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LEARNING PERSONALISATION IN VIRTUAL LEARNING ENVIRONMENTS APPLYING LEARNING ANALYTICS

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Abstract

The report aims to analyse application of learning analytics / educational data mining (LA / EDM) to support learning personalisation and optimisation (in terms of motivation, time, quality, and effectiveness) in virtual learning environments (VLEs) e.g. Moodle. LA / EDM are known as the measurement, collection, analysis, and reporting of data about learners and their contexts to understand and optimise learning and environments in which it occurs.

In the report, appropriate LA / EDM methods and techniques are identified to be applied to personalise students' learning in VLEs. The original methodology to personalise learning is presented. First of all, existing VLE-based learning activities and tools are analysed to be further interlinked with appropriate students' learning styles. For this purpose, Felder-Silverman learning styles model (FSLSM) is applied in the research. Students' learning styles according to FSLSM are interlinked with the most suitable VLE-based learning activities and tools using expert evaluation method. After that, a group of students should be analysed in terms of identifying their individual learner profiles according to Soloman-Felder index of learning styles questionnaire. After identifying individual learner profiles, probabilistic suitability indexes are calculated for each analysed student and each VLE-based learning activity to identify which learning activities or tools are the most suitable for particular student. From theoretical point of view, the higher is probabilistic suitability index the better learning activity or tool fits particular student's needs.

On the other hand, students practically used some learning activities or tools in real learning practice in Moodle before identifying the aforementioned probabilistic suitability indexes. Here we could hypothesise that students preferred to practically use particular VLE-based learning activities or tools that fit their learning needs mostly. Thus, using appropriate LA / EMD methods and techniques, it would be helpful to analyse what particular learning activities or tools were practically used by these students in VLE, and to what extent. After that, the data on practical use of VLE-based learning activities or tools should be compared with students' probabilistic suitability indexes. In the case of any noticeable discrepancies, students' profiles and accompanied suitability indexes should be identified more precisely, and students' personal leaning paths in VLE should be corrected according to new identified data. In this way, after several iterations, we could noticeably enhance students' learning motivation, quality and effectiveness.

Keywords: learning analytics, educational data mining, learning personalisation, virtual learning environments, students' learning styles

Contents

Introduction

The report aims to analyse application of learning analytics / educational data mining (LA / EDM) to support learning personalisation and optimisation in virtual learning environment (VLE) e.g. Moodle. LA is the analysis of electronic learning data which allows teachers, course designers and administrators of VLEs to search for unobserved patterns and underlying information in learning processes.

Learning personalisation is helpful to enhance learning motivation, quality and effectiveness. Learning personalisation by applying learning styles and intelligent technologies became very popular topic in scientific literature during last few years [1], [2], [3], [4], [5], [6], [7], [8], [9], [10]. Personalisation can be seen from two different perspectives, namely, while only one learning object [11], [12], [13], [14] or a learning unit / scenario [15], [16], [17] is selected, and while a set of them is composed, i.e. personalisation of a learning unit / scenario by finding a learning path [7]. The former perspective formulates learning objects selection problem, and the latter one solves curriculum sequencing problem [18].

Personalised learning units / scenarios are referred here as learning units / scenarios composed of the learning components having the highest probabilistic suitability indexes [19] to particular students according to Felder-Silverman Learning Styles Model [20].

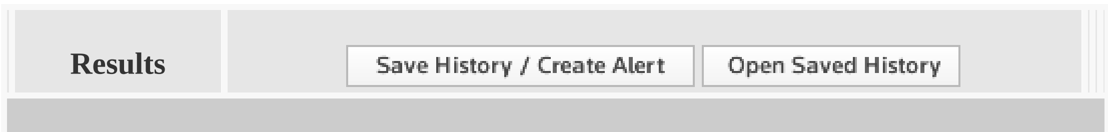
In the report, first of all, results of systematic review performed in Clarivate Analytics Web of Science database is presented. The following research questions have been raised to perform systematic literature review: "What are existing LA / EDM methods, tools, and techniques applied to support personalised learning in VLEs / Learning Management Systems (LMSs)?"

After that, the original learning personalisation methodology based on identifying students' learning styles and other needs is presented in more detail. At the end, the method on possible application of LA / EDM to support personalised learning in VLE is provided.

Systematic Review

During XXI century (2001-2017), 82 publications (from which – 35 articles) in English were found on March 26, 2017, in Web of Science database on the topic "TS=(virtual learning environment* AND learning analytics)", and 604 publications (from which – 264 articles) – on the topic "TS=(learning management system* AND data mining)" (Fig. 1):

Search History: 26 MAR



35	(TS=(virtual learning environment* AND learning analytics)) *AND* **LANGUAGE:** (English) *AND* **DOCUMENT TYPES:** (Article) *Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI Timespan=2001-2017*
264	(TS=(learning management system* AND data mining)) *AND* **LANGUAGE:** (English) *AND* **DOCUMENT TYPES:** (Article) *Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI Timespan=2001-2017*
604	(TS=(learning management system* AND data mining)) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI Timespan=2001-2017*
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Figure 1. Search history.

After applying B. Kitchenham's systematic review methodology [21], on the last stage 10 newest most suitable articles [21-30] were identified to further detailed analysis on possible application of LA / EDM to support learning in VLEs.

Systematic review has shown that LA / EDM are already quite actively used in VLEs e.g. Moodle to solve different problems e.g. academic assessment, predicting students' success and dropout, predicting instructional effectiveness of VLEs, etc. At the same time, LA / EDM are still rarely used to personalise learning in VLEs according to students' needs, and future research is needed in the area.

Learning personalisation methodology applying learning analytics in VLE Moodle

According to [31], learning software and all learning process should be personalised according to the main characteristics / needs of the learners. Learners have different needs and characteristics, that is, prior knowledge, intellectual level, interests, goals, cognitive traits (working memory capacity, inductive reasoning ability, and associative learning skills), learning behavioural type (according to his / her self-regulation level), and, finally, learning styles.

In personalised learning, first of all, integrated learner profile (model) should be implemented using e.g. Soloman-Felder Index of Learning Styles Questionnaire [32] [19]. After that, interlinking of learning components (learning objects, activities, and environments) with learners' profiles should be performed, and an ontologies-based personalised recommender system should be created to suggest learning components suitable to particular learners according to their profiles [31].

Interlinking and ontologies creation should be based on the expert evaluation results (e.g. [33]). Experienced experts should evaluate learning components in terms of its suitability to particular learners according to their learning styles and other preferences / needs. A recommender system should form the preference lists of the learning components according to the expert evaluation results.

Probabilistic suitability indexes [19] should be identified for all learning components in terms of its suitability level to particular learners. These suitability indexes could be easily calculated for all learning components and all students if one should multiply learning components' suitability ratings obtained while the experts evaluate suitability of the learning components to particular learning styles (like in [33]) by probabilities of particular students' learning styles (like in [19]). These suitability indexes should be included in the recommender system, and all learning components should be linked to particular students according to those suitability indexes. The higher the suitability indexes, the better the learning components fit the needs of particular learners.

Thus, personalised learning units / scenarios (i.e. personalised methodological sequences of learning components) could be created for particular learners. An optimal learning unit / scenario (i.e. learning unit of the highest quality) for particular student means a methodological sequence of learning components having the highest suitability indexes.

A number of intelligent technologies should be applied to implement this methodology, for example, ontologies, recommender systems, intelligent software agents, decision support systems to evaluate quality of learning units / scenarios etc.

This pedagogically sound learning units / scenarios personalisation methodology is aimed at improving learning quality and effectiveness. Learning unit / scenario of the highest quality for particular student means a methodological sequence of learning components with the highest suitability indexes. The level of students' competences, that is, knowledge / understanding, skills and attitudes / values directly depends on the level of application of high-quality learning units / scenarios in real pedagogical practice.

Existing VLE-based learning activities and tools should be analysed to be further interlinked with appropriate students' learning styles. For this purpose, Felder-Silverman learning styles model (FSLSM) [20] should be applied. Students' learning styles according to FSLSM should be interlinked with the most suitable Moodle-based learning activities and tools using expert evaluation method [33]. FSLSM classifies students according to where they fit on a number of scales pertaining to the ways they receive and process information: (a) By information type: (1) Sensory (SEN) – concrete, practical, oriented towards facts and procedures vs (2) Intuitive (INT) – conceptual, innovative, oriented towards facts and meaning; (b) By sensory channel: (3) Visual (VIS) – prefer visual representations of presented material e.g. pictures, diagrams, flow charts vs (4) Verbal (VER) – prefer written and spoken explanations; (c) By information processing: (5) Active (ACT) – learn by trying things out, working with others vs (6) Reflective (REF) – learn by thinking things through, working alone;

and (d) By understanding: (7) Sequential (SEQ) – linear, orderly, learn in small incremental steps vs (8) Global (GLO) – holistic, systems thinkers, learn in large leaps [20].

In Table 1, the main VLE Moodle tools / activities are interlinked with the most suitable learning styles according to FSLSM.

Table 1. VLE Moodle tools / activities and most suitable learning styles according to FSLSM

Activity	Description	Most suitable learning styles
Assignments	Enable teachers to grade and give comments on uploaded files and assignments created on and off line	REF
Chat	Allows participants to have a real-time synchronous discussion	ACT
Choice	A teacher asks a question and specifies a choice of multiple responses	INT
Database	Enables participants to create, maintain and search a bank of record entries	ACT
External tool	Allows participants to interact with Learning Tools Interoperability compliant learning resources and activities on other web sites	ACT
Feedback	For creating and conducting surveys to collect feedback	ACT
Forum	Allows participants to have asynchronous discussions	ACT
Glossary	Enables participants to create and maintain a list of definitions, like a dictionary	INT, GLO
Lesson	For delivering content in flexible ways	SEN, SEQ
Quiz	Allows the teacher to design and set quiz tests, which may be automatically marked and feedback and/or to correct answers shown	REF, SEN, SEQ
SCORM	Enables SCORM packages to be included as course content	REF, SEN, SEQ
Survey	For gathering data from students to help teachers learn about their class and reflect on their own teaching	REF, GLO
Wiki	A collection of web pages that anyone can add to or edit	ACT, GLO
Workshop	Enables peer assessment	ACT

Next, students should be analysed in terms of identifying their individual learner profiles according to [32]. After identifying individual learner profiles, probabilistic suitability indexes [19] should be calculated for each analysed student and each VLE-based learning activity to identify which learning activities or tools are the most suitable for particular student. From theoretical point of view, the higher is probabilistic suitability index the better learning activity or tool fits particular student's needs.

On the other hand, students practically used some learning activities or tools in real learning practice in Moodle before identifying the aforementioned probabilistic suitability indexes. Here we could hypothesise that students preferred to practically use particular VLE-based learning activities or tools that fit their learning needs mostly.

Thus, using appropriate LA / EMD methods and techniques, it would be helpful to analyse what particular learning activities or tools were practically used by these students in VLE, and to what extent.

The basic LA / EDM techniques and their application in VLE examples are shown in Table 2. These techniques can be used together or one after the other, depending on the complexity of the task solved.

Table 2. EDM techniques and application examples

LA / EDM techniques	Application examples
Classification	To classify each item in a set of data into one of predefined set of learners group
Clustering	To determine groups of students that need special course profiling
Association rules	To discover interesting relations between course elements which were used by particular students
Prediction	To predict dependencies of using Moodle activities and final student's learning outcomes

To determine and to set appropriate algorithm to a new data set is a difficult task because there is no single classificatory which equally well suited for all data sets. In practice it is very important to choose the proper classification / clustering or other algorithm to a particular data set.

After that, the data on practical use of Moodle-based learning activities or tools should be compared with students' probabilistic suitability indexes. In the case of any noticeable discrepancies, students' profiles and accompanied suitability indexes should be identified more precisely, and students' personal learning paths (i.e. learning units / scenarios) in VLE should be corrected according to new identified data. In this way, after several iterations, we could noticeably enhance students' learning quality and effectiveness.

Conclusion

Systematic review has shown that LA / EDM are already quite actively used in VLEs to solve different problems e.g. academic assessment, predicting students' success and dropout, predicting instructional effectiveness of VLEs, etc. At the same time, LA / EDM are still rarely used to personalise learning in VLEs according to students' needs, and future research is needed in the area.

In the report, original learning personalisation methodology applying LA / EDM in VLEs e.g. Moodle is presented. According to this methodology, first of all, Moodle-based learning activities / tools should be analysed to be further interlinked with appropriate students' learning styles. Students' learning styles should be interlinked with the most suitable VLE-based learning activities / tools using expert evaluation method (Table 1).

Second, groups of students should be analysed in terms of identifying their individual learner profiles. After that, probabilistic suitability indexes should be calculated for each analysed student and each Moodle-based learning activity / tool to identify which learning activities / tools are the most suitable for particular student. From theoretical point of view, the higher is probabilistic suitability index the better learning activity / tool fits particular student's needs.

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In the report, basic LA / EDM techniques and their application in VLE examples are presented (Table 2). These techniques are as follows: classification, clustering, association rules, and prediction. These techniques can be used together or one after the other, depending on the complexity of the task solved. To determine and to set appropriate algorithm to a new data set is a difficult task because there is no single classificatory which equally well suited for all data sets. In practice it is very important to choose the proper classification / clustering or other algorithm to a particular data set.

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