PREDICTORS OF INFORMATICS STUDENTS' PROGRESS AND GRADUATION IN UNIVERSITY STUDIES

Margus Niitsoo, Mirjam Paales, Margus Pedaste, Leo Siiman, Eno Tõnisson

University of Tartu (ESTONIA)

Abstract

In higher education, particularly in the fields of engineering and science, large dropout rates and slow progress through the curriculum are world-wide problems. In Estonia most dropout in the field of computer science usually occurs at the end of the first year of studies. The reasons for this have not been studied in detail in the local context. To see what effect the amount of effort students dedicate to studying has on this, a study was carried out on one full cohort of Computer Science majors who started their studies in fall 2012. All of the students were required to daily record the number of hours they spent studying. Our results show that both prior achievement in mathematics and time spent studying during the semester were significant predictors of students' academic performance, with students who spent more time studying having better performance after the first and second semesters. A statistically significant interaction between time spent studying and students' academic performance was also found showing that students with higher prior achievement had less effect from each additional hour spent studying. Finally, we devised a model that predicts whether a student will drop out based on the information gathered during the first semester. This model can help identify students at risk of dropout and thereby allow time for possible interventions in the second semester.

Keywords: ICT, study time, prior achievement, computer science curriculum, dropout, study progress.

1 INTRODUCTION

A high dropout rate for students in Computer Science curricula or in computing courses is a worldwide problem. Talton, Peterson, Kamin, Israel & Al-Muhtadi [1] report that around 25% of entering freshman at the University of Illinois in the United States drop out of the computer science program after the first year. In a study of seven higher education institutions in Ireland, computer science courses had the highest rate of dropout (27%) compared to courses in engineering (20%), law (3%), and medicine (2%) [2]. In the United Kingdom, computer science majors are also the most likely group of students to dropout compared to students majoring in other subjects [3]. At the Helsinki University of Technology in Finland between 30 to 50% of students drop out of the introductory computer programming course [4]. Hüsing et al. [5] estimate, based on statistical data from Eurostat, the average student dropout rate in computer science in Europe is around 19%.

It is important to note that the ICT industry is growing at a faster pace than many other sectors [6], and that there is a high demand for ICT specialists [7]. In the European Union, for example, Hüsing et al. [5] forecast that the unmet demand for ICT practitioners could rise by 2015 to between 372,000 and 864,000 and by 2020 to between 481,000 and 1,685,000 (according to different scenarios). They recommend reducing the rate of university dropouts in ICT studies by one fifth from 19% to 15%. However, in order to increase the number of qualified ICT professionals it is crucial to understand the problem of student dropout from the Computer Science curriculum and use that information to design and implement proper interventions.

The University of Tartu is the largest university in Estonia (with about 17,000 students) and one of the main universities responsible for preparing ICT specialists in Estonia. The three year Computer Science (Informatics) bachelor curriculum at the University of Tartu is the university's largest in terms of number of entrants (more than 150 every year). Unfortunately, the dropout rate in the Computer Science curriculum has in some years reached the 60% level. Since many students drop out during or immediately after the first semester, it is important to focus on this period to find patterns that can predict attrition. Students have different backgrounds, various levels of ICT preparation and a range of prior experiences that might all be related, in some degree, to dropout. The results of state examinations (which are widely used by Estonian universities for ranking student candidates) are perhaps not the best indicators of prior ICT knowledge or preparation, but since they play a prominent role in university admissions they offer one way to characterize pre-university students. In addition,

ISBN: 978-84-616-8412-0

some variation in students' potential for the ICT field might depend on learning methods and other school specific characteristics that are not necessarily reflected by examination scores.

Finally, students' efforts during their university studies should be very important. These efforts can be partially described by time spent studying (both in class and outside) and the study methods used by the students. If we can identify which patterns in the study process are effective for particular types of students then it might be possible to support them, avoid dropout and increase the number of graduates. We hypothesize that by revising admission procedures, providing appropriate support during the first study year or revision of the curriculum and teaching methods it is possible to increase the number of students that successfully finish their studies in computer science and continue their professional career without compromising the quality of their education.

In researching relations between study time and academic performance of college students, Nonis and Hudson (2006) applied methods and analyses we found to be useful in our study. For example, to collect study time data they asked students to maintain a diary for 1-week and update it daily with an estimate of the previous day's study time. Regular documentation of the number of hours spent studying potentially helps minimize recall bias from participants and thereby contributes to generating more accurate data. We adopted a similar method of data collection, but decided to stretch it out further in time, collecting data for 14 weeks rather than just one.

In addition, Nonis and Hudson [8] used time spent studying data in combination with other variables to search for interesting interactions, e.g. does study time interact with prior ability to influence academic performance. We try to replicate their results by testing two of their hypotheses for which we have data.

In this study we collected data from beginning Computer Science students regarding their pre-university admission scores, academic performance in computer science courses and time spent studying. Statistical analysis was performed on this data to test certain hypotheses. The following specific hypotheses were formulated based on the data available in our study:

(1) There is a relationship between time spent studying and academic performance at the end of the semester.

(2) Time spent studying will significantly interact with students' academic performance in the course. The academic performance will be higher for students who spend more time studying than for students who spend less time studying.

(3) Time spent studying in the first semester at university and prior performance are effective predictors of second semester results.

Additionally, we were interested in finding a predictive model for attrition. We chose not to fit this into the hypothesis testing framework since we wanted to approach it in a more explorative way with the main goal of finding a simple and robust model that would be both usable and useful.

2 METHODS

In this study we collected data from 156 students who started their Computer Science studies in fall 2012 at the University of Tartu in Estonia. Data about their academic progress was collected during their first academic year (i.e. two semesters), but information on study time was only collected during the first semester. During the first semester students were presented with 16 weeks of lessons in their courses, after which followed a four-week long period of exams. Exams were graded with scores on a 6-point scale, from A to F, but some courses ended with a non-distinctive assessment where there was only said if the student passed or not. Students were expected to complete five compulsory courses in the first semester. Each course gave the same amount of credit points (6 points) and reflected about 8 hours of work per week. Within this working time about three hours is dedicated to study at the university (1.5 h for lecture and 1.5 h for practical work) and the remaining time allotted to homework/out of class study.

2.1 Description of the Data

According to the hypotheses of our study, we collected information about students' time spent studying, prior achievement, academic performance, and dropout. Data was collected from all students who started their studies in 2012 at the University of Tartu in Estonia in the Computer Science curriculum.

Data about time spent studying at the university was collected with the help of an online study diary (a Google form accessible to anyone with a link) that was available for 96 days starting from the third week of the first semester up until the beginning of the exam period. Students enrolled in the first semester introductory course had to fill it out daily (with a delay of up to two days) throughout the semester. They reported how much time was spent studying in the university classes and outside of class. Filling in the study diary was a compulsory part of the first semester introductory informatics course. It was made clear to the students that the time reported in the study diary (even if the reported time was null) did not in any way influence their grade in the course. However, there was set a maximum number of idle study diary days (28 out of 96 total days) where a student who did not fill out the diary with information would not be allowed to pass the course. In the study diary students were asked to report the number of hours they spent learning and for which courses. Both time spent at university lessons and time spent studying outside of class had to be reported. In addition, it was asked what methods the students used while studying, e.g. reading, doing exercises, writing, etc., but this information was not the focus of the current study.

Once a week the study diary data was used to create personalized graphs so that students could compare how much time they spent studying in comparison to other students. The intent of the personalized graphs was to motivate students to fill out the study diary since the graphs would then provide essential feedback for students to evaluate if they were working too hard or not enough. A point to keep in mind is that the introduction of a study diary and weekly feedback may have increased the amount of time spent studying by this cohort computer science students compared to prior generations.

Students' academic performance was measured by the university's electronic study information system. Specifically, information about students' scores related to all subjects was extracted as well as whether a student exmatriculated or had taken academic leave.

Admission to the curriculum is based on a score that is calculated from the state exam results in mathematics (50%), mother tongue (25%) and foreign language (25%). This score is automatically set to 100 for students entering under special conditions (such as good results on national academic or sports competitions) and there were 23 students who were admitted this way. To avoid such a "ceiling" effect, we decided to instead use the national mathematics exam result as the measure of prior achievement – especially considering that most of the 23 students had taken the mathematics exam and their results were available to us.

Finally, information on students' gender and age was added to our data to check if there were specific patterns related to these characteristics.

2.2 Sample and Data Analysis

The initial population of the current study consisted of 156 students (the full cohort admitted to the curriculum for the 2012/13 academic year). However, only 137 students submitted study data at least once into the diary system. Of those, 119 did it regularly, skipping less than 29 days. These 119 students were used as the base sample for our analysis.

In the case of study diaries we summed the hours logged throughout the semester and used the total number of hours in our models. This metric seemed to have stronger predictive power than average number of hours per report, possibly because it penalized students who forgot to fill the diary more often by giving them smaller scores. The number of days not reported also seemed to have some additional predictive power (probably as a measure of conscientiousness) so it was also included as a factor in the models.

To make sure all students had a comparable grade point average (GPA), we constrained our analysis to first year students enrolled in two main courses: Programming and Elements of Discrete Mathematics. These two compulsory courses are graded on a scale from A to F and the presence of these courses reduced the number of students under analysis to 106. To get a more fine-grained achievement estimate, we used the average of the raw scores in both these courses (which were on a 100-point scale) instead of resorting to final grades (only on a 5 point scale) for the first semester "GPA". For the second semester, a more conventional GPA calculation was made by averaging the grades in all the courses the student had taken in that semester.

As hinted to before, our preliminary analysis indicated that the high school mathematics state examination score was considerably more predictive than the more general admittance score, and so we opted to use the former as the measure of prior achievement levels. This meant dropping 3 students who had no mathematics examination score on record, resulting in a sample of 103 students. There was also one student among the 103 that took no graded courses in the spring term, and was thus removed from the spring semester analysis.

To measure dropout, we decided to look not only at exmatriculation but also at academic leaves. Although academic leave has been formally meant for people who need time away from their studies (because of illness, other duties, etc.), students have been still permitted to take courses during academic leave, and as such, it has been a convenient loophole used mainly for adding an extra year of studying. Because we wanted to examine student dropout after the first year, the issue of academic leave had to be taken into account and we decided to define students in the process of “dropping out” as having been either formally exmatriculated or chosen to take academic leave after completing their first semester. In the initial sample, there were 17 students who had taken academic leave and 27 that had been exmatriculated and no students had done both. In the final sample of 103 students, the respective numbers were 6 and 11.

It is worth noting that this set of 103 students is definitely not representative of the 156 students originally admitted and the same is even clearer in the case of the 17 out of 44 who were categorized as in the process of “dropping out”. Nevertheless, this sample allows us to draw our first conclusions. As we selected students by participation in the first semester courses, we filtered out both students who never actually came to the university or instantly started academic leave (for instance because they decided to enlist in mandatory military duty) and also students who formally re-entered the university but in fact just continued their previous studies starting at the second or even third year courses. This was clearly illustrated by the considerably higher rates of “dropout” in the 53 students removed from the analysis, as 27 or over half of them either took academic leave (those serving in the army) or were exmatriculated (those not showing up at all). The selection therefore left us with students who were studying computer science for the first time at the university level, a group that is more homogeneous and interesting in terms of developing future possible interventions.

To test our hypotheses we used multiple linear regression analysis. We built two separate models, one for first semester scores and one for second semester GPA. In both models, we used the same regressor variables: Age and Gender (for controlling), reported time spent studying (Time), days missed in diary reporting (Missing), results of high school mathematics exam (Math) and interaction between Time and Math (Time x Math). For predicting attrition, we used logistic regression, which is considered more suitable for binary prediction problems than simple linear regression [9].

3 RESULTS

Table 1 lists the descriptive statistics for all the factors considered for the 103 students whose data was used in this study.

Table 1. Descriptive data of the students of the sample used in the current study.

Characteristic	Mean	SD	Min	Max
Age (years)	19.6	1.48	18	27
Study time (hours)	407.7	113.4	143	683.5
In class	231.4	51.8	86	364.0
Outside of class	176.3	80.1	1	385.5
Missing reporting days (days)	7.9	5.7	0	26
State examination score in mathematics (0 to 100 points)	81.8	12.5	30	100
Grade point average in first semester (0 to 100 points)	70	18.6	13.6	101[1]
Grade point average in second semester (0 to 5 points)	2.91	1.39	0.0	5.0

26 out of 103 students of the sample were women. It is noteworthy that males seemed to be less motivated to participate in the current study compared to females (62% vs. 81%). This should be kept

[1] Although grading was on a standard 100-point scale with 91+ meaning A, students were given the opportunity to get a few extra “bonus” points so the score could theoretically go as high as 108.

in mind while interpreting results. 17 out of 103 students of the study dropped out during the first study year (17%). In comparison, the dropout ratio in the whole population of students was much higher – 44 out of 156 students (28%). Thus, we might assume that the students who did present enough information to be involved in the current study also had some other issues related to their studies and this lead to a higher probability of dropout. However, it is a hypothesis that has to be tested in future studies.

Table 2 lists the slopes and marginal p-values[2] of the regressors as well as the cumulative R^2 scores resulting from consecutively adding variables.

Table 2. Factors interacting with academic performance (grade point average) of the students.

Factor	**Slope**	**Effect size**[3]	**SE**	**p**	**R^2**
First semester (N=103, R^2=0.474)					
Intercept	-90.23		44,3	<0.05	
Age	1.06	0,08	0.97	n.s.	0
Gender (F=1)	-13.2	-0.71	3,3	<0.01	0.056
Time	0.22	1.33	0.086	<0.05	0.197
Missing	-0.57	-0.18	0.27	<0.05	0.278
Math	1.56	1.04	0.47	<0.01	0.452
Time x Math	-0.0021	-1.21	0.001	<0.05	0.474
Second semester (N=102, R^2=0.424)					
Intercept	-7.4		3.57	<0.05	
Age	-0.0093	-0.01	0.076	n.s.	0.003
Gender (F=1)	-0.41	-0.29	0.26	n.s.	0.004
Time	0.019	1.56	0.0068	<0.01	0.243
Missing	-0.049	-0.2	0.021	<0.05	0.317
Math	0.108	0.96	0.037	<0.01	0.399
Time x Math	-0.00017	-1.33	0.000082	<0.05	0.424

In our study, the first hypothesis was confirmed. Time spent studying was significantly connected to academic performance both after the first and after the second semester, with direct correlations to achievement and time being 0.31 and 0.47, both significant at the 1% level ($p<0.01$). Even after controlling for other variables (as in the models in Table 2) the results remain significant, although only at 5% level. Our third hypothesis was also confirmed with p values being even smaller for the second semester model.

Concerning the second hypothesis the results are somewhat more surprising. Namely, we find a (barely) significant interaction between time spent studying and prior achievement, but in our case the interaction has a reverse sign compared to the study by Nonis and Hudson [8], meaning that additional prior knowledge *diminishes* the effects of time spent studying.

In building a model for predicting dropout we were guided by practical considerations of identifying students at risk. For that reason, we discarded our original intended model (with the same regressors as the models used for the hypothesis) that, despite explaining a significant portion of the variance (32% with McFadden's Rho^2 of 0.56) proved useless at the practical prediction task, getting 17 wrong

[2] Marginal p-value is the probability of the factor having this much influence just by chance, given that all the other factors in the model are controlled for. They are strictly larger than consecutive p-values (so a significant marginal p-value implies a significant consecutive p-value but not vice versa) as they measure the influence with respect to all other factors as opposed to just the factors added before. They are therefore considered more informative, as they are independent of variable order and thus less prone to manipulation.

[3] Effect size is the effect of one standard deviation of change in that dimension in standard deviations of the predicted value. This is calculated by multiplying the respective slope with the standard deviation of the regressor variable and dividing by the standard deviation of the dependent variable. This puts all the slopes in a comparable scale. For categorical values, effect size is usually taken to be just the slope coefficient divided by standard deviation of the dependent variable.

in leave-one-out cross-validation, thus having the exact same error rate as always predicting "not dropping out" would.

To get a better, more robust model, we decided to replace the interaction term (which seemed to add relatively little) with the first semester "GPA" score, under the rationale that study diary data would also be available no sooner than the end of the semester, so anyone making predictions based on one would also have access to the other. For simplicity, we also dropped the interaction term from the model, as it did not seem to add any information beyond what was already contained in the individual variables in the case of this model, but it did interfere with marginal p-values of the other individual variables. After this, we also reordered the variables for most pronounced effect for later discussion. The statistics of the resulting model are shown in Table 3, where the statistics were chosen to match those for multiple linear regression as close as possible.

Table 3. Factors interacting with drop-out of the students during the first study year.

Factor	Slope	SE	p	PVE[4]
Full model (N=103, Rho^2=0.66)				
Intercept	18.2	10.3	n.s.	
Age	-0.74	0.46	n.s.	0.019
Gender (F=1)	1.49	1.03	n.s.	0.039
Math	0.046	0.044	n.s.	0.053
GPA	-0.095	0.031	<0.01	0.371
Time	-0.0112	0.0052	<0.05	0.466
Missing	0.051	0.063	n.s.	0.473
Constrained model (N=103 , Rho^2=0.60)				
Intercept	6.37	1.77	<0.001	
Time	-0.090	0.0036	<0.05	0.179
GPA-1	0.075	0.021	<0.001	0.384

To get a more robust model that is more likely to generalise to future datasets, we also constructed a model based on just two significant factors from the full model: Time and GPA. A chi-squared test comparing the two models found the difference between the full model and the constrained model to be insignificant with p=0.085, whereas both models are significantly better than the intercept-only model with p<0.001.

Leave-one-out cross-validation fails to distinguish between the constrained and the full models, with both having an average squared error of 0.095 and both discretely misclassifying 14 out of the 103 students (mostly false negatives). This is unfortunately still only just slightly better than 17 misclassifications of the "always not dropping out" predictor. There is one important thing to note about the full model. Namely, the mathematics exam result explains only 1.4% of the total variance (after controlling for age and gender, but before introducing any other variables that might detract from its effects). This seems to imply that prior achievement levels seem to have practically no influence on whether a student will dropout – a finding, if confirmed by later studies would definitely be interesting as well as practically useful in the interventions.

4 DISCUSSION

Our study demonstrated that there is a relationship between time spent studying and academic performance. Nonis and Hudson [8] found a similar trend but their results were not statistically

[4] Proportion of Variance Explained – for linear models (such as multiple linear regression), R^2 corresponds exactly to the PVE (as given by ANOVA) and no distinction is made. For logistic regression, this is not the case due to certain mathematical technicalities. However, PVE (as given by ANOVA with binomial model and logit link) can still be interpreted in a similar way, with bigger values implying the variable has bigger effect. The table should therefore be read similarly to the multiple linear regression tables.

significant. In our findings this relationship was significant. Furthermore, there are at least two more important aspects of our findings that differ from [8].

First, it is important to note that we collected information about the entire time spent studying – both in and outside of class. In the study of Nonis and Hudson [8] only time spent outside of class was investigated. However, it is important to also count time spent in class since in many countries, including Estonia, class attendance is not mandatory. This sometimes results in a situation where students who do not attend class claim that their independent learning outside of class is more effective. In our study the average time spent studying in class was slightly larger than the time spent studying outside of class, which shows that learning during class time is substantial. This result, when interpreted together with our finding that more time spent studying is associated with better academic performance leads us to conclude that students should be strongly urged to attend class as well as study outside of class. We recommend university lecturers guide students toward both active participation in lessons and assign required homework. Although the positive effect of homework on students' learning outcomes (academic performance) is only likely if students actually spend time on it. In introductory informatics courses at the University of Tartu students are motivated to do homework by systematic checking and feedback on their work. It is assumed that this helps lead to continuous study habits.

A second difference between our work and Nonis and Hudson [8] is that their study was in the context of economics education whereas we studied computer science education. Thus, similarity of these findings demonstrate that we have found a more general principle that could be probably generalized and taken into account planning supportive activities in different curricula.

These differences might help explain the fundamentally different results on the second hypothesis. Data of Nonis and Hudson [8] suggested that the interaction term is positive, so that those of higher prior achievement benefit more from each subsequent hour of (independent) study. Our results suggest the opposite, implying that the more the student already knows, the less each hour of studying adds. In some sense, both claims have intuitive appeal: the former might be due to those of higher ability also being better learners, while the latter might be explained by diminishing returns on learning. Which effect is prevalent might, however, be domain-dependent. It is also possible that the inclusion of in-class time skews the results, as teachers usually focus to the average student in the lectures, giving credence to the diminishing returns theory.

There are a few other points deserving further discussion. Firstly, from looking at effect sizes we see that both prior achievement and time spent studying play nearly equal roles (with time spent studying having just a slightly larger effect size) when it comes to predicting end-of-semester academic performance. This supports the position that a diligent student who spends considerable effort studying for university courses can possibly overcome problems of unpreparedness due to factors such as incomplete pre-university schooling and catch up to his classmates who may be better prepared but less diligent in studying. From our data, one point on the national mathematics exam is equivalent to roughly 7 hours of extra time spent studying, or just 5 hours if considering second semester GPA results.

Secondly, it is curious how little effect prior achievement seems to have in the dropout model. Although at first sight it might seem that the prior achievement effect is mediated via the GPA score, this turns out not to be the case on closer examination as the model with just control variables and the mathematics score explains just 5.3% of the variance with larger jumps coming only later with GPA and Time spent. Also telling is that the slope coefficient is positive, which, if it were significant, would imply students with higher prior achievement would be more likely to drop out, not less. The hypothesis that first year dropout is in fact independent from prior achievement is something that definitely warrants further research. In the same model, Time spent studying does indeed seem to play a pretty important role, as those dropping out spend on average 27% less time (311 h compared to 427 h) than those continuing while the difference in mathematics exam scores is only 4% (79.1 vs 82.3).

Third, we note that some of the effects of study time could be mediated by conscientiousness. Psychology research shows that conscientiousness (a tendency to act dutifully, a willingness to work hard) is the strongest predictor among personality traits for predicting academic performance [10]. In our case, the more diligent and careful students who missed reporting on fewer days had a slight advantage, so our evidence is in line with the hypothesis that conscientiousness may play a role in the final results.

Fourth, it is interesting to note that there are considerable gender differences in the first semester model, with girls scoring on average 13.2 points less than boys. On closer examination, this effect seems to be entirely due to the (introductory) Programming course scores, with no gender differences for the Elements of Discrete Mathematics course. This again suggests future follow up work.

Fifth, we found some interesting ideas for predicting dropout of students during their first study year but these aspects need further study. The combination of study habits with prior achievement in predicting dropout suggests an emphasis on remedial coursework may be warranted for informatics students at risk of dropout. Without the necessary prior experience, students may be overwhelmed by rigorous introductory computing classes. Difficulty with computer programming is often a reason students drop out of the computer science program. Moskal, Lurie, & Cooper [11] applied an intervention to teach programming to students with low mathematics qualifications and minimal programming experience using a visual programming environment, rather than a conventional syntax-based programming language. The visual programming environment offered novice students the opportunity to learn computing concepts without overly focusing on programming syntax. The authors reported that students who first participated in this intervention and then later enrolled in a rigorous programming class were retained in the computer science program at a significantly higher percentage (88%) than students with weak mathematics and programming background that did not undergo the intervention (47%). Even more interesting was that the intervention group was retained at a higher percentage than students who did not undergo the intervention but had high levels of prior mathematics and programming experience (75%). Thus it appears that there are beneficial interventions that can be applied if informatics students at risk of dropout can be identified early.

Finally, we should describe some potential limitations of our study. First, it was not possible to use in our analysis data about all students since a specific group of students did not fill in study time diary data systematically. This group might have had an effect on the conclusions. Second, our data collection method through diaries could have some effect on students' behaviour. It might be that some diligent students started to spend more time studying due to the diary reporting and feedback mechanism. There may also be concerns that students could have reported more study hours than they actually did. However, it is our opinion that this was not a very large issue as it was emphasized that this information had no effect whatsoever on their grades, and fabricating numbers is cognitively more demanding than reporting roughly correct ones.

5 CONCLUSIONS

In conclusion, our findings demonstrate that study time can help students overcome weakness in preparation, but that prior achievement still plays a role. If beginning computer science students spend more time studying then they can improve their academic performance. Students who are less prepared to learn computer science, yet willing to work hard, can achieve similar performance outcomes compared to well prepared, but lazy students, who succeed academically simply on the strength of their prior knowledge. However, laziness (not spending enough time studying) is one of the two best predictors for dropout.

The outcomes of this study can be applied for detecting students who might dropout and for providing support to them to manage their learning according to their personal needs. New directions for future research are also opened up by this study. Future studies are needed for in-depth analysis of specific groups of students – to understand when unprepared students fail in their studies, when they improve, what kind of interventions are effective in supporting them, or how to support students who might be well prepared for their studies but too lazy and thus resulting in academic performance that does not corresponding to their potential level of results. More information is also needed about the role of pre-university activities – what is needed to prepare student candidates for successful studies at university.

ACKNOWLEDGEMENT

This research was partly supported by the European Union through the European Regional Development Fund's project 'Conceptual framework for increasing society's commitment in ICT: approaches in general and higher education for motivating ICT-related career choices and improving competences for applying and developing ICT'. Special thanks to the students who participated voluntarily in the study.

REFERENCES

[1] Talton, J. O., Peterson, D. L., Kamin S., Israel D., & Al-Muhtadi J. (2006). Scavenger hunt: Computer science retention through orientation. Proceedings of the 37th SIGCSE Technical Symposium on Computer Science Education, pp. 443-447.

[2] Higher Education Authority. (2010). A study of progression in Irish higher education. Dublin. Retrieved from http://www.hea.ie/files/files/file/New_pdf/HEA%20Study%20of%20Progression%20in%20Irish%20Higher%20Education%202010.pdf

[3] National Audit Office. (2007). Staying the course: The retention of students in higher education. HC 616, London. Retrieved from http://www.nao.org.uk/wp-content/uploads/2007/07/0607616.pdf

[4] Kinnunen, P. & Malmi L. (2006). Why students drop out CS1 course? Proceedings of the Second International Workshop on Computing Education Research, pp. 97-108.

[5] Hüsing, T., B. Korte, W. B., Fonstad, N., Lanvin, B., van Welsum, D., Cattaneo, G., Kolding, M.,Lifonti, R. (2013) e-Leadership. e-Skills for Competitiveness and Innovation Vision, Roadmap and Foresight Scenarios. Final Report. http://ec.europa.eu/enterprise/sectors/ict/files/eskills/vision_final_report_en.pdf

[6] US Bureau of Labor Statistics. (2012). Employment outlook: 2010-2020. Retrieved from http://www.bls.gov/opub/mlr/2012/01/art5full.pdf

[7] European Commission. (2013). Commission issues action call in Davos - with IT sector and telecoms companies - to close digital skills and jobs gap in Europe. Retrieved from http://europa.eu/rapid/press-release_IP-13-52_en.htm

[8] Nonis, S. A. & Hudson, G. I. (2006). Academic performance of college students: Influence of time spent studying and working. Journal of Education for Business, 81, pp. 151-159.

[9] Peng, C.-Y. J. & So, T.-S. H. (2002). Logistic regression Analysis and Reporting: a Primer. Understanding statistics, 1, pp. 31-70.

[10] Noftle, E. E., & Robins, R. W. (2007) Personality predictors of academic outcomes: Big five correlates of GPA and SAT scores. Journal of Personality and Social Psychology, 93(1), pp. 116-130.

[11] Moskal, B., Lurie, D., & Cooper, S. (2004). Evaluating the effectiveness of a new instructional approach. In Proceedings of the 35th SIGCSE Technical Symposium on Computer Science Education, pp. 75-79.