Design and Implementation of Intelligent Tutoring System using Enhanced Personalization in e-Learning

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Abstract: ***A review of different E-learning Experience considers the need for personalization of learning contents to enhance the experience of learners. The current scenario of education shows that more and more learners are using e-learning to earn their degrees, build upon their knowledge base and acquire new skills. E-Learning is a $56.2 billion industry today and will double by 2017. Statistics show that by 2019, roughly half of all educational institutions will offer e-Learning based training. This initiates the study of various methodologies which analyze the profiles, learning styles, behavior, and capabilities for mapping the appropriate learning content to appropriate user. A review of approaches and methods was conducted by studying articles of past9 years (2006-2015) by extracting information for techniques used for improving e-learning experience. A five stage literature review of personalization of learning contents using various approaches was conducted. The strengths and weaknesses followed by gaps in the related work are discussed. Further an intelligent tutoring model is proposed as the solution to enhance personalisation in e-learning.***

Keywords: e-Learning, personalization, data mining, learning styles, contents and behaviour, e-learning platforms, intelligent tutoring systems, recommender system, blended approach

1. Introduction

The present research is presented with a view to study personalization and adaptation of learning contents to the e-learners based on their requirements. With the advance in IT, human knowledge and learning content have an incredible increase in the quantity and variety of digital content. The trends have implications on the quality and relevance of knowledge and learning content delivered to organization workers and e-learners. The benefits of using e-learning are obvious but the process is effective only if the learner is provided with appropriate learning objects, aligned with his learning style, capabilities and requirements. As a result of this growing online knowledge and learning content there is an urgent need of designing learner centric e-learning systems.

There are many factors that influence the extent of learning. These would include factors such as learner‟s learning style and motivation for learning. An important role of e-learning content providers is to recognize that their pedagogy and educational material must cater for the individual learner‟s requirements. There is an immediate need to move away from "one size that fits all" paradigm and offer personalized learning experience. Based on reviews undertaken for improving the e-learning experience, a comprehensive approach for enhancing the e-learning experience is proposed.

2. Literature Review

Instructors use various tools to deliver the online contents to e-learners. The challenge for content developers is to provide appropriate content to the users to satisfy their individual needs.

Improving e-Learning experience through Personalization of e-learning contents

This method deals with providing appropriate contents to the learners after analyzing the learner‟s needs and capabilities. **Static Personalization** deals with collecting the necessary data from the user and then analyzing the data using techniques of Data Mining to find individual needs and providing learning contents useful to them. **Dynamic Personalization** involves studying and analyzing the behavior and capabilities of the users and then dynamically mapping the contents to the user. **Intelligent Tutoring Systems and Recommender System** considerdeveloping a middleware or an agent based model to use the data from the learning systems to provide a recommendation for the requirements of the learners.Major challenge for e-content designers is that the content should be user specific and should satisfy the needs of various different learners. Moreover it is difficult to dynamically map the contents to the user‟s specific needs and the users may not be able to specify the needs correctly.

3. Key Findings with Solution Approaches

This section discusses solution approaches which have been used by the researchers to validate or simulate their results and findings, the type of methodologies adopted, technology platform and details of hardware/ software used to obtain or validate their results

Table 6: Personalization using Intelligent Tutoring and Recommender Systems

Ref. No. Study type	*Purpose*	*Data Input*	*Data source*	*Data size*	*Parameters studied*	*Methodology*	*Software /Tools*	*Performance Parameters*	*Results*
[15] Prototype Design and evaluation	Multi-agent system for Web Intelligent Tutoring	Student Profile Student feedback	User Profile database Questionnaire from students of Southwest University of China	320	Frequency of use Interactivity Efficiency Usefulness Convenience	Mathematical Model for recommendation Statistical methods for evaluation	Mathematical equation	Strongly disagree to strongly agree: 5 point scale	Average for Personalized learning : 4.43
[4] Comparative study of AEH	Quantitative approach for Evaluating Learning Style AEH	AEH Systems features	Random selection	24 AEH Systems	Intervention time Minimum group size Scientific objectivity	Statistical procedures **Case studies:** WHURLE-LS, DEUS, Empirical study, User trials	Correlation using multiple regression, SPSS, t-test, Chi-Square, ANOVA	Approach: Equal Greater Important	Comparison Table
[14] Experimental study	Ontology Extraction Method for Adaptive Learning	Short messages on online discussion forum for 10 minutes Questionnaire for assessment	Postgraduate students of management course	Topics 1 to 10 and topics 41 to 50 First 1000 web pages retrieved via Google Search API	Accuracy Cohesiveness Isolation Hierarchy Readability	Context sensitive text mining Fuzzy domain ontology extraction algorithm Concept extraction : BMI method Relation extraction : SSIM method	Java Server Pages 2.1 Servlet 2.5 TouchGraph Apache Tomcat 6.0 web server	Mean score For concept map Assessment : Very Good Good Average Bad Very poor	Mean scores : Accuracy : 4.23 Cohesiveness: 4.22 Isolation : 4.15 Hierarchy : 4.31 Readability : 3.95
[17] Experimental	Motivation Prediction	- Intrinsic - extrinsic motivation data	Questionnaire data of students for behavior pattern	180	Motivation Indexes: - Autonomous - Controlled - e-learning motivation, - no. of hits	- Likert type scale - P- value - statistical procedures - Correlation for motivation Index	SPSS	- Fairly constant - Slightly irregular - Quite irregular	Positive correlation of extrinsic factor for controlled Motivation
[24] Experimental study	Mining educational data to improve adaptation in e-learning	Normalised Learners log, resources info., activities log,	LMS MOODLE	66 students	Effect of Algorithmic Induction of Decision trees, pruning tactics on classification accuracy	Data Clustering : KSimpleMeans Clustering Data Classification : ID3-Decision Tree	J48 Algorithm Clustering, Multivariate Analysis	Learning style wise clustering Ranked attributes	Clustered Instances Concrete LS: 38% Concept LS; 35% Observe LS : 21% Experiment : 6% Highest Rank 0.72531
[5] Experimental study	Personalised e-learning LearnFit using dynamic learner‟s personality	Students learning style and preference using a set of 60 questions	Students of Computer Information Systems at FSSM, UCAM, Morocco	Control Group : 24 Experimental Group : 24	Post test : Mean Score Standard deviation T value P value	Student t-test, Kolmogrov-Smirnov-test for checking distributions	Mathematical model	Post test score	T value = -4.53 P value = 0.02
[7] Experimental Analysis	Student Learning profile identification based on user context of interaction	Forum logs Discussions logs Exercise logs Questionnaire logs	LMS logs of civil, computer and electric engineering students of 2010 batch	297	Perceptive Formative Participative styles based on FSMLS	Distributions tabulated using mathematical algorithm Least Square Approximation Student brain model K Nearest Neighbor for classification	Mathematical model	No. Of learning style profiles : Intuitive Sensory Verbal Visual Reflexive Active	**Perceptive** Intuitive : 37 Sensory: 260 **Formative** Verbal : 51 Visual : 246 **Participative** Reflexive : 7 Active : 290

[27] Case study	Disengagement prediction	Problem solving activity data, test and quiz data	Study 1: Log file from HTML-Tutor Study 2: iHelp data university of Saskatchewan	**Study 1:** 11 students, 108 sessions, 450 sequences **Study 2:** 21 students, 218 sessions, 735 sequences	Accuracy, True positive rates	Simple Logistic Classification 2 validation studies Statistical methods Pair t-test	WEKA Chi-Square Evaluator	Mean Significant Difference	MSD = 3.0
[6] Experimental study	Document Recommendation Model	Data set : Documents	Social networks and E-commerce site	Topics = 50 Test dataset = 100	Predictive utility based on Document Ranks	Latent Dirichlet Allocation for Document-Topic Coefficient Matrix Integrated Recommendation Algorithm built	-	Similarity between documents viewed & unseen documents	Highest Predictive Utility
[23] Experimental study	User centric retrieval of Learning objects	Topic Sub-topic Author Age Educational level Time Space – Geo Learning space	LMS logs	400	Topical, Personal and Situational Relevance	Min-Max Normalization Technique Z-score Normalization K-mean & SOM for clustering and scatter plot	TANAGRA tool kit	Cluster cohesion (SSE) Cluster Separation (Squared Error) BSS (Between cluster Sum of Squares TSS = WSS + BSS RS = TSS/BSS	RS = 0.73 to 0.76 Significant difference between clustered groups
[20] Descriptive Study	Learning resource recommendation based on transfer learning	Already classified new data Old data	Web	-	Users Interest, Nearest Neighbours Top – N : recommended set	Statistical Modelling : Cosine Similarity, Pearson Correlation Coefficient Metric for related similarity Machine Learning Algorithm	Statistical tools	Users interest in target resources feature set	Provides Solution to sparse solution collaborative – filtering and cold start-up problem
[11] Experimental Study	Attribute – based recommender system for Learning Resource by Learner Preference tree	Historical accessed recourses	Metadata for Architectural Contents in Europe	1148 Learners 12000 resources	Number of neighbours (5-40)	MAE, MACE, Normalized mean absolute error, Rank accuracy metrics, Bayesian Network, Correlation Learner Preference Tree	Statistical techniques	Precision, Recall for recommender system MAE for prediction quality metric	Prediction accuracy improves with decreasing sparsity
[21] Suggestive Framework for recommender agent	Track learning pattern and personalise using adaptive recommender agent (IPBARA)	Log of navigation sequence of learner	LCMS application server	-	Signature pattern of learners	Concept manager, pattern recogniser, User behaviour analysis, generate user navigational patterns in application env. **Algorithm** : gen_signature pattern, Gen_Repetitive_Seq	Mathematical model used	Generation of concept map tree by concept map manager Generation of signature pattern by Recommender	Successful

[2] Experimental evaluation	Personalised recommendation based on Semantic Analysis	User logs	Easy Learner Website for mathematics	30 users 170 learning contents 1325 learning logs	Performance of Collaborative Filtering, Sequential Pattern Mining, Semantic Analysis Algorithm	Video Structurised Description lexical parsing Semantic Mapping Rule Auto Updating mathematical model	Java, JSP, SQL, Eclipse, Apache Tomcat 6.0	Mean Absolute Error for CF, SPM and SAA	MAE CF, MAE SAA, MAE GSP decreased using RAU
[26] Comparative Study	Predicting Academic performance using learning analytics in VLE	Student-system Interaction Logs, report logs for each classification	MOODLE logs interactions Data from informal learning processes outside VLE	20 to 30 students, 2 to 3 teachers 100 hours 10 units	Number of interactions for each course Moderating factors like Agent Frequency Mode	Multiple linear regression between student interactions Variance of dependent variable as linear combination of independent variables Data analysis of backward multiple regression	SPSS 18 (PASW)	Average interaction per course for each classification	No relation between creating class interaction and final academic performance
[1] Case Study	User Behaviour Mining for personalising in e-Learning system	Learner behaviour, learning progress, learning resources used, test taken, homework library content	History of learner behaviour Client side Web logs Server logs	Not mentioned	Personalised recommendations	Web- Browser Plugin technology If- then- else model used for browser plugin	XML file for learner history VC++	Behaviour mining in personalised recommendation engine	Support for individual learning
[3] Prototype Design and Evaluation with experimentation	Interoperable Intelligent Tutoring System	Student Maths Activity Data	Student Interaction with the course and tutor interfaced with MOODLE, Odijoo, SRTE & SCORM Cloud	Not mentioned	Grading Skills Students : Skillometer (0% -100%)	Comparison of functionality and features of LMS and GRAPPLE Approach, T-Maestro Approach and Prototype	PROLOG or LISP for inner and outer Loop Dreamweaver IDE for web development RELOAD IDE for SCORM- PIF	Functionalities : – Inner Loops – Outer Loops Features : - Supports - Provides	Prototype satisfied all functionalities and features
[22] Experimental study	Student classification for academic performance using Neuro Fuzzy Logic	Four categories of data good, satisfactory, good, very good	Questionnaire, Quizzes on Entrepreneurship class in JTETI UGM	71 respondents 13 questions	Percentage value for Categories	Student Classification Model evaluated using RMSE Training data processed by ANFIS Editor generating Sugeno fuzzy type and split the membership function	ANFIS editor on Matlab"s Fuzzy Logic Toolbox	RMSE value	Average RMSE after 3 iteration : 0.25611
[9] Descriptive Analysis	Prototype for personalised Recommendation based on Hashtags on e-Learning System	User behaviour, user profiles, Datasets in Floksinory	Web logs, LMS logs	Not given	Hash tag definitions, semantic distance between definitions for each hashtag	Clustering groups of similar definition using Markov Clustering Algorithm	PDF to organise hashtags in alphabetic order	Definition sense clustering	Floksinory Approaching 89.21831 with ground truth

[8] Experimental Case study	Design of longest common subsequence based on genetic algorithm	Chapters Groups of LO Results of questionnaire	Courses Groups based on initial sequence Questionnaire: bio-computing students	7 courses 6 groups 4 different cases 36 results	Common sequences	Algorithm personalising Los based on students suggestions Recommending sequence using fitness function, mutation and crossover	Sequences Proposed by students	Mathematical model used	High efficiency
[16] Experimental analysis	Dynamic delivery of learning contents using text mining and ontology approach	Learning contents, learning log activities, forum logs, quiz scores	Learning logs from LMS	125 learners of scientific writing course during 3 weeks Total activity logs: 7883	Quiz scores Learning material preference for 4 groups of students	Text mining using deterministic filtering rule, clustering Ontology approach for mapping learning contents	SPARQL to match learning style Comparison using charts ,	Score: fair, good, excellent Chart to compare learning preference	Higher activity participation : excellent scores
[25] Framework design and experimental evaluation	Framework based on fuzzy learner model and optimised Fuzzy Item Response Theory	Learners style characteristics	LMS data log, Learning style Questionnaire	40 valid learners	Learners satisfaction feedback Educational sucess	200 rules generated for courseware recommendation Learners ability estimation :Maximum likelihood and Bayesian estimation procedure used for generating item information function	Mathematical model developed	Questionnaire : five point Likert Learners ability : Medium, High	More than 83% learners satisfied and showed educational progress
[18] Experimental	Learning Style prediction	Normalized Learning style data, learning information	Log files of learners	50	Learning style dimensions : - Sequential/Global - Active/ reflective - Sensing/ Intuitive - Visual/ Verbal	Classification Clustering learners 6 runs of Learning Pattern Recognition	Cluster core construction algorithm Simulated Annealing Algorithm	Prediction accuracy	90% accuracy
[12] Experimental study	Personalised Learning Recommender System using Augmented Reality (AR) browser for fieldwork	Preference Thesaurus each consisting of 165 3DCG browsing behaviour	Animals and Plants 3DCG database, textbook database, Geometry database for Banff National Park	165 3DCG records 70 self produced 3DCG of animals and plants	Frequency of 3DCG manipulations : Transfer Rotation Scaling Screenshot Annotation touch	Mapping animal and plant data to geographical information Create term behaviour matrix Summing behaviour vectors normalised with 1-norm Personal ranking based on similarity score	Query in excel Charts in excel using all results of classification of personalised ranking	Observation points : start and end for four users	AR browser boost motivation in fieldwork
[13] Model Proposal	Recommender System for assessing student"s activity for supporting e-Learning	Students activity data via API or RSS	Students of University of Rijeka, Croatia Web 2.0 tools	Not mentioned	Impact of recommender on students" performance during e-tivities.	Algorithms and Rules for generating recommendation on the basis of activity, student, group models Surveys, interviews (students satisfaction)	Web 2.0 tools, SPSS	Points per e-cities for control and experimental group	System not tested with experimental group

[10] Recommender System – Experimentation Case study for evaluation	Fuzzy tree matching based personalised e-learning Recommender System	Movies treated as learning activities and movie users as learners Case study: learners profile, feedback, subjects data	MovieLens Data set Case study: random data entered for learners	2113 users rated 20 movies each Case study: 5 learners 8 subjects	CF similarity Ratings of matched learning activity	Fuzzy tree-structured data model to model learners activities and learners profile Seven step recommendation process	Fuzzy category tree built for sequential relation between learning activities Case study: Netbeans development platform, JSF,EJB and JPA frameworks PostgreSQL database	Mean Absolute Error assessed and compared with Bobadilla‟s approach	Accuracy improved by 25.9%, 23.9% and 21.3% on 50%, 40% and 20% testing sets

3.1 Gaps in the Published Research

After completing a review of more than hundredpapers in the field of „Design of Intelligent tutoring systems using Enhanced Personalization in E-learning environment‟, certain issues were found to be having a significant role in effective personalization for online learners. Some gaps found in the published research are:

- Learner‟s information should be updated as the learner progresses through his e-learning course based on performances and behavior.
- Learner‟s information could be collected and analyzed dynamically.
- Most of the researchers have proposed various recommender models but very few have provided experimental proof.
- It is necessary to keep track of learner‟s performance and changes in the learning style and behavior and update his profile accordingly for effective personalization.
- It is desirable to build generic models that can be integrated to various Learning Management Systems for selecting and recommending appropriate learning objects to the learning.

3.2 Strengths in the Published Research

- Researchers worked in the area Personalization of e-learning contents by collection information about the users using various e-learning platforms and mediums and then statically analyzing them using various techniques like Data Mining, Link analysis, Network analysis and also Statistical analysis like ANOVA for aligning the appropriate contents to the e-learners to meet their specific needs.
- Most of the Researchers used Data Mining techniques like clustering, classification, associations, prediction, ontologies and artificial neural network as solution approach for mapping learning objects to learners.
- Most Researchers have implemented the model developed by them using MOODLE and fetched good results.
- Some Researchers have also tried to dynamically map the contents to matching the learner‟s profile, needs and capabilities.
- Researchers proposed to build recommender and intelligent tutoring systems considering learning styles of the learners.

3.3 Limitations in the Published Research

- Very few Researchers collected learner‟s information on e-learning platforms dynamically.
- Very few researchers provide dynamic mapping of learning contents to the user.
- Most of the Researchers have used static methods of collection and analysis of user information.
- Most of the researchers proposed various models for recommendation and personalization but very few researchers have considered its implementation or provide experimental proof for the same.

4. Discussion on Proposed Model

The main objective of the proposed model:

- To collect data related to Personalization parameters like user profile and Learning Styles and analyze them with reference to motivation and involvement for the learners from LMS.
- To create learning objects on the learning management system and group the learning objects into level.
- To select appropriate set of Personalization parameters and design a module to interface with LMS that includes feedback ensuing improved learning experience.
- To create ontology based mapping of learning objects based on students profile (static).
- To update the profile of the learner based on the behavior and performance of the learner.
- To implement and validate the model through some selected software and hardware setup.

4.1 Methodologies/Technologies to be used

The proposed model would be designed such that it can be integrated with any CMS or LMS, use the log files to classify the learners based on their capabilities using Felder-Silverman‟s learning style theory, using data mining techniques. Based on the learning style and capabilities of learner, learning objects would be displayed. The learner can then choose to take an assessment for the learning objects and based on the GPA score the learner can then choose to progress to the next level and choose the learning objects from the next level. This design is close to traditional teaching learning model as after completion of learning the student is allowed to take assessment to capture learning outcomes. It is self-paced as the learner chooses learning objects and then chooses the assessment pattern (could be subjective or objective) as desired by the learner. The next level of learning objects are displayed once the learner completes the current level like in the gaming scenario where the user is always motivated and engaged to take up new challenges.

4.2 Proposed Software support

The software proposed for model includes:

- Data Mining Techniques of Classification for classifying learners based on their capabilities.
- Middleware based on Mathematical Model applying fuzzy logic for mapping the learning objects to learners. Its main function being collection of data on learning behavior of the learners from the log files and update the same as and when the learner progresses through the course.

4.3 Data Requirement

- Historical data of learners collected using log files from LMS or CMS.
- Analysis of data to classify learners based on their capabilities
- Mapping learning objects to the specific learners applying fuzzy logic
- Evaluate learning outcomes of learners using the scores generated
- Capture and update progress of each learner
- Analyze the learner‟s capabilities to offer new level of learning objects to learners.

4.4Utilization of the outcome of Research

This study will provide a design for a generic model that can be integrated with any Learning Management System so as to provide recommendation for displaying learning appropriate to the learning styles of the learners based on the previous learning outcomes captured in the log files. The model developed is close to the conventional teaching-learning model where learning outcomes are evaluated at each stage of learning when the learner progresses through his course. The study would be very useful to the instructor who desire to use a blended e-learning model and evaluate the learning outcome of individual student and at the same time allow self-regulated and self-paced e-learning which is a drawback with the conventional face-to-face model. The model is similar to the gaming model as it requires the learner to complete the previous level of training before selecting the next level learning objects therefore will motivate learners to take up new challenges during learning.

5. Conclusion

Review process was adopted in the area of e-Learning and different approaches of personalization using statically generated data collected on the e-Learning platforms and also dynamically generated data in the virtual environment of e-learning were reviewed with the aim of enhancing experience of e-learners. It was found that most of the researchers worked in the area personalization of e-learning contents by collection information about the users using various e-learning platforms and mediums and then statically analyzing them using various techniques like Data Mining, Link analysis, Network analysis and also Statistical analysis like ANOVA for aligning the appropriate contents to the e-learners to meet their specific needs. Some Researchers have used the above techniques for future prediction of the grades. Most Researchers have implemented the model developed by them using MOODLE and fetched good results. Some Researchers have also tried to dynamically map the contents to matching the learner‟s profile, needs and capabilities.From the above discussion, it is found that very few Researchers collected the learner‟s information on an e-learning platform dynamically. Very few researchers provide dynamic mapping of learning objects tousers. Most of the Researchers used static methods of collection and analysis of information. Comprehending all the above points it is found that more work can be done for analyzing the e-learner‟s information and allocating the learning content dynamically. More work can be done to analyze the cognitive style of the learners and align the learning contents to their needs and requirements. Capabilities of Learning Management systems can be enhanced using tutoring or recommender systems for improved personalization of learning contents.

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