QT_1}\} \) obtained ranks of the set of concerns \( \mathcal{C} \) and the set of qualifier tags of the \( 1st, \ldots, nth \) concern, respectively; ii) rank of each available option (combination of one tag per concern) is calculated based on the ranks of the qualifier tags that are associated i.e. \( r(<qt_1^1, \ldots, qt_m^m>) = f(r_{c_1} \ast r_{qt_1^1}, \ldots, r_{c_n} \ast r_{qt_m^m}) \), where \( f \) is a predefined function (i.e., minimum, maximum, or mean).

Furthermore, CS-AHP also allows for setting conditional preferences. For example, learners are often aware that requirement of expertise is hard to meet, so they may define a compromise: they are only prepared to wait for response from a learner with expert knowledge, if it the waiting time is kept at a very minimum; otherwise, they are willing to contact learners with lower level of expertise but with medium delays in response. CS-AHP is simple to perform, and requires quadratic number of comparisons, which brings linear time complexity to the number of available options (Ognjanovic, Gasevic and Bagheri, 2013).

As previously explained TCP-Nets and CP-Nets algorithms address conditional preferences with qualitative data inputs. It can be seen that these three algorithms (CS-AHP, TCP-Nets, CP-Nets) are developed for addressing similar kinds of conditional preferences with different data inputs, and thus imposed different characteristics of complexity estimations and consistency checking.

AHP algorithm in learning environment

AHP algorithm is already recognized as promising solution in learning environment (Coboa, Rocha and Rodríguez-Hoyosc, 2013) (Ognjanovic and Sendelj, 2012). In this section we will follow scenario-based approach and introduce how hierarchical structure of concerns and qualifier tags can be set in those domains. By analyzing existing research in PLE, the following scenarios are defined:

**Scenario I** (Ognjanovic and Sendelj, 2011) - recommendation of appropriate peers for collaboration and communication who use PLE based on their learning activities, learner models and learning context.

**Scenario II** (Ognjanovic and Sendelj, 2012) - adaptation of learning system by allocation of available resources based on general requirements (previously accepted learning goals, objectives and timelines), students’ assessments and achieved results, students’ personal requirements about learning style and contents.

**Scenario III** - in addition to Scenario II, this is focused on making recommendation of learning resources from the set of both, resources generated and/or recommended by...
teachers, and resources opened and available online (Jeremic, Jovanovic and Gasevic, 2009).

Prior to detailed description of each scenario, the analysis of available data sources is needed in PLE, as follows.

**Input data in learning environment**

In order to develop a user-friendly service for the implementation of CS-AHP in a PLE, a structure of concerns and qualifier tags is built on the Preview framework related to learning environments. The following three categories of concerns are recognized from the aspect of definition and management issues (Ognjanovic and Sendelj, 2012): statically defined concerns, concerns dynamically defined for each call of recommendation service, and concerns with dynamic updates.

Statically defined concerns present general information about a learner who is looking for another peer appropriate for conversation; examples include, such as the known language(s) knowledge, preferable subject area, and availability for F2F contact, etc. Having in mind non-changeable nature of those concerns, it is naturally to expect that learners profile can be modeled by containing values for each static concern. Information in the profile may be changed upon the learner’s request; otherwise, it remains unchanged, representing the learner’s characteristics that are used during in each call of the service.

On the other side, some concerns are directly related to the contexts of the upcoming call of recommendation strategy (e.g. concerns dynamically defined for each conversation), and, thus learners are enabled to define them explicitly. In this case, it is naturally to enable explicit definition of each concern value whenever it is needed.

Finally, the third group of concerns represents concerns that could be cumulatively updated simultaneous for each completed use of recommendation service. It is mostly often related to expressing some experiences’ rates, personal assessments and measurements.

**Scenario I: recommendation of peers for collaboration**

For the purpose of peers recommendation, the structure of concerns and qualifier tags is built on our Preview framework related to learning environments (Ognjanovic and Sendelj, 2012). The following concerns are identified and categorized in mentioned three categories:

- statically defined concerns: known language(s), preferable subject area;
- availability for F2F contact, etc.;
- dynamically defined concerns for each invoke separately: for example, a learner can may define the type of conversation (e.g. the service information needed administration/service question, help in understanding, etc.) and/or the, urgency level (e.g. extra urgent), etc;
- concerns with dynamic update: e.g. concern defined as Conversation Rate should be cumulative updated simultaneous for each completed conversation. In order to use this concern, learner should be asked to rate each peer after communication, and based on the learner’s feedback the results of average ratings should be updated and later used in for further communications with the same peer. Furthermore, if no rate is previously aggregated, initial selection of N/A represents indifferent and undeclared learner (no specific neither positive nor negative rate is specified).

**Scenario II: recommendation of learning paths and learning structures**

For the purpose of making recommendation of learning structure of specific courses and therefore making construction of learning paths, two disjoined dimensions of adaptivity in
The following two approaches have clear interpretation and correspond to the nature of historical data needed to be integrated:
- AHP - HB (Analytic Hierarchy Process History Breadth) is based on extension of the first level in the AHP hierarchy (i.e. the level of concerns) by adding additional concern “Previous experience”. This concern is used for adding cumulative experience and allowing student to define explicitly which is his/her interest in respecting previous experience. It means that, by defining preferences at the level of concerns, student is asked to compare the importance of previous experience with all other criteria. Illustrative example of AHP-HB is given on the Figure 1.

- On the other side, AHP-HD (Analytic Hierarchy Process History Depth) is developed by extension of each set of qualifier tags separately. It means that additional qualifier tag representing previous experiences is added for each concern. The general idea behind this approach is focused on analyzing historical data separately for each concern, and thus no considering overall decisions made in the past. This idea is imposed by willingness to understand which criteria influenced on made decision, and thus their integration at current recommendation process.

**Conclusion**

In this paper we presented different approaches for integration of AHP family of methods in PLE. The main conclusion is that there is no general approach for making adoptions, since different kinds of available data with different kinds of requirements are identified in different scenarios for recommendation strategies.

On the other side, to the best of our knowledge, there is no developed user-friendly tool for defining requirements, and thus, implementation aspects of the proposed approach are special issue for further development and research. However, impressive results of AHP use in different filed and areas, give optimistic wave for making extensions of existing PLEs and allowing integration of such recommendation strategies. To the best of our knowledge, this paper gives comprehensive review of existing approaches in
recommendation strategies and the innovative integral approach that is based on AHP adoptions for different scenarios in PLEs.

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This research paper was presented to DisCO-2014 Conference, June 23-25, Prague, Czech Republic