Assessment of Learner's Motivation In Web Based E-Learning

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Abstract—Due to the rapid growth of the use of computers and Internet in education a large number of Web Based E-Learning (WBEL) systems have been developed and implemented. However, most these systems do not consider the learner's motivation level during the learning process, while motivation is one of the most important factors for student achievement in learning. In this paper we argue that motivation assessment is very important for WBEL systems, therefore more research is needed in this area. A critical review of previous research on motivation assessment in e-Learning systems is also presented, and finally suggestions of how to assess the learner's motivation during a learning activity in a WBEL system. Benefits from our approach would maintain a learner's motivation during the learning process resulting in a higher performance level within the WBEL system.

Index Terms— E-Learning, asynchronous e-learning, synchronous e-learning, motivation theories, Web Based E-Learning, motivation assessment, ARCS model.

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1 Introduction

THE role of technology in education has evolved and radical changes have occurred since the emergence of the Internet. The Internet has provided various ways of learning delivery where the web can be used as a medium for education such as Web-Based E-Learning (WBEL), Adaptive Hypermedia, and Intelligent Tutoring Systems. Learning via the web may enable everyone to obtain all types of knowledge, at all levels, at any time and in any place.

E-Learning is an education paradigm that is based on the electronic delivery of learning materials via electronic media, including the Internet, intranets, extranets, satellite broadcast, audio/video tape, interactive TV, and CD-ROM [1]. In an e-learning system, information can be delivered in two different methods. The first is the asynchronous method where students can acquire knowledge at any time and in any place; they can learn following their own pace. The most popular forms of asynchronous e-learning are instructional websites, email, and forum. The second is the synchronous method where the teacher and the student interact in real time, which include real-time web chats and video conferences [2].

Studies have illustrated that motivation is a key element of education and plays an important role in the success of the learning process, since motivation is regarded as one of the important factors that drive student's performance [3-6]. According to Hrastinski synchronous e-learning learners felt more motivated than asynchronous learners since synchronous communication closely resembles face-to-face communication [2]. Although there are similarities with motivational problems in all e-learning settings, there are specific motivational challenges within each major system. One important challenge in asynchronous communication is drop-out rates that tend to be higher than in face-to-face settings, since learners often feel isolated and levels of learning interactivity are often considered trivial [7].

For a long time, motivation has been seen in an e-Learning filed as a matter of design. In other words, proper instructional design and suitable learning activities would engage all learners [8]. Although designing a motivating e-learning environment is important, keeping students motivated for the entire learning period is one of the biggest challenges, not only in e-learning, but also in all forms of learning[9]. However, while in traditional face-to-face learning and synchronous e-learning, teachers have direct contact with the learner, thus being able to analyze the learner's whole behavior and thus can infer his/her motivational state. But in the context of asynchronous e-learning (e.g. WBEL) motivation detection is a more challenging process [9]. Information about the motivational state of the learner would allow tailoring content and enhancing the motivation of the learner.

Due to the importance of motivation as one of the major factors that contribute in the success of the learning process; there has been an increasing amount of research interest that tries to detect e-learning systems learners' motivation. There are two types of learner's motivation detection model in these researches; one of these types is applicable for research purpose only such as Derbali and colleagues researches [10, 11] where they try to use some sensors to assess learner's motivation, and the other type may be applicable for the purpose of motivation detection in e-learning systems such as de Vicente [12] motivation model, del Soldato [13] motivational tactics, and Qu and Johnson [14] motivational states modeling. Although there are numerous research in the field of e-learning which tries to detect learners' motivation in e-learning systems, there is few research that has been conducted to assess a learner's motivation in web based e-learning. In this context, there is a need for having effective web based e-learning systems that can assess learner's motivation in real time. This paper addresses new challenges for web-based e-learning: how to assess learners' motivation during the learning activity.

This paper is organized as follows: Section two provides the related work. Section three suggests a solution for assessing learner's motivation in web based e-learning. Finally, section

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four presents the Summaries.

2 Related Work

Motivation has always been one of the most important factors for student achievement in learning [3-6], as students with high motivation engage more in learning activities and are more likely to complete a course [15]. Experienced teachers usually infer student's motivation from observational cues such as posture, gesture, conversational cues etc. which are difficult to be processed by computer systems [11, 12, 16]. Therefore, most of the researches in the field of e-learning are directed towards finding a way to assess motivation from cues that can be easily processed by the e-learning systems (e.g. learner's actions, time spent on a task, his/her statements about his/her level of motivation).

2.1 Theories of motivation

There are plenty of literatures on motivation in which many definitions can be found. Eccles and Wigfield [17] see the study of motivation as the study of action. For example, a student who studies hard may be described as 'highly motivated', while a student who is 'lowly motivated' may not study hard. Thus it seems that motivation can have an influence on student's behavior [18]. There are a large amount of motivational theories and models exists in the literature, as a result, there are several attempts that try to categorize these theories.

According to Weiner [19] there are two main types of motivational theories: mechanistic theories and theories based on a cognitive approach. Mechanistic theories are based on the idea that a human works as a machine where their motivation is based on needs, drives and instincts. On the other hand, in cognitive theories human motivation is based on thoughts and beliefs, therefore, they have choices with regards to their actions. However, as de Vicente [12] state this is not an absolute classification as some theories share ideas from both kinds of theories.

Eccles and Wigfield [17] classify motivational theories into four categories. The first category focuses on beliefs about competence and expectancy for success (self-efficacy theory and control theories). The second category focuses on the reasons why individuals engage in different activities; this category consists of the following constructs: intrinsic and extrinsic motivation, achievement values, interests and goals (self-determination theory, flow theory, interest theories, and goal theories). The third category combines expectancy and value constructs (attribution theory, modern expectancy-value theories, self-worth theory) while the fourth category describes links between motivational and cognitive process (social cognitive theories of self-regulation and motivation, motivation and cognition theories, theories of motivation with volition).

2.2 Assessing motivation in e-learning

As we explained previously, we believe that the issue of assessing the learner's motivational state is crucial for developing a successful e-learning environment, but to do this is not straightforward. Therefore, most of the researches in the field of e-learning try to assess motivation from cues that can be easily processed by the e-learning systems.

Table 1 presents previous research work on the assessment of learner's motivational state in e-learning environments and motivational factors used to indicate the existence of motivation, the learning variables measured, the measurement type, the assessment type, and the motivational theories(or model).

2.3 Key Theories of Motivation

As stated previously there are a large number of motivation theories to be found in the literature, thus, as previously mentioned there are several attempts to categorize these theories. Methaneethorn [18] states that these motivation theories focus on identifying factors that are likely to influence motivation, and different theories focus on different factors. However, sometimes these factors are intertwined in their nature.

Although there are many theories found in the literature, only a small number of them have been practically applied to research in the area of assessing learner's motivational state in e-learning environment. As shown in Table 1 the theory of motivation that has been widely accepted by researchers in the e-learning field is that of Keller [20]. Keller created a theory of motivation and also, built a model named as Keller's ARCS [21] to design and incorporate motivation in instruction. The acronym ARCS is derived from four categories of motivational factors Attention, Relevance, Confidence, and Satisfaction. Keller used existing research on motivational psychology to aggregate motivational concepts and theories according to their shared and discriminative attributes to constitute this model [22].

The first category of the ARCS motivation model is Attention (interest), which refers to gaining attention, building curiosity, and sustaining active engagement in the learning activity. This category has three sub-level categories: perceptual arousal, inquiry arousal, and variability. The second category is Relevance, which includes concepts and strategies that establish connections between the instructional environment and the learners' needs and wants. This category has three sub-level categories: goal orientation, motive matching, and familiarity. The third category of the ARCS motivation model is confidence (expectancy), which incorporates variables related to students' feelings of personal control and expectancy for success. This category has three sub-level categories: learning requirements, success opportunities, and personal control. The fourth category of the ARCS motivation model is satisfaction, which comes from being able to see the impact of learning. This category has three sub-level categories: natural consequences, positive consequences, and equity. [21, 23]

Malone & Lepper's Taxonomy of Intrinsic Motivation Model [24] is another widely used model for the assessment of learners' motivation which can be used as guidelines for the design of intrinsically motivating learning environments (e.g. WBEL) [18]. The taxonomy focuses on several factors that can intrinsically influence a learners' motivation. These factors are: challenge, sensory curiosity, cognitive curiosity, control and fantasy. Social Cognitive Learning Theory [25] is also another sound theoretical base for the assessment of motivation which has been widely studied in several research disciplines.

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Table1. Previous research on the assessment of learner's motivational state in e-learning environment (adapted from Ghergulescu and Muntean [9])

Research	Input	Output(Motivational factors)	Measurement type	Approach	Motivational theories(or model)
del Soldato [13, 26]	response given by students	effort, confidence, independency	direct interaction(dialog based, questionnaire)	rule inference, prediction	Motivational design [21], and motivational tactics [24]
de Vicente and Pain [27],de Vicente [12]	response given by students, actions	control, challenge, independency, fantasy, confidence, sensory interest, cognitive interest, effort, satisfaction	direct interaction (dialog based, questionnaire)	rule inference, prediction	Keller's ARCS model and Malone and Lepper's taxonomy
Zhang et al. [28]	Counter of compiling (how many times the learner compile the program for the task), time to perform task, number of hints requested, Counter of compiling without errors, times to execute the program	attention and confidence	log based analysis	log files computation	Keller's ARCS model
Beck [29]	question response time, answer correctness	engagement	log based analysis	item response time-prediction	………………
Qu and Johnson [30,14]	time to perform task, reading time, number of finished task, number of extra tasks taken, time to decide to perform a task	confidence, confusion, effort	log based analysis, eye tracking analysis	prediction model	Keller's ARCS model
Kim et al. [31]	question response, help request, number of activities taken, time spend	confidence, effort	direct interaction (dialog based), log file analysis	direct computation- fuzzy logic function	Keller's ARCS model and Soldato motivational tactics
Hershkovitz and Nachmias [32]	time on task percentage, average session time, exams activities percent, quiz (game) activities percent, average time between session, average activities pace, number of new words learned	engagement, energization, source	log based analysis	log files computation and construct group	Self-Determination Theory
Takemura et al. [33]	Likert scale answers	importance, expectation	direct interaction (questionnaire)	direct computation	Keller's ARCS model
Cocea [16], Cocea and Weibelzahl [34,35]	number of pages read, time spend reading pages, number of tests/quizzes, time spend on test/quizzes	engagement, self-esteem, self-regulation, goal orientation	log based analysis, direct interaction (questionnaire)	predictions models	Social Cognitive Learning Theory

3 Assesing Motivation In Web Based E-Learning

This section presents how motivation can be assessed during the learning activity in web based e-Learning. Investigating various research approaches for assessing motivation in e-learning, the most important motivational factors as shown in table1 was: confidence, effort, and engagement. The majority of related researches have taken into consideration time variables such as: the time spend reading pages, the time spend on test/quizzes, the time spent on performing the task and the average time between sessions. These time variables have been used to measure most motivational factors. However, the previous studies did not clearly discuss the range of times values. In an learning activity this time range may be identi fied by the teacher (e.g. minimum and maximum time to perform the task). In WBEL this time variables can be measured easily by tracking learner activity. In this way, the barriers imposed by the need of the range for time variables may disappear in the WBEL environment.

This paper proposes that motivation can be assessed in WBEL in real time by taking into consideration motivational factors such as: confidence, effort, and engagement. Next, a solution on how these factors can be assessed is presented.

3.1 Modeling Confidence

According to De Vicente [27] confidence refers to "the student's belief in being able to perform the task at hand correctly". In e-learning, student confidence/competence was measured using self reports questionnaire and dialog based interaction. An example of a dialog based interaction is presented in Figure1. Although this way may be very good to infer learner's confidence level, it's too boring to answer questionnaires frequently. Therefore we need to decrease the number of questionnaires and dialog.

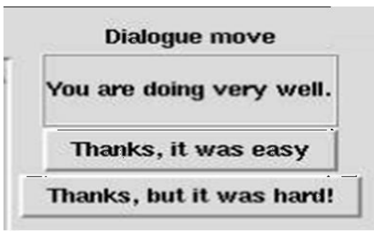

Figure1.Dialog used in assessing motivation in e-learning [12].

According to Del Soldato [13], less confident learners are likely to: 1) Avoid tasks perceived as difficult; or 2) Give up a task before attempting to perform it. The first point can be detected by interaction between the tutor and the student such as present the student with options of answers that explicitly mention the difficulty of the task (e.g. "No, thanks, it is too difficult", "I prefer an easier problem"). Possibility of student giving up can be defined in terms of help requests and the number of steps in the problem solving process.

Zhang and colleagues [28] used time variables as indicators for student confidence such as times to do the task. They state that if a learner can start to do the task quickly, it means that he/she has the assuredness to success, and he/she has high confidence. Time is a good indicator of student confidence but it's not always accurate, for example if learner takes less time in performing task it's an indicator of high confidence but maybe the opposite is true; he/she rushing because the task is too difficult and he/she have low confidence. Therefore we need to ask the learner about his level of confidence.

Qu and Johnson [14] state that there are three major sources of information for a human tutor to infer learner's confidence: 1) the learner's hesitancy in performing actions after reading the tutorial; 2) the history of task performance (for example, how many tasks the learner has successfully completed.); and 3) the frequency of the learner's requests for help on certain tasks. For example, if the learners perform the task after reading the tutorial without much hesitancy, this implies that they must have high confidence.

In this paper we propose to use the time variable as indicators for student confidence combined with other indicators such as help requests and the number of steps in the problem solving process. Additionally dialog based interaction may be used in more complicated situation.

3.2 Modeling Effort

According to De Vicente [27] effort refers to the amount of work that the student is doing in order to perform the learning activities. De Vicente used the level of student giving up and student performance as indicators for student effort level.

Del Soldato [13] tries to classifying students' effort as a function of their persistence to solve the problem and requests for help to perform the task. he assumed that persistence to solve the problem can be measured through the number of attempts to get a solution, or steps performed, so that many steps reflects a greater degree of effort from the student. In addition to the number of steps performed, a student who requests hints from the tutor or accepts help offered by the tutor spends less effort than students who try to perform the task on their own.

Qu and Johnson [14] state that a human tutor can infer the learner's effort for a task by estimating how much time the learner has already spent on this task. Therefore based on how the human tutor infers the learner's effort during in-person interactions, Qu and Johnson derive inference rules to detect the learner's effort.

In this paper we propose to use the time variable such as time spent on the task as indicators for student effort while other indicators such as the number of attempts to complete a task and requests for help to perform the task may also be combined as indicators.

3.3 Modeling engagement

Cocea [16] see engagement as an indicator of motivation, where the person is motivated to do the task he/she is engaged in, or the other words, if the person is disengaged, he/she may not be motivated to do the task. Cocea proposed to use behavioral cues detection as indicators for disengagement such as browsing fast rather than reading, skipping sections, non-systematic progression, and answering questions quickly (in less time than the minimum required time for at least reading the questions).

Hershkovitz and Nachmias [32] used the time variables as indicators for student engagement such as time on task percentage (Total time of active sessions divided by total time frame documented.) and Average session duration as time variables.

In this paper we propose to use cues as indicators for engagement/disengagement to include browsing fast rather than reading, skipping sections, and time to perform the task or answering the questions.

4 SUMMARY

Nowadays, the technological developments significantly improve the area of e-learning. In this paper various research approaches in assessing learner's motivation were presented, these approaches considered various motivational factors. Assessing motivation during the interaction with WBEL systems is challenging because information about learner's observational cues such as posture, gesture, and conversational cues are difficult to be collected. Therefore, the emphasis of this research is to assess motivation by analyzing other types of information such as times variables, learner's actions, and learner statements about his/her level of motivation. However future research may extend this model to become a general model with consideration to the variety of actions that could occur in WBEL environment. It's hoped that our proposed approach would be able to sustain a learner's motivation during the learning process resulting in a higher performance level within the WBEL system.

REFERENCES

[1] Alian, M. and Al-Akhras, M.T. "AdaLearn: an adaptive e-learning environment", In Proceedings of ISWSA., 2010, pp. 21-21.

[2] Hrastinski, S. "A study of asynchronous and synchronous e-learning methods discovered that each supports different purposes", EDUCAUSE Quarterly, vol. 31, No.4, 2008, pp.51-55.

[3] Weiner, B. "An Attributional Theory of Achievement Motivation and Emotion", Psychology Review, Vol. 92, 1985, pp.548-573.

[4] Ames, C. "Classroom: Goals, structures, and student motivation", Journal of Educational Psychology, Vol. 84, 1992, pp.261-271.

[5] Anderman, E. and Maehr M. "Motivation and schooling in the Middle grades", Review of Educational Research, Vol. 64, 1994, pp. 287-309.

[6] Lin, K., Wu, T., and Wang T. "Using Competitive Digital Game-Based Learning to Improve Learning Motivation", Frontier Computing: Theory, Technologies and Applications, 2010 IET International Conference.

[7] Keller, J. M. and Suzuki, K. "Learner motivation and E-learning design: A multinationally validated process", Journal of Educational Media, Vol. 29, No.3, 2004, pp.229-239.

[8] Cocea, M., Weibelzahl, S. "Motivation–Included or Excluded From E-Learning", In Proceedings of CELDA, 2006, pp.435–437.

[9] Ghergulescu, I., Muntean, C. H. "Assessment of motivation in games based e-learning", In Proceedings of CELDA, 2010, pp. 71-78.

[10] Derbali, L., Chalfoun, P., and Frasson, C. "A Theoretical and Empirical Approach in Assessing Motivational Factors: From Serious Games To an ITS", In Proceedings of FLAIRS Conference. 2011.

[11] Derbali, L., Chalfoun, P., and Frasson, C. "Assessment of Learners' Attention While Overcoming Errors and Obstacles: An Empirical Study", In Proceedings of AIED. 2011, pp.39-46.

[12] de Vicente, A. "Towards tutoring systems that detect students' motivation: an investigation", Ph.D. Univ. of Edinburg, 2003.

[13] del Soldato, T. "Motivation in Tutoring Systems", Ph.D. Univ. of Sussex, UK., 1994, Available as Technical Report CSRP303.

[14] Qu, L. and Johnson, W.L. " Detecting the Learner's Motivational States in An Interactive Learning Environment", In Proceeding of the 2005 conference on Artificial Intelligence in Education, Amsterdam, Netherlands, 2005, pp.547-554.

[15] Militiadou, M., and Savenye, W. "Applying social cognitive constructs of motivation to enhance student success in online distance education", AACE Journal, Vol. 11, 2003, pp.78-95.

[16] Cocea, M. "Assessment of Motivation in Online Learning Environments", M.Sc. National College of Ireland, 2007.

[17] Eccles, J. S., and Wigfield, A. "Motivational beliefs, values, and goals", Annual Review of Psychology, Vol. 53, 2002, pp.109-132.

[18] Methaneethorn, J. "Towards Motivation Modeling within A Computer Game Based Learning Environment: An Empirical Study", Ph.D. Univ. of Glasgow, 2008.

[19] Weiner, B. "Human Motivation: Metaphors, Theories, and Research", Sage Publications Inc., Newbury Park, London, 1992, p. 17.

[20] Keller, J. M. "Motivation and instructional design: A theoretical perspectives", Journal of Instructional Development, Vol. 2, No.4, 1979, pp.26-34.

[21] Keller, J.M. "Development and use of the ARCS model of instructional design", Journal of Instructional Development, Vol. 10, No.3, 1987, pp. 2-10.

[22] Song, S. and Keller, J.M. "Effectiveness of motivationally adaptive computer-assisted instruction on the dynamic aspects of motivation", Journal of Educational Technology Research and Development, Vol. 29, No.2, 2001, pp. 5-22.

[23] Keller, J. M. "First principles of motivation to learn and e3-learning", Distance Education, Vol. 29, No.2, 2008, pp.175-185.

[24] Malone, T. and Lepper, M. "Making learning fun: A taxonomy of intrinsic motivations for learning", In Erlbaum, 1987, pp. 223-253.

[25] Bandura, A. "Social Foundations of Thought and Action: A Social Cognitive Theory" Englewood Cliffs, N.J.: Prentice-Hall, 1986.

[26] del Soldato, T. and du Boulay, B. "Implementation of motivational tactics in tutoring systems", Journal of Artificial Intelligence in Education, Vol. 6, No.4, 1995, pp.337–378.

[27] de Vicente, A. and Pain, H. "Informing the detection of the students' motivational state: an empirical study", In Proceedings of Intelligent Tutoring Systems: 6th International Conference, ITS 2002, Biarritz, France and San Sebastian, Spain, pp.79–86.

[28] Zhang, G., Cheng, Z., He, A., and Huang, T. "A WWW-based Learner's Learning Motivation Detecting System", In Proceedings of International Workshop on (Research Directions and Challenge Problems in Advanced Information Systems Engineering), Honjo City, Japan, September 16–19, 2003.

[29] Beck, J.E. "Using response times to model student disengagement", In Proceedings of ITS 2004 Workshop on Social and Emotional Intelligence in Learning Environments, Maceio, Brazil.

[30] Qu, L., Wang, N. and Johnson, W.L. "Using Learner Focus of Attention to Detect Learner Motivation Factors", In Proceedings of User Modeling, 2005, pp.70-73.

[31] Kim, Y.S. et al. "An Intelligent Tutoring System with Motivation Diagnosis and Planning", In Proceeding of 15th International conference on Computers in Ed., Hiroshima, Japan, 2007.

[32] Hershkovitz, A. and Nachmias, R. "Developing a Log-based Motivation Measuring Tool", Educational Data Mining, Vol. 5, 2008, pp.226-233.

[33] Takemura, Y. et al. "Assessing the Learners' Motivation in the E-Learning Environments for Programming Education", Advances in Web Based Learning–ICWL2007, 2008, pp.355–366.

[34] Cocea, M. & Weibelzahl, S. "Log file analysis for disengagement detection in e-Learning environments", User Modeling and User-Adapted Interaction, Vol. 19, No.4, 2009, pp.341-385.

[35] Cocea, M.; Weibelzahl, S. "Disengagement Detection in Online Learning: Validation Studies and Perspectives", Learning Technologies, IEEE Transactions on, Vol. 4, No.2, 2011, pp.114-124.