Algorithmic Skills Transferred from Secondary CSI Studies into Tertiary Education

Piroska Biró, Mária Csernoch, János Máth, Kálmán Abari

Abstract—Testing the first year students of Informatics at the University of Debrecen revealed that students start their tertiary studies in programming with a low level of programming knowledge and algorithmic skills. The possible reasons which lead the students to this very unfortunate result were examined. The results of the test were compared to the students' results in the school leaving exams and to their self-assessment values. It was found that there is only a slight connection between the students' results in the test and in the school leaving exams, especially at intermediate level. Beyond this, the school leaving exams do not seem to enable students to evaluate their own abilities.

Keywords—Deep and surface approaches, metacognitive abilities, programming and algorithmic skills, school leaving exams, tracking code.

I. INTRODUCTION

COMPUTER Sciences and Informatics (CSI) education absorbs a large number of students, inviting and accepting more and more of them into tertiary education [1]. This would be the most natural course of events, considering the development of CSI in the last couple of decades. However, it is not that simple. The increase in the number of students entering tertiary CSI education raises many questions that need to be considered. Are the students prepared for advanced CSI studies? Do they know what advanced studies in CSI mean? Are the universities and colleges prepared for this new generation of students with all their advantages and disadvantages?

However, one thing is for sure: studies in tertiary CSI education require an advanced level of algorithmic skills. We have been expecting that with the introduction of CSI into primary and secondary education the students will arrive at the Faculty of Informatics with at least an intermediate level of algorithmic skills, which would serve as the basis for further studies in programming. However, the high number of dropout students and the high number of semesters spent in these studies would suggest [2], [10], [18] that there is a level of misunderstanding between the students and these higher education institutions. One of the reasons for this misunderstanding could be the different expectations of the parties involved, while another could be students' preparation

for these studies, i.e. the knowledge brought from previous studies. To see clearly how developed the students' CSI knowledge is, their concept of computer, their usage of terminology, and their algorithmic skills at the point they start their studies as programmers in different majors, we launched a project called Testing Algorithmic and Application Skills (TAaAS) in the 2011/2012 academic year at the University of Debrecen, Hungary [15]–[21], [13]. In this study we focus on the algorithmic skills of the students in the three different majors of the Faculty of Informatics.

II. METHODS

A. Sample

The TAaAS project was launched at the beginning of the 2011/2012 academic year at the Faculty of Informatics of the University of Debrecen, Hungary. The tests used in the project were repeated in the following two years with the students of the three major programming BSc courses: Software Engineering (SOE), System Engineering (SYE), and Business Information Management (BIM) (Table I).

TABLE I
THE NUMBER OF STUDENTS PARTICIPATING IN THE TAaAS PROJECT AT THE UNIVERSITY OF DEBRECEN

	SOE	SYE	BIM	Sum
2011/2012	115	86	109	310
2012/2013	108	111	101	310
2013/2014	115	115	90	320
Sum	338	312	300	950

SOE – Software Engineering, SYE – System Engineering, BIM – Business Information Management

The testing takes place on the first week of the first semester, right at the beginning of the students' studies in tertiary education. Our purpose in administering the tests at this point was to test the knowledge the students brought in from previous studies, the knowledge whose official source is primary and secondary school courses in CSI.

The testing has two phases in a strict consecutive order. In the first phase the general and self-evaluation questionnaire is filled in and is collected; subsequently, the real test is administered. In this paper we report the results of the tests' two programming tasks, compared to the students' self-assessment values and their results in the school leaving exams in Informatics [5]–[7].

The school leaving exams in Hungary run on two levels: intermediate and advanced. On both levels, there is a written – problems to be solved on computers – and an oral section [6], [7]. In the written section at intermediate level only

P. B. is with the University of Debrecen Faculty of Informatics, Debrecen, 4028, Hungary (phone: +36-52-512-900/75227; fax: (52) 512-996; e-mail: biro.piroska@inf.unideb.hu).

M. Cs. is with the University of Debrecen, Faculty of Informatics, Debrecen, 4028, Hungary (e-mail: csernoch.maria@inf.unideb.hu).

J. M. and K. A. are with the University of Debrecen Faculty of Arts and Humanities, Debrecen, 4032, Hungary (e-mail: math.janos@arts.unideb.hu, abari.kalman@arts.unideb.hu).

World Academy of Science, Engineering and Technology
International Journal of Energy and Power Engineering
Vol:9, No:2, 2015

application tasks are included, while at the advanced level there are more demanding tasks, mainly in terms of complexity, including applications tasks and one programming task.

The self-assessment test was launched in the 2012/2013 academic year, after recognizing in the first year of the project that the students' results do not harmonize with the expectations of the different participants in tertiary education. In the 2012/2013 academic year a 6-point Likert-scale was offered to mark the self-assessment values, while in the following year the students were asked to provide this value as a percentage. In this paper we focus on the algorithmic skills of the students; consequently, only the programming self-assessment values are considered.

Unfortunately, for security reasons, we do not have access to the data regarding the students' results in the programming section of the advanced level school leaving exam, the year in which the students completed the school leaving exam, and the year they started their secondary education. These data would provide further insights into the circumstances and the knowledge the students bring in, but both the university and the government of our country refused our request. The year of the school leaving exam and the starting year of secondary education would be important because in the 2009/2010 academic year a new base curriculum was launched in Hungary. In this curriculum the number of CSI classes in secondary education was almost tripled – it was increased from to 2 to 5.5 classes – and we were interested to see the effect of this change, if any. Since we do not have access to data on the students' secondary education, we use the year of entry in tertiary education, assuming that most of the students in Hungary arrive in tertiary education straight after finishing secondary education.

B. Tasks

The tasks used in the project are borrowed from the programming section of the Nemes Tihamér National Competition of Informatics in Hungary, 2008/2009, round I, level 5–8th grades (Figs. 1 and 2).

You draw two cards (X, Y) from two packs. In both packs you can find cards with the letter A, cards with the letter B and cards with zero. Give the points in the last column of the table according to the algorithm given below!

```
V:=X="A" or Y="A"
W:=X="B" or Y="B"
If V and W then Point:=0
else If V then Point:=1
else If W then Point:=2
else Point:=3
```

X	Y	Point
A	A	
A	B	
A	0	
B	A	
B	B	
B	0	
0	A	
0	B	
0	0	

Fig. 1 Task 1, testing the knowledge of logical operators [3], [4]

In Task 1 nine questions have to be answered, based on the source code and the nine pairs of inputs. The source code is a multilevel IF structure testing the knowledge of logical operators. The task is lightened to some extent, compared to a

real programming task, since the answers are one of the four numbers of the possible outputs of the algorithm – 0, 1, 2, and 3. We must point out here that the context in which the code is placed does not make any difference to the answers; it is only a decoration.

What do the following programs do? What is stored in variable DB and M?
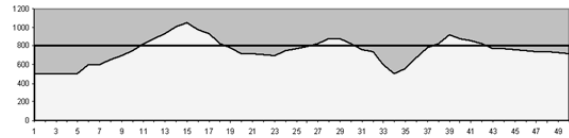
N=50, measured values: 500,500,500,500,500,600,600,650,700,750,820,880,930, 1010,1050,980,930,830,780,720,720,710,700,750,770,790,820,880,880,820,760, 740,600,500,560,670,780,820,920,880,860,820,770,770,760,750,740,740,730,720.

```
DB:=0
Loop from i=1 to N
    If X(i)>800 then DB:=DB+1
End loop
```

```
DB:=0
Loop from i=2 to N−1
    If X(i)<X(i−1) and X(i)<X(i+1) then DB:=DB+1
End loop
```

```
M:=0
Loop from i=2 to N
    If X(i)−X(i−1)>M then M:=X(i)−X(i-1)
End loop
```

Fig. 2 Task 2, testing the students decoding ability in a context based environment [3], [4]

Task 2 is more demanding than Task 1. In this task three pseudo codes are presented – Task 2.1, Task 2.2, and Task 2.3. These codes should be decoded and the answers should be given in full natural language sentences. However, unlike Task 1, here the environment of the task has to be taken into consideration, and the answer sentences should be placed in the given context.

Both Tasks 2.1 and 2.2 are counting problems; however, Task 2.1 is less difficult than Task 2.2, since in the latter there is an AND connection in the condition. Task 2.3 is made even more difficult because here a maximum selection should be recognized, as well as the maximum of the increasing slopes. Two different actions – selecting the maximum and the condition – are embedded into this code, and consequently they are not as obvious as in Task 2.2 [8], [9], [22].

The students' results were evaluated using the different levels of understanding of the SOLO taxonomy [11], [12], [14], [23], [24].

- Ignored (1)
- Prestructural (2)
- Unistructural (3)
- Multistructural (4)
- Relational (5)
- Extended abstract

The extended abstract category was left out, due to the special context and environment of the task. We did not ask nor expect our students to give answers beyond this special environment. However, one additional category was added to

World Academy of Science, Engineering and Technology
International Journal of Energy and Power Engineering
Vol:9, No:2, 2015

the already existing categories, with a value of 1, for those students who ignored the tasks, and/or marked them as 'I do not know.' For further details of the ratings see [20].

C. Hypotheses

The testing of the first year students of the Faculty of Informatics could provide answers to our hypotheses and further guidelines for their tertiary studies, considering the knowledge which they bring from previous studies.

H1. The test results of the SOE students are higher than those of the other two programming majors. The SOE students arrive with a higher level of algorithmic skills than the other majors.

H2. The higher results in the school leaving exams in Informatics lead to higher results in the test.

H3. The higher results in the school leaving exams in Informatics make the students more confident; consequently, the higher results in the school leaving exams lead to higher self-assessment values.

H4. The students' results in the 2013/2014 academic year are higher than in the previous years, because this is the first year in which students studied CSI in secondary education with the increased number of classes.

III. RESULTS

In the preliminary phase of the statistical analysis the students' results in the four tasks, in the different years and in the different majors were analyzed and compared to the self-assessment values.
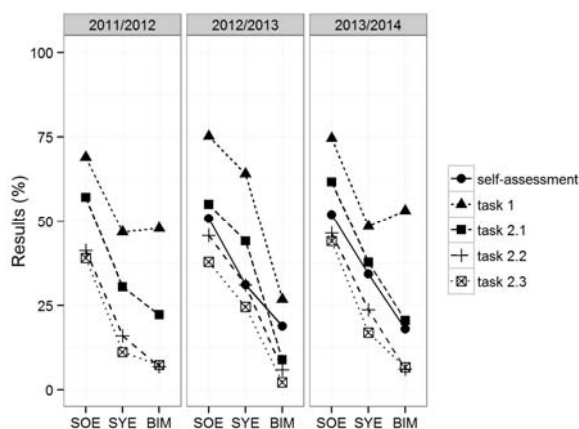

Fig. 3 The comparison of the self-assessment values and the results in the four tasks of the test of the students of the three programming majors in three academic years

Fig. 3 shows that the order of difficulty of the tasks from the easiest to the most difficult is: Task 1, Task 2.1, Task 2.2, and Task 2.3 – the difference, based on the Friedman-test is significant, $p < 0.001$. Beyond this result, the Mann-Whitney-tests ($p < 0.001$) proved that Task 1 is significantly easier than the other three problems. The graphs in Fig. 3 also show the order of the majors. The SOE students achieved the best results, followed by the SYE students, and the results of the BIM students are the worst. If the results of the majors are

compared regardless of the year of the test – sample is presented in the last row of Table I –, a significant decrease was found in the previously mentioned order of the majors (Jonckheere-Terpstra Test: $p < 0.001$, in all four problems).

In the comparison of the years, a slight improvement in the results was detected in all four problems; however, the differences are not significant if the results of the 2013/2014 academic year are compared to the average of the other two years (with the Mann-Whitney probes the lowest is $p = 0.201$).

A. Knowledge-Based Clusters of Students

The students' results are the highest in Task 1 in all the three years and in all the three groups. These results were used to create knowledge-based clusters of the students tested. Cluster 4 consists of those students who ignored or partly finished Task 1. The input for the cluster analysis was the nine variables of the completed task – the nine questions of Task 1 – and the four optional answers of Task 1 – 0, 1, 2, and 3. These values served as categorical data for the Two-step Cluster Analysis in SPSS. Based on these premises, three clearly distinguishable knowledge-based clusters were found – Clusters 1–3. This structure of clusters exactly matches the structure which was found by testing students from different Hungarian universities and colleges [13].

The results of the three clusters are presented in the nine graphs of Fig. 4, where the title of the graphs shows the order of the problems and their input values (Fig. 1, X-Y pairs). The domain of the graphs is the four possible solutions to the problems (Fig. 1, source code), while the range is the percentage of the correct answers in the clusters.
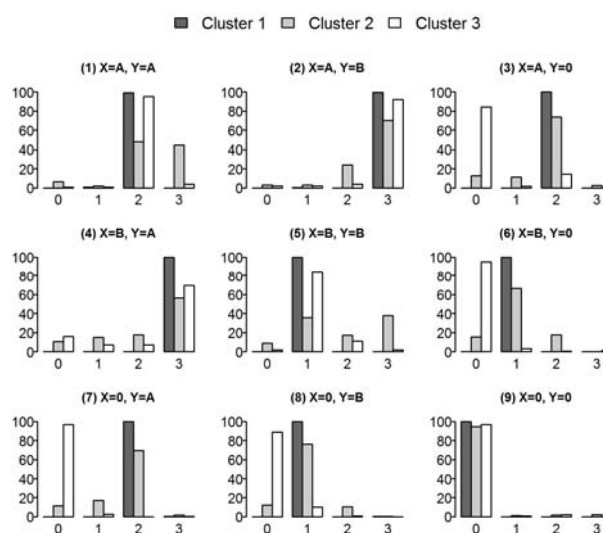

Fig. 4 The results of Task 1 in the 3+1 clusters

The students in Cluster 1 solved Task 1 with excellent results; consequently, the black columns in Fig. 4 show the correct answers to all the nine pairs of inputs. Cluster 2's results fluctuate, without any recognizable pattern. However, the results of Cluster 3 are quite remarkable. On one hand, this cluster did well in those problems where the inputs were A and B (Fig. 4, problems 1, 2, 4, and 5). On the other hand, if

World Academy of Science, Engineering and Technology
International Journal of Energy and Power Engineering
Vol:9, No:2, 2015

any of the inputs was 0 they provided a 0 output, regardless of the algorithm (Fig. 4, problems 3, 6, 7, 8, and 9). The major characteristic of Cluster 3 is that these students have a limited knowledge. This means that until they reach their limit their problem-solving ability is quite reliable. However, when the problem is more demanding these students are lost, and from that point on the quality of their performance is extremely low. The other characteristic of this group of students is that they try to find escape routes in a quite arbitrary way and this strategy leads to results lower than those for Cluster 2.

TABLE II
THE 3+1 CLUSTERS' SELF-EVALUATION VALUES (S-A), THEIR RESULTS IN THE TASKS, AND IN THE SCHOOL LEAVING EXAMS AT INTERMEDIATE (ISLE) AND ADVANCED LEVEL (ASLE)

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
N	279	168	195	308
S-A (%)	46.9	39.1	31.9	23.3
Task 1 (%)	99.8	65.8	52.1	0.0
Task 2.1 (%)	57.3	43.5	38.3	19.2
Task 2.2 (%)	46.1	27.5	19.7	10.3
Task 2.3 (%)	38.8	24.7	17.3	8.4
ASLE (%)	74.6 (N=85)	67.2 (N=35)	65.3 (N=27)	63.6 (N=33)
ISLE (%)	84.1 (N=154)	82.2 (N=110)	81.5 (N=135)	81.5 (N=206)

The connections between the 3+1 clusters and the years of the test and the majors of the students were investigated. These data served as the variables of the loglinear model. It was found that for the three variables – year, major, cluster – fit the (major×cluster year) loglinear model ($\chi^2(2)=16.6$, p=0.16). This means that there is a connection only between the clusters and the majors. The data supporting this connection are presented in Table III.

TABLE III
THE NUMBER AND THE PERCENTAGE OF THE STUDENTS IN THE 3+1 CLUSTERS WITHIN THE MAJORS

		Cluster 1	Cluster 2	Cluster 3	Cluster 4
BMI	N	47	42	66	145
	%	15.7	14.0	22.0	48.3
SYE	N	78	65	67	102
	%	25.0	20.8	21.5	32.7
SOE	N	154	61	62	61
	%	45.6	18.0	18.3	18.0
Total	N	279	168	195	308
	%	29.4	17,7	20.5	32.4

The percentage of students in Cluster 2 and 3 is similar in the all the three majors. However, in Cluster 1 and 4 there are differences in all the three majors (Khi-square probe: $\chi^2(6)=101.7$, p<0.001). The loglinear analysis proved that there is no connection between the clusters and the years; consequently, the four clusters in all the three years occurred with similar percentages.

B. Clusters and the Results of the School Leaving Exams

The clusters and the results of the school leaving exams also show differences: the students' results in the school leaving exams are not equal for each cluster (Table II). Cluster 1 is significantly better at both intermediate and advanced levels

than the other three clusters (Kruskal-Wallis probe advanced level: $\chi^2(3)=14.7$, p=0.002, Kruskal-Wallis probe intermediate level: $\chi^2(3)=8.7$, p=0.033), and the difference is greater at advanced level (Fig. 5). The results for Cluster 1 in the Informatics school leaving exam are significantly higher than the three other clusters together at advanced level (Mann-Whitney probe: p<0.001) and also at intermediate level (p=0.002). However, no significant difference was found in Clusters 2, 3, and 4 at either level.
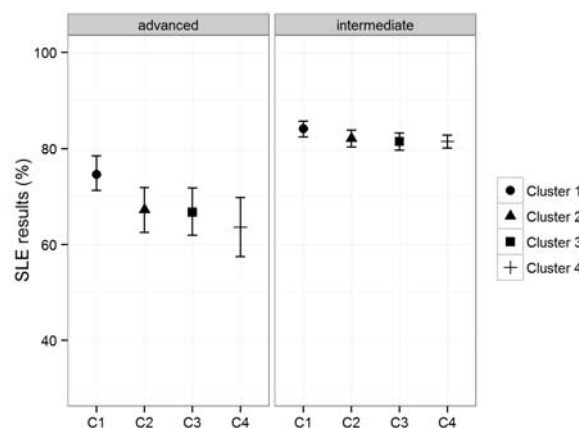

Fig. 5 The results of the school leaving exams in the 3+1 clusters at intermediate and advanced levels

This result leads us to the conclusions that (1) Cluster 1 exceeds the other clusters, and, beyond that (2) the school leaving exams are not able to distinguish between the three levels of "weaknesses" recognized in Clusters 2, 3 and 4.

C. Clusters and the Results of Task 2

It is clear from the data presented in Table II that in the three pseudo codes of Task 2, with the increase in the number of the clusters the results of the students are significantly lower (Jonckheere-Terpstra Test: p<0.001 in all the three codes). The Mann-Whitney test proved that in all the three pseudo codes the adjacent clusters differ significantly (p<0.05), with the exception of Clusters 2 and 3 in Task 2.1, but even in this case the direction of the difference is the same as with the other pairs. This exceptional behavior of Cluster 3 can be explained by their already mentioned limited knowledge. Since Task 2.1 is the easiest among the three pseudo codes, the knowledge which is required to solve this problem might be close to their limit.

In the following phase of the analyses the results of Task 2, in the 3+1 clusters found in Task 1, were further examined. As was mentioned in Section II.B, in the evaluation process of the tasks the SOLO categories of understanding were applied and modified to match our circumstances, with values ranging from 1–5 (Fig. 6).

Similarly to Task 1, the students in Cluster 1 achieved the best results in the three problems. However, we must note here that the percentage of those students who could not solve these problems even in Cluster 1 is high. This means that compared to Task 1, where this cluster's result was close to the

World Academy of Science, Engineering and Technology
International Journal of Energy and Power Engineering
Vol:9, No:2, 2015

maximum, the decoding of these simple pseudo codes seems too difficult for them. It is also clear from Fig. 6 that the percentage of those students who were not able to solve these problems increases with the order of the clusters and within the clusters with the order of the pseudo codes. These results justified our original intentions, considering the order of the pseudo codes and their presentation in ascending order of difficulty.

The graphs in Fig. 6 present the characteristics of the differences between Clusters 2 and 3 more subtly. It is clear that there is a higher percentage of students in Cluster 2 reaching level 3 than in Cluster 3. This is the consequence of Cluster 3 stopping at level 1, due to their ignorance of the task. Cluster 4 provided the lowest results in all the three pseudo codes.
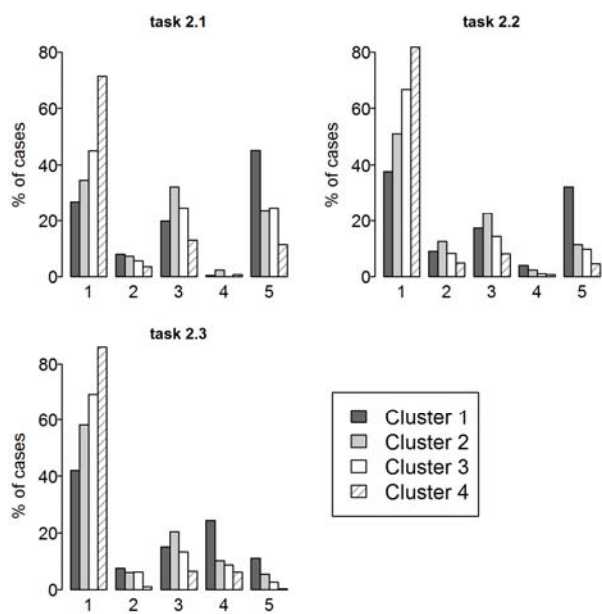

Fig. 6 The results of task 2 in the 3+1 clusters

D. Self-Assessment Values and the Results of the School Leaving Exams

In the 2012/2013 and 2013/2014 academic years we collected data to compare the students' self-assessment values with their results in the test and in the school leaving exams (Section II *A*). At advanced level school leaving exams (ASLE) we found a moderate positive correlation, while at intermediate level (ISLE) there was only a weak or negligible positive correlation (Table IV).

These results imply that there is no direct connection between the self-evaluation of the students and their results in the school leaving exams. We can conclude that when forming their self-assessment values the students do not consider the school leaving exam as a reliable source. This is especially true for the intermediate level exams, while at advanced level the results of these exams might influence their self-evaluation.

TABLE IV
THE RESULTS OF THE COMPARISON OF SELF-ASSESSMENT VALUES AND THE TEST RESULTS (SPEARMAN'S RHO)

	2012/2013	2013/2014
ISLE	0.16 p=0.031	0.09 p<0.208
ASLE	0.36 p<0.005	0.52 p<0.001

E. The Results of the School Leaving Exams and the TAaAS Tasks

In the next phase the question was how the results of the school leaving exams affect the results of the tasks of the TAaAS test. In the case of the advanced level school leaving exams a moderate correlation (Spearman's rank) was found between the results of the tasks and the school leaving exams (Table V). However, the analysis found that at intermediate level the connection is less strong, and only a weak effect is detectable.

TABLE V
THE RESULTS OF THE COMPARISON OF THE SCHOOL LEAVING EXAMS AND THE TEST (SPEARMAN'S RHO)

	Task 1	Task 2	Task 2.1	Task 2.2	Task 2.3
ISLE	0.09 p=0.022	0.22 p<0.001	0.23 p<0.001	0.20 p<0.001	0.17 p<0.001
ASLE	0.26 p<0.001	0.42 p<0.001	0.38 p<0.001	0.31 p<0.001	0.37 p<0.001

The comparison of the results of the test and the school leaving exams indicates that our school leaving exams are not able to measure the level of the students' programming abilities and their algorithmic skills. This result highlights one unfortunate characteristic of the application tasks at both levels, namely, that solving these tasks does not require any algorithmic skills. At advanced level the effect of the programming task on the students' algorithmic skills is detectable, but the three application tasks dominate the output of the school leaving exams.

IV. CONCLUSION

The algorithmic skills of Hungarian students of Informatics were tested at the first week of their tertiary education in three consecutive academic years. The timing was set deliberately for the first week of the first semesters to enable us to see what programming knowledge and skills are transferred from previous CSI studies into tertiary courses specialized in programming. Beyond that we wanted to see, based on further data available to us, what other circumstances would alter the students' results and their beliefs about their results.

Our first hypothesis, regarding the order of the three majors of the faculty, was proved. It is clear from the results of the students that the order of the majors is SOE, SYE and then BIM, moving from the highest results to the lowest, respectively. Consequently, the SOE students start their university studies with highest level of programming knowledge and algorithmic skills. We have to note here, however, that the tasks were borrowed from a programming competition for 5–8th graders, aged 11–15 years. The results proved that even the best students are at the level of well-

World Academy of Science, Engineering and Technology
International Journal of Energy and Power Engineering
Vol:9, No:2, 2015

developed primary school students.

A slight increase in the students' results is detectable in the following years; however, the differences found are not significant. The 2013/2014 academic year would be the first year when those students starting their tertiary education who arrive from secondary education have studied informatics in an increased number of classes. The fact that the 2013/2014 academic year does not show significant differences might be due to several reasons: not all the students started their secondary education in 2009; the number of classes did not increase because classes were already held at that frequency or higher, especially in CSI-specialized high schools; the increase in the number of classes alone does not guarantee a higher level of algorithmic skills; formal studies in CSI should start earlier than grade 9. To prove or dismiss the fourth hypothesis further data and investigations are required.

A connection between the results of the school leaving exams and the results of the test was only found in the best cluster, Cluster 1, at both levels of the school leaving exam, but the difference was greater at advanced level. However, there was no difference in the results of the school leaving exams in the other three clusters. This means that with the exception of the best students, regardless of the level of knowledge and algorithmic skills the school leaving exams can be completed with similar results. Our second hypothesis is only proved in the case of the best students. We can conclude that the school leaving exams are not able to distinguish the different levels of algorithmic skills and programming knowledge. These exams are only able to distinguish two categories: (1) those students who know something, who have an acceptable level of algorithmic skills, and (2) the others. Consequently, the five grades of the school leaving exams and the percentage of the results are meaningless numbers.

In the comparison of the results of the school leaving exams and the self-assessment values no strong connection was found. At advanced level a moderate, while at intermediate level only a weak positive connection was detected. We can conclude that the results of the school leaving exams might influence students' self-evaluation, more at advanced level than at intermediate level, but other factors might also play important roles. In conclusion, we can say that the school leaving exams are not considered, especially at intermediate level as something which would measure CSI knowledge. The students' intuition was proved by our analyses – with the rejection of our second hypothesis –, namely, that the school leaving exams in Informatics are not able to differentiate between the different levels of CSI knowledge. Consequently, our third hypothesis is neither proved nor rejected, but it is highly unlikely that the students are influenced by the results of their school leaving exams.

REFERENCES

[1] M. Ben-Ari, "Non-Myths About Programming". Communication of the ACM, Vol. 54, No. 7., 2011, pp. 35-37.
[2] G. Tan, and A. Venables, "Wearing the Assessment 'BRACElet'". Journal of Information Technology Education: Innovations in Practice. Vol. 9, 2010, pp. IIP 25-34.
[3] "Nemes Tihamér National Competition of Informatics 2008-2009 round I, 5-8th grade. Exercices (Nemes Tihamér Országos Informatikai Verseny 2008-2009 I. forduló, I. korcsoport, 5-8. osztály. Feladatok)" in Hungarian. Retrieved May 17, 2013 from http://nemes.inf.elte.hu/2009/nt09-1f1.doc.
[4] "Nemes Tihamér National Competition of Informatics 2008-2009, round I, 5-8th grade. Solutions (Nemes Tihamér Országos Informatikai Verseny, I. forduló, I. korcsoport, 5-8. osztály. Megoldások)" in Hungarian. Retrieved July 8, 2013 from http://nemes.inf.elte.hu/2009/nt09-1m1.doc.
[5] "Results of graduation exams 2007–2013 (Érettségi eredmények 2007 – 2013)" in Hungarian. Retrieved June 7, 2013 from https://www.ketszintu.hu/publicstat.php.
[6] "School leaving exams in Hungary – Tasks and correcting guides (Központi írásbeli feladatsorok, javítási-értékelési útmutatók)" in Hungarian. Retrieved June 15, 2014 from http://www.oktatas.hu/kozneveles/erettsegi/feladatsorok.
[7] "The tasks and the correction guides of the graduation exams. 2005–2013 (Központi írásbeli feladatsorok, javítási-értékelési útmutatók. Korábbi vizsgaidőszakok vizsgaanyagai - vizsgaidőszakok szerint 2005–2013)" Retrieved June 7, 2013 from http://www.oktatas.hu/kozneveles/erettsegi/feladatsorok.
[8] E. Soloway, "Should we teach students to program?" Communications of the ACM. October 1993/Vol.36, No.10, pp. 21–24.
[9] E. Soloway, J. Bonar, and K. Ehrlich, "Cognitive strategies and looping constructs: an empirical study", 1983. Commun. ACM, vol. 26, n. 11, pp. 853–860.
[10] G. Schraw, C. Horn, T. Thorndike-Christ, and R. Bruning, "Academic Goal Orientations and Student Classroom Achievement." Contemporary Educational Psychology, 1995, 20(3), pp. 359–368.
[11] J. B. Biggs, and K. E. Collis, "Evaluating the Quality of Learning: The SOLO Taxonomy". New York: Academic Press, 1982.
[12] J. L. Whalley, R. Lister, E. Thompson, T. Clear, P. Robbins, P. K. A. Kumar, and C. Prasad, "An Australasian study of reading and comprehension skills in novice programmers, using the bloom and SOLO taxonomies", in Proceedings of the 8th Australasian Conference on Computing Education - Volume 52, Darlinghurst, Australia, Australia, 2006, pp. 243–252.
[13] P. Biró, M. Csernoch, K. Abari, and J. Máth, "First year students' algorithmic skills in tertiary Computer Science education", 9th International Conference on Knowledge, Information and Creativity Support Systems.Cyprus, November 6–8., 2014., submitted.
[14] J. Sheard, A. Carbone, R. Lister, B. Simon, E. Thompson, and J. L. Whalley, "Going SOLO to assess novice programmers", SIGCSE Bull., 2008, vol. 40 (3), pp. 209–213.
[15] M. Csernoch, "Introducing Conditional Array Formulas in Spreadsheet Classes", EDULEARN12 Proceedings. Barcelona, Spain. 2-4 July, 2012. Publisher: IATED, pp. 7270–7279.
[16] M. Csernoch, and P. Biró, "Spreadsheet misconceptions, spreadsheet errors", Oktatáskutatás határon innen és túl. HERA Évkönyvek I., ed. Juhász Erika, Kozma Tamás, Publisher: Belvedere Meridionale, Szeged, ISSN 2064-6755, 2014, pp. 370-395.
[17] M. Csernoch, and P. Biró, "Teachers' Assessment and Students' Self-Assessment on the Students' Spreadsheet Knowledge". EDULEARN13 Proceedings July 1st-3rd, 2013 — Barcelona, Spain. Publisher: IATED. 2013, pp. 949–956.
[18] M. Csernoch, and P. Biró, "Testing algorithmic and application skills (Algoritmikus és alkalmazói készségek tesztelése)" in Hungarian, INFODIDACT Conference 2013, Zamárdi, Hungary, 21–22. November, 2013.
[19] M. Csernoch, and P. Biró, "The investigation of the effectiveness of bottom-up techniques in the spreadsheet education of students of Informatics (Button-up technikák hatékonyságának vizsgálata informatika szakos hallgatók táblázatkezelés-oktatásában)" in

Hungarian. Ed. T. Kozma, and I. Perjés, Új kutatások a neveléstudományokban 2012, Publisher: ELTE Eötvös, 2013, pp. 352–369.

[20] P. Biró, and M. Csernoch, "Deep and surface structural metacognitive abilities of the first year students of Informatics". 4th IEEE International Conference on Cognitive Info-communications, Proceedings, Budapest, 2013, pp. 521–526.

[21] P. Biró, and M. Csernoch, "Programming skills of the first year students of Informatics". XXIII. International Conference on Computer Science 2013, EMT, in Hungarian, 2013 pp. 154–159.

[22] R. E. Mayer, "The Psychology of How Novices Learn Computer Programming", ACM Comput. Surv., vol. 13 (1), pp. 121–141, 1981.

[23] R. Lister, B. Simon, E. Thompson, J. L. Whalley, and C. Prasad, "Not seeing the forest for the trees: novice programmers and the SOLO taxonomy", in Proceedings of the 11th annual SIGCSE conference on Innovation and technology in computer science education, New York, NY, USA, 2006, pp. 118–122.

[24] R. Lister, E. S. Adams, S. Fitzgerald, W. Fone, J. Hamer, M. Lindholm, R. McCartney, J. E. Moström, K. Sanders, O. Seppälä, B. Simon, and L. Thomas, "A multi-national study of reading and tracing skills in novice programmers", SIGCSE Bull., 2004, vol. 36 (4), pp. 119–150.

Piroska Biró was born in 1983 in Ditro, Romania. She received her M.Sc. degree in Computational Mathematics in University of Babes-Bolyai, Faculty of Mathematics-Informatics. Currently she works as assistant lecturer in the University of Debrecen, Faculty of Informatics in Hungary.

Her research interests are didactics of Informatics, algorithmic thinking, high level programming languages and computer aided education.

Mária Csernoch was born in 1963 in Szentes, Hungary. She received her MSc in 1986 at Kossuth Lajos University, PhD in 2006 and Habil. in 2012. Currently she works as associate professor at the University of Debrecen, Faculty of Informatics in Hungary.

Her research interests are didactics of Informatics – specialized in developing algorithmic skills, computational thinking, and teaching programming languages –, computational linguistics and computer aided language teaching and learning.

János Máth was born in 1959 in Cegléd, Hungary. He received his PhD in 1997 at Kossuth Lajos University. Currently he works as assistant professor in the University of Debrecen, Faculty of Arts and Humanities in Hungary.

His research interests are statistics, knowledge space theory and cognitive load theory.

Kálmán Abari was born in 1971 in Debrecen, Hungary. He received his PhD in 2013 at University of Debrecen. Currently he works as senior lecturer in the University of Debrecen, Faculty of Arts and Humanities in Hungary.

His research interests include Speech Research (acoustic characteristics of speech sounds), Statistical Analysis (functional data analysis) and Statistical Software (R).