Predicting Student Retention from Behavior in an Online Orientation Course

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ABSTRACT

As higher education institutions develop fully online course programs to provide better access for the non-traditional learner, there is increasing interest in identifying students who may be at risk of attrition and poor performance in these online course programs. In our study, we investigate the effectiveness of an online orientation course in improving student retention in an online college program. Using student activity data from the orientation course, Engage, we make use of machine learning methods to develop prediction models of whether students will be retained and continue to register for program-specific courses in the *e*Versity program. We then discuss the implications of our findings on improvements that may be made to the existing orientation course to improve student retention in the program.

Keywords

Prediction modeling, online orientation course, student retention

1. INTRODUCTION

With the widespread development of online learning programs in institutes of higher learning, access to a college education has improved by a considerable amount. Despite increased enrollment rates within these online degree programs, however, student attrition or dropout rates also tend to be correspondingly higher than in traditional face-to-face degree programs [4, 21]. Dropout can occur early for many students in online programs; some students drop out even before they register for their first course [24]. As such, it has become increasingly important for facilitators and administrators to identify factors that may influence attrition and retention in these online course offerings, and implement targeted interventions to increase retention.

Some of these targeted interventions involve the use of machine learning to provide timely information on student progress within a course to teachers and facilitators [1, 12, 17]. These interventions allow them to identify at-risk students earlier on within an online course, and take steps to encourage student retention. Another type of intervention involves the development of online orientation courses taken before the beginning of the program. These courses aim to provide students with the support and resources they may need during their progression through the program [3, 8]. A combination of the above interventions may also be implemented where machine learning models are developed to identify patterns in student behavior within online orientation courses themselves, which could help inform teachers and facilitators of students at risk of dropout even earlier on within an online program.

In this study, we use machine learning to investigate student behavior within a required online orientation course, Engage, for students registered in an online university, *e*Versity. *e*Versity is a completely online course program established and developed by the University of Arkansas System (UAS). Using student data in this online orientation course, we developed a model that allows us to predict the likelihood of their continued participation in the online college program, through their registration in future program-specific courses.

2. LITERATURE REVIEW

There has been extensive research in recent years to identify factors that lead to low student retention rates, particularly within the context of online learning programs [9, 16, 25]. Attrition and retention can be defined in several ways. Since this paper is focused on an online course program that emphasizes learning at students' own pace and preferred time(s), we make use of the definition proposed by Pascarella and Terenzini [22] (p.374), where retention is defined as progressive re-enrollment, whether continuous from one term to the next, or temporarily interrupted and then resumed, until completion with a degree.

Several researchers have found that student dropout rates in online courses are due to a variety of circumstances, including personal, job, or technology-related reasons [25], and are typically independent of demographic factors such as gender and race [2, 11, 25]. Park et al. [20] also found that organizational support and course relevance are better predictors than demographic variables, and significantly predict student persistence as well as student dropout in online course programs. Both O'Brien & Renner [18] and Jung et al. [14] replicated these findings and found that online courses that increase opportunities for student interaction, such as group work, tend to improve student engagement, thereby reducing student dropout.

A popular intervention that has been implemented to improve student retention, based on these findings, is the development of orientation courses that seek to provide new students with organizational support, guidance, and resources that they may need to support their online learning. Studies have found that such online orientation courses can be effective at improving retention and the overall student learning experience [5, 8, 13].

Other interventions have focused on providing information to instructors, academic advisors, and facilitators on which students are at risk, so that the student can be contacted and better supported [1, 12, 17]. Increasingly, these types of interventions have been driven using automated models that can identify students who are at risk of dropping out or performing poorly, so that instructors and facilitators can focus intervention efforts on the students who are most likely to be benefit from an intervention. The use of data mining techniques has enabled course facilitators to identify at-risk students early on within a course. For instance, Dekker and colleagues [7] made use of data mining techniques to identify students at risk of dropping out from an electrical engineering program, after the first semester of their studies, or even before they enter the program. In another study, Lauria et al. [15] developed models to predict student performance based on course management system data as well as student academic records.

Such models have then been used by higher education institutions to provide support through early interventions to at-risk students. This type of intervention has been developed and implemented by various universities and companies, including Purdue University, Marist College, Civitas Learning, and ZogoTech [1, 10, 12, 17]. Arnold & Pistilli's work [1], for example, examines the development and implementation of Course Signals at Purdue University. Course Signals makes use of learning analytics to help course faculty provide accurate real-time feedback to their students about whether they are on track to succeed in their current course. Analyses of student performance showed that students who participated in at least one Course Signals course achieved better grades and experience higher retention rates than their peers who did not participate in any Course Signals courses. Similarly, Fritz [10] makes use of learning analytics to develop an intervention called "Check My Activities", where students are given the opportunity to compare their online course activity against an anonymous summary of their peers in the course, thus providing early system feedback directly to the students so that they are more aware of their own levels of engagement within a course.

3. EVERSITY – ONLINE LEARNING

The *e*Versity is a fully online institution for the University of Arkansas System, which is comprised of institutions of higher education across the state. The mission of *e*Versity is to provide online education specifically for adult learners; in particular, at-risk learners who may have previously dropped out of college and may require additional support to be successful academically. Currently the *e*Versity student population is 65% female, 69% white, 27% black or African American, and the average age is 36. Each academic term runs for a short 6 weeks to allow enrolled students maximum flexibility in fitting the online courses within their schedules.

To better serve students, *e*Versity offers a free credit-barring orientation course, Engage. This course fulfills two functions, both related to the goal of improving student retention: to introduce students to the tools and information they need to be successful in an online learning environment, and for the institution to get to know its students. Engage also aims to provide resources and guidance to new students as they continue on to register in program-specific online courses within *e*Versity. Upon enrollment in the *e*Versity program during any of the seven terms throughout the year, students are automatically registered in Engage. Within Engage, information is organized into 6 Steps: Welcome, Getting to Know You, Funding My Future, Supporting My Academic Success, Developing My Learning Plan, and My Financial Plan. Students are free to explore the six course sections at their own pace within the six-week academic term.

To ensure student participation within each section of the course, students are required to complete knowledge checks and assessments at the end of each Step before they can access the next Step. These assessments and checkpoints help students to process the information provided within each Step, and provide students with practice opportunities to complete work in online formats that will be commonly used within later program-specific courses, such as uploading assignments and journal entries, and taking online quizzes. Completion of the Engage course is required for students who wish to continue on to register for program-specific courses on *e*Versity.

4. METHODS

4.1 Orientation Course Data

The dataset used for analysis was obtained from the Blackboard online learning system, and included student data from the first rollouts of the Engage course in the October 2015 and January 2016 terms. As discussed above, each term spans approximately six weeks. The data set provided resource access information per student, including date accessed and page accessed, as well as actions performed while on these pages. Resources accessed and respective actions include:

1. Journals: add journal entry, view draft, edit journal entry
2. Assessments: launch assessment, review attempt, save attempt, submit assessment
3. Assignments: upload assignment
4. Discussion Boards: discussion entry, discussion reply
5. Messages: view messages, email instructor, email select students
6. Gradebook: check grade

We also obtained demographic data consisting of each student's age, gender, race, whether or not their parents attended college, and whether or not they registered for a class in any of the three academic terms immediately following the completion of the Engage orientation course. Of the cohort, a total of 151 students registered for courses after completing the Engage orientation course.

We then built a prediction model to identify which student features are more strongly associated with future registration in for-credit courses on *e*Versity.

4.2 Data Cleaning and Feature Generation

The data set obtained from *e*Versity included resource access data, and demographic and enrollment data. It represented 97,298 page accesses and actions across 325 students.

During their use of Engage, these students interacted with course content (i.e., video lectures), journals, assessments in the form of online quizzes, assignments, discussion boards, messages, and the gradebook. Each transaction within the access log contained a user ID, date stamp (with no time data available), page accessed, and, where relevant, the action performed.

The features investigated in this study included:

1. Total counts – total number of times student accessed each resource regardless of what action they performed (e.g., total count for journal access is the sum of the total count of journal access to write a new post and the total count of journal access to edit an existing post)
2. Days till first access – number of days since start of interaction until a student accessed any of the resources and performed each of their specific actions
3. Days between – average number of days between specific resources accesses and actions performed (e.g., average number of days between two journal views, average number of days between creation of a journal post and editing or submitting the same journal post)
4. Inactivity – average number of days inactive (i.e., number of days between any two transactions)
5. Descriptive statistics – average, standard deviation, minimum, and maximum values per resource access across days the student interacted with Engage

In calculating these features, we excluded behaviors that were required to complete the Engage course. Completing the Engage course was required in order for a student to continue on to register for a program-specific course, so any feature required to complete Engage would be tautologically connected to registering for a program-specific course. Specifically, we excluded student activity around completing assessments, uploading assignments, and adding journal entries. We thus removed these features in order to identify other student actions that may be related to future student registration in an *e*Versity course, but are not explicitly required for the student to register in an *e*Versity course.

4.3 Prediction Modeling

Prediction models of student activity were created using RapidMiner 5.3 in order to determine which combination best predicts whether a student will register in a program-specific course after completing Engage. We attempted to predict this variable using J-Rip classification and J-48 decision trees, with 10-fold student-level cross-validation. Cross-validation splits the data points into *N* equal-size groups. In the case of the current study, data points were split into 10 groups. It then trains on all groups but one, and tests on the last group, and does so for each possible combination.

J-48 decision trees, the RapidMiner Weka Expansion Pack implementation of the C4.5 algorithm, can handle both numerical and categorical predictor variables. The algorithm repeatedly looks for the feature which best splits the data in terms of predictive power for each variable. It later prunes out branches that turn out to have low predictive power. Different branches can have different sets of features. In cases where numerical predictors are used, the algorithm tries to find the optimal split. J-Rip is the RapidMiner Weka Expansion Pack implementation of the Repeated Incremental Pruning to Produce Error Reduction (RIPPER) [6], a propositional rule learner. J-Rip produces a set of rules, through stages of growing and pruning, that account for all classes and minimizes error.

Model variable selection was conducted using forward selection, where the feature that most increases fit is added to the current model, until no additional features improve the model. The resultant models' performance was assessed using Cohen's Kappa and AUC ROC. Kappa indicates the degree to which the detector is better than chance at identifying a modeled construct. 0 means that the model is no better than chance, and 1 means perfect performance. AUC ROC is the area under the ROC curve, and is also the probability that given 1 instance of 'registered' and 1 instance of 'not registered', the model is able to tell which instance is which. It is computed using the A' implementation to control for artificially high AUC ROC estimates due to having multiple data points with the same confidence. An AUC ROC value of 0.5 indicates chance level of performance, while a value of 1 means perfect accuracy.

4.4 Demographic Cross-Validation

Some prior research has shown that prediction models may have different levels of accuracy for different subgroups within the data set [19]. To determine whether this was a concern, we evaluated the performance of the models across different demographic groups in our data set. After the models had been developed and cross-validated, we took the model's prediction on the test sets and evaluated their performance on sub sets of the data based on the different demographic groups in our sample. In particular, we compared the performance of the model by gender (male versus female), race (white versus African-American) and parents' college education (parents attended college versus parents did not attend college). In addition to the majority of white and African-American students analyzed, 7 students were Native American. This number of students was insufficient to allow for a valid calculation. We then calculated performance metrics for each of these demographic groups.

5. RESULTS

5.1 Model and Performance

Prediction models created using the W-J48 and W-JRip classification algorithms resulted in high kappa and AUC values. Both algorithms used resulted in comparably high performance. As such, we will discuss both of these models below. The full set of models run and their respective performance values can be found in Table 1.

Table 1. Cross-validated performance of models of student enrollment with different classification algorithms

Classifier	Kappa	AUC
J-48	0.806	0.925
J-Rip	0.825	0.913

5.1.1 J-48 Model

With the J-48 model, a total of four features were selected in some folds of the cross-validation, but not all of them were selected in the final model fit on all data:

- number of days before grades were first checked by the student,
- minimum number of times grades were checked by the student,
- total number of views of online messages within the course platform, and
- total number of views of the Discussion Board Reply page.

The four features initially selected in some of the cross-validation folds indicate that students who checked their course grades earlier and more frequently, responded more to discussion board posts, and viewed in-course messages more frequently were more likely to register in a program-specific *e*Versity course after completing Engage.

The final decision tree generated using this algorithm contained 3 leaf nodes and 2 decision nodes. The decision tree generated by the prediction model is shown in Figure 1.

As can be seen in the figure, only 2 of the selected features had strong enough associations with future course registration to be included in the pruned decision tree built on all data: Number of views of the Discussion Board Reply page, and the number of days till the first time the student checks their course grades.

The decision tree generated with the J-48 model, shown in Figure 1, provides an indication of how each student's future course registration is predicted, and the confidence level assessed for each student's prediction.

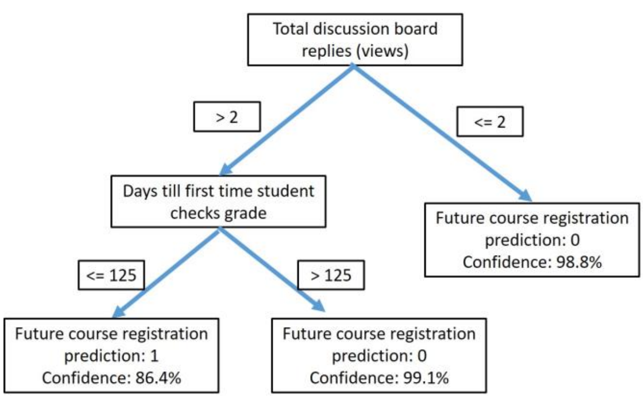

Figure 1: Visual representation of the decision tree generated by the J-48 algorithm

The decision tree in Figure 1 shows that a student who has made fewer attempts to respond in the discussion board is less likely to register in a program-specific course in the future, with a confidence of 98.8%. Similarly, we can see that students who checked their course grades earlier on during the term were more likely to register for a program-specific course afterwards, with a confidence of 86.4%. In contrast, students who only viewed their course grades much later after the start of the orientation course or not at all had a 99.1% confidence of not registering for another *e*Versity course in the future.

5.1.2 J-Rip Model

In the J-Rip model, on the other hand, only one feature was selected: the total number of views of the Discussion Board Reply page. Based on the J-Rip model classification rules, students who viewed the Discussion Board Reply page more often (>= 3 times) within the duration of the orientation course had a higher probability of registering in an *e*Versity course afterwards, with a confidence of 82.4%. In contrast, students who viewed the Discussion Board Reply page 3 times or fewer during the course had a lower likelihood of registering in another course later on, with a confidence of 98.8%.

The J-48 and J-Rip models obtained comparable performance metrics, with the J-48 model having a marginally higher AUC value than the J-Rip model, and the J-Rip model having a slightly higher Kappa value than its J-48 counterpart. This implies that the J-Rip model had a higher proportion of correct predictions when thresholded, but because only one classification rule was selected, there were only 2 confidence values that were associated with these predictions, hence resulting in a lower AUC value. In contrast, more features were selected in the J-48 model (and more differentiations were made), which could explain the slightly higher AUC value for that model than the J-Rip model.

5.2 Performance for Demographic Groups

We then tested both the cross-validated predictions models by three sets of demographic comparisons: gender (male .vs. female), race (white .vs. African-American) and whether the student's parents attended college or not. For the J-48 model, we found that it performed relatively well across all the demographic groups tested, and close to the performance values obtained in the overall model. The model performances of the various demographic groups are listed in Table 2 below. Our J-48 model performed at similar levels for most of the demographic groups that were tested. However, it performed marginally worse for African-American students (Kappa = 0.728, AUC = 0.905). When compared to the model's performance on the full data set (Kappa = 0.806, AUC = 0.925), its performance was still quite good in absolute terms even for this group.

Table 2. Performance of J-48 models of student enrollment for different demographic groups

Group	Kappa	AUC
Female	0.833	0.894
Male	0.753	0.946
African-American	0.728	0.905
White	0.826	0.932
Parents attended college	0.763	0.908
Parents did not attend college	0.829	0.933

Similarly, we found that our J-Rip model performed at comparable levels of performance across different demographics when compared to performance on the full data set. As with the J-48 model, the J-Rip model was least accurate for African-

American students, but still obtained good predictions, with Kappa = 0.748, AUC = 0.907.

Table 3. Performance of J-Rip models of student enrollment for different demographic groups

Group	Kappa	AUC
Female	0.833	0.937
Male	0.811	0.875
African-American	0.748	0.907
White	0.751	0.906
Parents attended college	0.774	0.896
Parents did not attend college	0.854	0.921

These findings suggest that the models obtained here are reliable across demographic groups, indicating that they can be used without concern regarding equity in their predictions.

6. DISCUSSION

To increase access to higher education for non-traditional students, institutions of higher learning have increasingly embraced online learning platforms to provide greater flexibility for working adults looking to return to school. Despite easier access, student retention and attrition has remained an important issue that online orientation courses like Engage aim to address.

In our study on students taking the orientation course Engage, we generated a total of 139 features based on student actions within the Blackboard course platform and developed models to predict future student registration in a program-specific for-credit course within the state of Arkansas's online *e*Versity. The features selected by our model were able to predict with high confidence levels the likelihood that students would register in a program-specific course after the orientation course. It is also notable that both the J-48 and J-Rip models selected the same feature (total number of views of Discussion Board Reply page) to be positively associated with future course registration. This finding echoes and provides support for earlier research suggesting that student participation in discussion boards is associated with better retention and achievement [18, 23].

The features selected in both our models, while not surprising, provide important implications that help guide administrators and facilitators to design interventions that can better identify at-risk students who may not continue on after the orientation course. For instance, the feature of discussion board reply views appeared to have a very strong association with future registration in an *e*Versity course. According to previous research, students' interactions within a course help improve student retention rates [14, 23]. Students who accessed the Discussion Board Reply page more often are more likely to be interacting with other students and course facilitators. In this manner, these students may experience greater engagement in the course and the *e*Versity program, which in turn could explain the association between the students' usage of the discussion board and future course registration within *e*Versity.

Within the J-48 model, three other features were selected in addition to discussion board reply views. The total number of views of the Messages page was also included in some models during cross-validation, even though it was not included in the final decision tree built on the entire data set. Like the Discussion Board Reply page views feature, this feature suggests that students who have more interactions with other students and course facilitators are more likely to register in another *e*Versity course afterwards.

Features on the number of days and frequency of the student checking of course grades appear to have positive associations with future course registration as well. From the decision tree generated with the J-48 algorithm, students that only view their course grades after a long period of time have a high likelihood of not registering for another *e*Versity course in the future. This can be another useful indicator of students who may not be as engaged in the *e*Versity program and their achievement in the orientation course, and who have a lower likelihood of registering for another *e*Versity course.

After developing our models, we tested their reliability across different demographic groups. We found that the models performed equally well across students of different race and gender, as well as between groups of students with parents who attended or did not attend college. These findings suggest that our model is not overtly biased towards or against a specific demographic group.

Based on our models' performance and the features selected, course administrators and facilitators could make further improvements to Engage to increase student retention in the online *e*Versity program. Since some of the selected features involve student interactions, course facilitators could try to embed more interactive activities within Engage to encourage students to reach out to their peers as well as to the program facilitators, and participate more actively in *e*Versity's social community. Given that discussion board views had high predictive power for future course registration within *e*Versity, Engage course facilitators could encourage student participation in discussion boards early on in the course, and maintain a stronger presence within discussion boards to provide a more robust and consistent form of support for students embarking on the *e*Versity program. Nevertheless, it is worth noting that student participation in discussion boards may also be a proxy for student interest in the course content or their overall goal of studying within *e*Versity. Actions taken by course facilitators to encourage student participation in discussion boards may not be as helpful in increasing student engagement or interest in the course content. Alternatively, it may be more effective for course facilitators to tweak the discussion board activities to ensure that they are optimally interesting and relevant to the learners participating in the orientation course.

7. CONCLUSION

In this study, we made use of student interaction data from a credit-baring online orientation course, Engage, in a completely online university, to build a prediction model of student registration in future program-specific courses. The prediction models were developed using machine learning algorithms and tested across different demographic groups. Two algorithms were tested; the performance of both models was high, and the models provide indicators that predict future student registration in program-specific courses within the online *e*Versity program. These prediction models thus provide *e*Versity administrators and course facilitators with fine-grained information on student behavior within the orientation course that could improve student retention on *e*Versity. As such, further improvements could be made to the orientation course Engage to accurately target students at risk of dropping out of the online *e*Versity program, and provide further support to these students at an earlier stage in their higher education journey.

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9. REFERENCES

[1] Arnold, K.E. et al. 2012. Course signals at Purdue: Using learning analytics to increase student success. *2nd International Conference on Learning Analytics and Knowledge*. May (2012), 2–5.

[2] Boston, W.E. et al. 2011. Comprehensive Assessment of Student Retention in Online Learning Environments. *School of Arts and Humanities, APUS*. Paper 1 (2011).

[3] Brewer, S. a. and Yucedag-Ozcan, A. 2012. Educational persistence: Self-efficacy and topics in a college orientation course. *Journal of College Student Retention: Research, Theory and Practice*. 14, 4 (2012), 451–465.

[4] Carr, S. 2000. As distance education comes of age, the challenge is keeping the students. *Chronicle of Higher Education*. 46, 23 (2000).

[5] Carruth, A. K.; Broussard, P. C.; Waldmeier, V. P.; Gauthier, D. M.; Mixon, G. 2014. Graduate Nursing Online Orientation Course: Transitioning for Success. *Journal of Nursing Education*. 49, March (2014), 14–17.

[6] Cohen, W.W. 1995. Fast effective rule induction. *Twelfth International Conference on Machine Learning*. (1995), 115–123.

[7] Dekker, G.W.. et al. 2009. Predicting students drop out: A case study. *EDM'09 - Educational Data Mining 2009: 2nd International Conference on Educational Data Mining*. (2009), 41–50.

[8] Derby, D.C. and Smith, T. 2004. An orientation course and community college retention. *Community College Journal of Research and Practice*. 28, 9 (2004), 763–773.

[9] Fike, D.S. and Fike, R. 2008. Predictors of First-Year Student Retention in the Community College. *Community College Review*. 36, 2 (2008), 68–88.

[10] Fritz, J. 2011. Classroom walls that talk: Using online course activity data of successful students to raise self-awareness of underperforming peers. *Internet and Higher Education*. 14, 2 (2011), 89–97.

[11] Hoskins, S.L. and Hooff, J.C. Van 2005. Motivation and ability: Which students use online learning and what influence does it have on their achievement ? *Communications*. 36, 2 (2005).

[12] Jayaprakash, S.M. et al. 2014. Early alert of academically at-risk students: An open source analytics initiative. *Journal of Learning Analytics*. 1, 1 (2014), 6–47.

[13] Jones, K.R. 2013. Developing and implementing a mandatory online student orientation. *Journal of Asynchronous Learning Networks*. 17, 1 (2013), 43–45.

[14] Jung, I. et al. 2010. Effects of different types of interaction on learning achievement, satisfaction and participation in web-based instruction. *Innovations in Education and Teaching International*. 39, 2 (2010), 153–162.

[15] Lauría, E.J.M. et al. 2012. Mining academic data to improve college student retention : An open source perspective. *Proceedings of the Second International Conference on Learning Analytics And Knowledge - LAK '12*. May (2012), 139–142.

[16] Lee, Y. and Choi, J. 2011. A review of online course dropout research: Implications for practice and future research. *Educational Technology Research and Development*. 59, 5 (2011), 593–618.

[17] Milliron, M.D. et al. 2014. Insight and action analytics: Three case studies to consider. *Research and Practice in Assessment*. 9, (2014), 70–89.

[18] O'Brien, B. and Renner, A.L. 2002. Online student retention: Can it be done? *World Conference on Educational Multimedia, Hypermedia and Telecommunications* (2002).

[19] Ocumpaugh, J. et al. 2014. Population validity for Educational Data Mining models: A case study in affect detection. *British Journal of Educational Technology*. 45, 3 (2014), 487–501.

[20] Park, J.-H. and Choi, H.J. 2009. Factors Influencing Adult Learners´Decision to Drop Out or Persist in Online Learning. *Educational Technology & Society*. 12, 4 (2009), 207–217.

[21] Parker, A. 1999. A study of variables that predict dropout from distance education. *International Journal of Educational Technology*. 1, 2 (1999), 1–10.

[22] Pascarella, E.T. and Terenzini, P.T. 2005. How college affects students: A third decade of research. *How College Affects Students: A Third Decade of Research*.

[23] Roberts, J. and Styron, R. 2010. Student satisfaction and persistence: factors vital to student retention. *Research in Higher Education Journal*. 6, 3 (2010), 1–18.

[24] Tyler-Smith, K. 2006. Early Attrition among first time eLearners: A review of factors that contribute to drop-out, withdrawal and non-completion rates of adult learners undertaking eLearning programmes. *Journal of Online Learning and Teaching*. 2, 2 (2006), 73–85.

[25] Willging, P.A. and Johnson, S.D. 2009. Factors that influence students' decision to dropout of online courses. *Journal of Asynchronous Learning Network*. 13, 3 (2009), 115–127.