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Advancement of inductive reasoning of engineering students

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RESEARCH ARTICLE

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ABSTRACT

The task of higher education is twofold: (1) to prepare students to meet the expectations of the labor market and (2) to create a learning environment and conditions so that as many students can meet the subject requirements as possible, the dropout rate should be the lowest possible. Input and continuous monitoring of students' transversal competencies can be a suitable method to meet this dual requirement. The range of these competencies is very diverse. In our present study, we focused on inductive thinking, which plays an important role in problem-solving. The research involved 212 first-grade BSc technical students. Our measurement tool is widely used in the selection of the workforce, which the students had to fill in online. The gained results were evaluated using IBM SPSS Statistics. The analysis included a comparison of inductive thinking and its two subcomponents, abstract reasoning, and diagrammatic cognition, in terms of background variables, as well as time consumption, and the definition of specific performance. We found a functional relationship between time consumption and the performance achieved in the test. Students have advanced analogical cognition in terms of abstract thinking; however, their diagrammatic thinking shows very different levels of development, which can cause difficulties in solving technical problems.

KEYWORDS

engineering education, problem solving, logical thinking, inductive thinking, abstract reasoning, diagrammatic cognition

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INTRODUCTION

Problem-solving competence, and within that inductive thinking, is of decisive importance in technical higher education from two aspects. On the one hand, in terms of meeting the expectations of the labor market, and on the other hand, in terms of effective adherence to studies and avoiding dropouts.

As for *labor market expectations*, the role of higher education has increased in recent decades because of the requirements of the knowledge economy, thus third and fourth generation universities have committed themselves to develop students' competencies making them able to meet the dynamically changing demands of modern society, including the workplaces (Kozma & Pusztai, 2018; Lukovics & Zuti, 2014). This means that in addition to the acquisition of expertise, competence development has become the focus of higher education.

According to several studies, there is a strong demand from the labor market that graduates have advanced communication, organizational and problem-solving skills, analogical and logical thinking, creativity, interpersonal skills, emotional intelligence, as well as being assertive and open to motivation. The literature calls these labor market or transversal key competencies (soft skills). At the same time, they point out that career starters arrive from higher education to the labor market lacking exactly these competencies (Engler, 2019), and companies often consider these competencies to be more important than professional skills (Veroszta & Nyüsti, 2015) and call on the attention of educators to their development (Kautz, Heckman, Diris, ter Weel, & Borghans, 2014). According to a study by Manpower Group (2015), 16% of jobs in Europe could not be filled due to the lack of soft skills. Opinions are strongly divided as to which competencies belong to soft skills and transversal competences (Holik, Kersánszki, & Sanda, 2021). Graduates are most likely to have deficiencies in intra- and interpersonal and certain cognitive competencies and attitudes. Several studies highlight more serious shortcomings in so-called higher cognition, including problem-solving, critical thinking, and decision-making ability. At the same time, in the world of work, they appear as demand in their organic relationship system (Balcar, 2014; Carnevale, 2013; Cornalli, 2018; Eger & Grossmann, 2004; Khine & Areepattamannil, 2016). In other words, it is not enough to have only professional knowledge, transversal skills play a key role in career building and proper employability (Kövesi & Kálmán, 2019).

Problem-solving ability is one of the essential transversal skills in the workplace. Employers look for employees with creative problem-solving personalities (Neubert, Mainert, Kretzschmar, & Greiff, 2015) who will take through and bring to success what is committed to them, not stopping at the sight of obstacles. Problem-solving requires not only analytical, creative, and critical skills but also a specific way of thinking (Greiff, Holt, & Funke, 2013), a soft skill that often relies on strong teamwork, as it is important to know from whom support can be expected in solving the certain problem.

Hungarian data exceed the average *dropout* rate of 25–30% in the EU member states by almost 10%. For example, in the field of technical higher education, based on the results of 2016, the proportion of graduates was 41.6% (completion rate), the dropout rate was 39.6%, while the share of those who had not yet graduated or had switched over to another training was 18.8%. Dropout is understood as non-graduation in the study field.

Several empirical studies have been implemented during the past 40 years to find the real causes of dropout (Bean, 1985; Heublein, Hutzsch, Schreiber, Sommer, & Besuch, 2010; Larsen, Kornbeck, Kristensen, Larsen, & Sommersel, 2013; Spady, 1970). Analyzing these, the following categories can be distinguished: (1) Cognitive deficits (existing knowledge, skills, abilities, and capabilities), (2) Affective deficits (commitment to the chosen profession, interest, motivation, perseverance, values, career prospects, prestige, stress tolerance); (3) social reasons (financial difficulties, livelihood, student work, housing, lack of a supportive moral environment, unfavorable socioeconomic status); (4) reasons originating from the insufficient selection functions of the education system (recruitment procedure); (5) reasons rooted in the improper functioning of the institution (deficiencies in learning support, in the quality of teaching and equipment). Cognitive deficits include developmental deficiencies in problem-solving competence, and within that, inductive thinking.

One component of problem-solving, convergent thinking is characterized by sub-abilities such as logical inference, abstraction, and the ability to recognize regularities. For example, intelligence tests and the test applied in our research are used to examine their development.

Carroll (1993) mentioned inductive and deductive thinking as “sub-abilities” of logical reasoning. We need *inductive thinking* primarily when we want to utilize our observations and experiences in completely new (productive problem solving) and in partly new, similar (reproductive problem solving) situations. New knowledge gained through such a procedure always contains the possibility of uncertainty or error. The main goal of inductive reasoning is to recognize regularities or generalizations (Mousa, 2017). Klauer (1999) considers comparison processes to be an essential feature of inductive thinking. In the process, we first identify the characteristics of the elements of reality and the relationships between each element, followed by similarities and differences through which we recognize rules. Based on the rules identified during the analysis of the observed cases, we can formulate generalizations and predictions, and in this step, we make inductive conclusions.

Inductive reasoning plays a key role in cognitive processes, interpreted as a general thinking ability (Molnár, Greiff, & Csapó, 2013; Pellegrino & Glaser, 1982), which is related to almost all higher thinking skills (Csapó, 1997; Molnár et al., 2013; Söderqvist et al., 2012), such as general intelligence (Klauer & Phye, 2008), knowledge acquisition and application skills (Hamers, De Koning, & Sijtsma, 2000), abstract thinking (Goswami, 1991) and also for problem-solving.

Inductive thinking is also mentioned as a means of acquiring new knowledge, as an indicator of learning potential, and is also ascribed an important role in the transferability of knowledge (Resing, 1993). Researchers aiming to explore general intelligence identify it as one of the determinants of the effectiveness of different operational processes of thinking (Carroll, 1993; Demetriou, Spanoudis, & Mouyi, 2011). An empirical study of students starting their university studies focused on inductive thinking (Pásztor, 2019) revealed that a quarter of the students might face learning difficulties during their university years.

GOALS AND RESEARCH QUESTIONS

The basic objective of our survey was *to get to know the development level of the competencies of the students entering higher education*. The results of the research can serve as a basis for the methodological development of education, because of which, on the one hand, *engineering students will be able to meet the expectations of the labor market,* and on the other hand, *they will* *be less exposed to the risk of dropping out*. After the test, students also receive feedback on their competencies, the areas to be developed, which can contribute to their self-knowledge, including self-regulated learning.

Our research took place in the framework of the competence measurement of first-year students, and we aimed to map transversal, i.e., non-professional competencies.

In this study, we seek answers to the questions of (1) how the inductive thinking of first-grade engineering students can be characterized, (2) what differences it shows according to subsamples, and (3) whether specific performance is suitable to characterize students' cognition speed?

METHODS AND SAMPLE

The study was conducted on an online interface in an IT room under the supervision of teachers, in groups of 15–20 students per study program. Participating students completed the questionnaire and test at the start of their graduate studies in September 2020.

Eductive abilities refer to logical operations based on inference, through which new knowledge is created from perceived information by recognizing and understanding the interrelations, considering the contextual contents. Understanding the whole problem requires a holistic approach while solving it requires the ability to recognize the relationships and correlations between the parts. Interpreting the problem is more than a comprehensive pattern recognition (Gestalt), it is also necessary to emphasize the essence and ignore the irrelevant things. These are mostly not verbalizable, so it is mostly geometric shapes (squares, polygons, circles, etc.) that make up the measuring instruments. The perception of these geometric shapes, the recognition of their characteristic properties, and the insight into the relationships between them depend on the existing knowledge and certain cultural influences (Kane & Brand, 2003). The former is consistent with inductive operations (Klauer & Phye, 2008). Concerning the latter, it is worth mentioning that one of the main advantages of the test is that it can be considered culture-independent to a certain extent.

Based on the Raven test but taking the aspects of technical jobs into account more strongly, Paul Newton and Helen Bristoll (n. N.) developed an inductive cognition test. To examine thinking based on inductive reasoning, the capability structure shown in Fig. 1 was developed.

For the solver, the problem lies in the difficulty of recognizing the logical relationships behind the patterns in the tasks, which originates from the difficulty of recognizing the change or the repetition of the following properties: (1) shape, (2) size, (3) color, (4) pattern. The tasks consist of visual patterns and geometric shapes, and they (one- and two-dimensional matrices) must be continued or the element not fitting into the series be recognized by understanding the logical connections behind them.

One- (series) and two-dimensional matrices require the ability to recognize different correlations, relationships that in many cases are not clear at first glance. Recognition of the relationships between geometric shapes can be separated from the identification of individual shapes. This should be clear to all participants. According to Spearman (1927), the perception of the geometric shapes immediately triggers knowledge of relationships, and vice versa. All this means that perception, observation, and abstract thinking form a unity in cognition. During problem-solving, all the properties of the geometric shapes must be observed simultaneously,

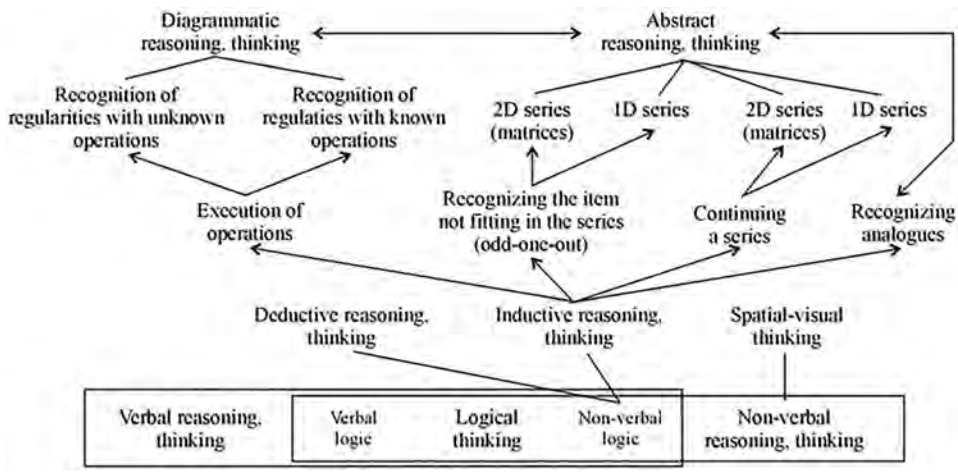

Fig. 1. Task system of the inductive cognition test

their connections understood, and the perception must be accurate in detail. A good solution cannot be found without recognizing the "whole," but the exact identification of the "parts" is also crucial (Georgiev, 2008).

In our present research, the distribution of task types was as follows:

–Continuing a 1D series (Task 1)
–Recognizing the item not fitting in the 1D series (Task 2)
–Recognizing analogous (Task 3)
–Recognition of regularities with unknown operations (Task 4)
–Recognition of regularities with known operations (Task 5)

Each task type consisted of 6 items. Tasks and items similar to the applied inductive test can be viewed at www.psychometric-success.com.

As for the sample, 212 first-grade students participated in the survey in September 2020. The total sample included 167 (79%) male and 45 (21%) female respondents, but the gender distribution varied by discipline. The mean age of the respondents was 20.17 years (Me = 20 years, SD = 2.023). Examining the education of the parents, we found that 30 percent (N = 63) of the fathers had a degree, and this rate was 38% (N = 81) in terms of the mothers. The interviewed students started their studies in 9 different departments of the two faculties of the Óbuda University (Land Surveying and Land Management (BSc) 10% (N = 22), Mechanical Engineering (BSc) 6% (N = 12), Industrial Product and Design Engineering (BSc) 14% (N = 29), Light Industry Engineering (BSc) 0.5% (N = 1), Environmental Engineering (BSc) 4% (N = 8), IT Engineering (BSc) 29% (N = 61), IT engineering (higher-level VET), 14% (N = 30), Technical (higher-level VET), 20% (N = 42), Technical Manager (BSc), 3% (N = 7)). 18 percent (N = 37) of the students surveyed began their studies in the form of dual training.

48 percent (N = 101) of first-grade students surveyed graduated from secondary grammar schools and 50 percent (N = 105) from secondary vocational schools. 3 percent (N = 6) have already gained a higher education degree.

RESULTS

The online system was able to record time consumed by items, making it possible to screen out students who did not pay enough attention to solving the tasks. Students who spent less than 10 min on the inductive test (15 people) were not considered in the analysis (M_{time}= 371.20; SD_{time}= 160.09872; M_{score}= 9.67; SD_{score} = 3.95811).

Table 1 shows the results of 197 students. According to Kolmogorov and Smirnov, the inductive thinking variable is not normally distributed (KS = 0.066; df = 197; P = 0.039), but because of the permissive conditions (Kurtosis/Std. Error of Kurtosis = 1.39 and Skewness/St. Error of Skewness = 0.86, i.e., smaller than 1.96) we still take it as that (Rumelhart, 1989). The time consumption variable does not follow a normal distribution (K–S = 0.084; df = 197; P = 0.002), not even under the permissive conditions. It shifts slightly towards higher time consumption values.

As seen earlier, the inductive test consisted of five types of tasks, with a maximum of 6 points for each task. The students solved the tasks with very different results (Fig. 2). The best average result was gained in the task of recognizing analogs, while the worst in the diagrammatic task included known operations. In contrast, the average result of the diagrammatic task aimed at recognizing an unknown operation was hardly below that of the recognition of analogs.

Diagrammatic tasks aimed at the recognition of regularities measure the ability of someone to follow logically arranged sequences of signals. Each item consists of simple flowcharts, the solution of which requires the individual to be able to keep track of changes in the shape, color, and size of the objects. This capability is particularly important, for example, in the analysis, error correction, and system design of technical system processes (Stieff, Hegarty, & Dixon, 2010).

In the diagrammatic task containing unknown operations, the sequence of signals at the input and the output of the flowchart is known, while the intermediate operations are unknown. These must be deciphered and then applied to a given sequence of signals and its output determined. In the diagrammatic task with known operations, four known operations are performed on the signal sequence specified at the input, but the partial results must be memorized, then known

Table 1. Descriptive statistical indicators of the score gained and time used during the inductive test

		Inductive thinking	Time consumption
Mean		19.53	1,506.57
95% Confidence Interval for Mean	Lower Bound	18.92	1,453.58
	Upper Bound	20.13	1,559.56
Std. Deviation		4.2947	377.1396
Minimum		8	622
Maximum		29	2,072
	5%	11	805.8
	10%	14	898.8
	25%	17	1,232
Percentiles	50%	20	1,574
	75%	23	1,827.5
	90%	25	1,959.4
	95%	26	2,038.1

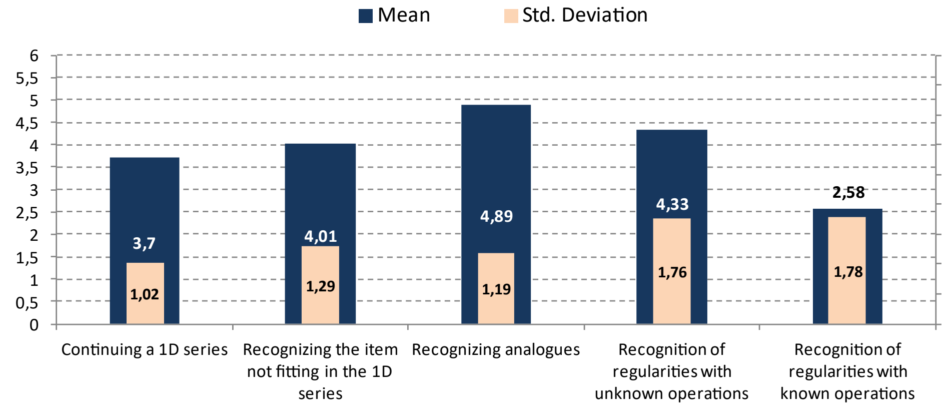

Fig. 2. Mean results and standard deviations of the inductive test tasks

operations must be performed on them, and finally, the correct final result must be selected from a list. The question arises as to what can cause the significant difference between the mean scores of the two diagrammatic problems. To answer this, we first performed item-by-item analyses for the two task types (Figs 3 and 4). The score available per item is 1.

Concerning the task type with unknown operations, consistently good mean scores were gained in terms of all items, except perhaps the second one. In contrast, for the task type with known operations, the very poor result of item 1 can be traced back to comprehension problems. This is also indicated by the high level of meantime consumption. For the latter type of task, the mean scores of each item show an improving trend but are far from reaching the average of the items of the previous task. The time spent per item is also much higher. In addition to the initial comprehension difficulties, the students may also have had difficulty memorizing several intermediate states during the solution of each item and then performing more and more operations on them. Memorizing these intermediate states may have led to errors and increased the time used to resolve the items. The solution of this type of task was also complicated by the fact that the correct solution had to be selected from five options instead of four.

The item-by-item analysis of the solutions highlighted an additional problem (Figs 5 and 6; the good solution is presented in parentheses). In the case of the items of the diagrammatic task

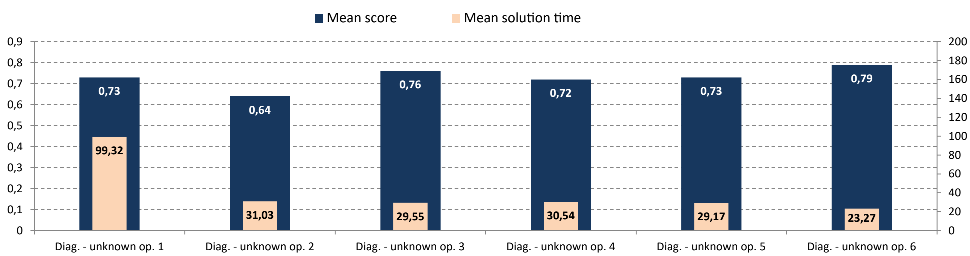

Fig. 3. The mean and the mean solution time of each diagrammatic problem containing unknown operations

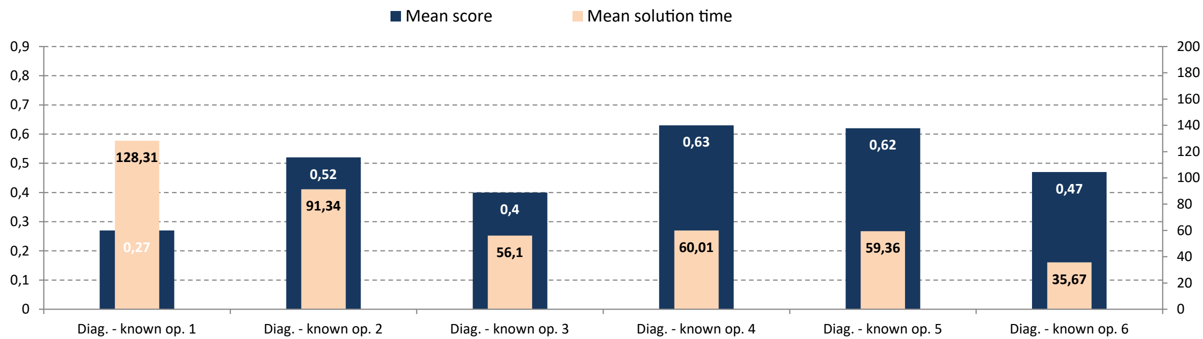

Fig. 4. The mean and the mean solution time of each diagrammatic problem containing known operations

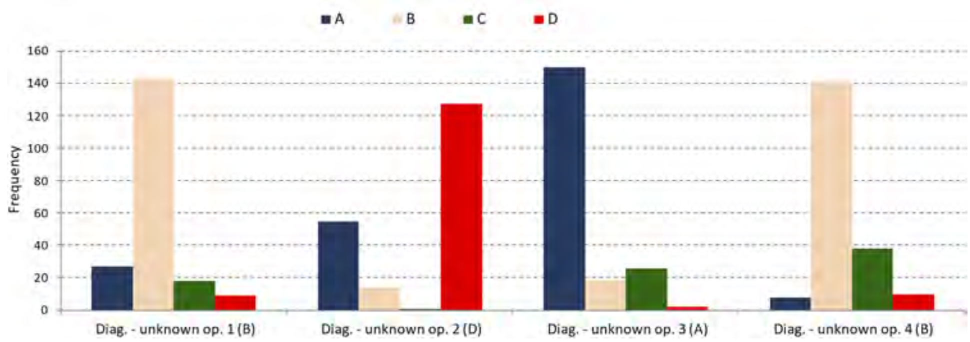

Fig. 5. Distribution of the solutions per item of the diagrammatic task containing unknown operations

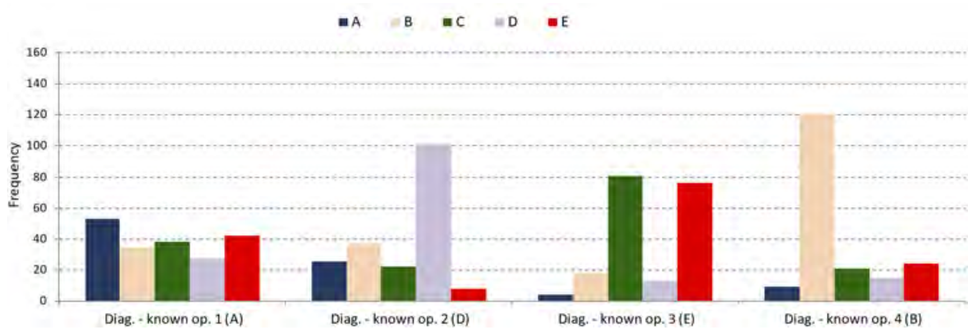

Fig. 6. Distribution of solutions per item of the diagrammatic task containing known operations

containing unknown operations, the students chose the good solutions evenly with few errors, while in the case of the other task the students understood what the task was only for item 4. The intent to guess can be observed mainly in item 1, in item 3 the two seemingly good solutions have already been mixed. The result of step 4 in Fig. 5 is a good solution, while several marked the result of step 3 as the correct answer (Fig. 7).

Analyzing the time frames spent on solutions, it can be stated that for item 1, in the cases of either of the options chosen, the students kept thinking for a long time, but the time required for the good solution (A) was one of the least. This is also true for item 2 (D). For item 3, much less time was already spent choosing the option that seemed correct, but the time consumption for the good solution (E) was one of the largest and by far the largest standard deviation. Roughly the same can be said for item 4 (B is the good solution).

After performing the normality test for all the five tasks of the inductive test, it can be concluded that the recognition of analogs and the diagrammatic task containing unknown operations do not satisfy the conditions even under the permissive conditions (Rumelhart, 1989). Both variables are shifting towards better results. However, the other three variables can be considered as normally distributed under the permissive conditions (Continuation of one-dimensional series: Kurtosis/St. Error of Kurtosis = 0.69 and Skewness/Std. Error of

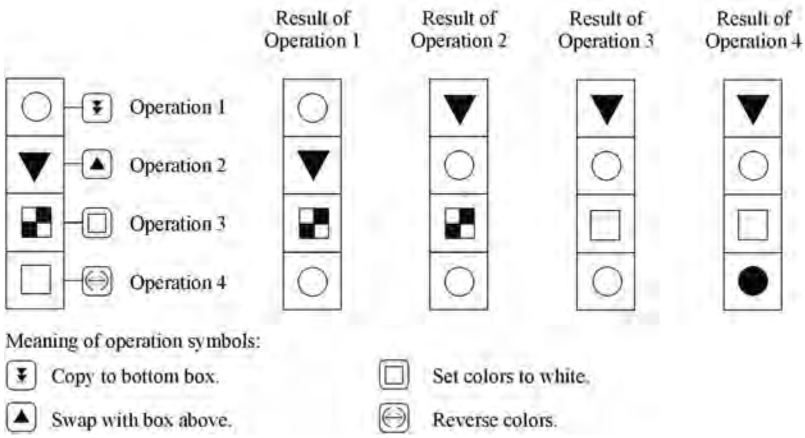

Fig. 7. Phases of the solution algorithm of item 3

Skewness = 1.7; Recognition of elements that do not fit into one-dimensional series: Kurtosis/Std. Error of Kurtosis = 1.82 and Skewness/Std. Error of Skewness = 1.56; Recognition of regularities – known operations: Kurtosis/St. Error of Kurtosis = 2.45 and Skewness/Std. Error of Skewness = 1.36, i.e. less than 1.96).

The correlations between the components of inductive thinking were found to be weak to moderate, according to Spearman, indicating well distinguishable tasks and ability components (Table 2). The correlation between the continuation of the 1D series and time expenditure (r = 0.246), the continuation of elements not fitting into the 1D series and time consumption (r = 0.187), and between the diagrammatic – known and time expenditure (r = 0.597) we found weak and a strong moderate relationship (P = 0.01). No correlation was found between the other two ability components and their time consumption.

There was a strong medium correlation between the individual time expenditures, except for the diagrammatic – known variable.

We examined the relationship between the results of the inductive thinking test and the time spent on the solution. The best fit can be described by a so-called Arrhenius function relationship (Fig. 9).

$$Score\ of\ Inductive\ reasoning = e^{3.283 - \frac{470.173}{Time\ consumption}}$$

The above correlation explains 20.7% of the total variance, while the accuracy of the forecast is acceptable (SEE = 0.215). The existence of the relationship was confirmed by F-test (F = 50.831; $P < 0.05$). In the above context, the significance of the reciprocal of the constant in the exponent and time consumption is also less than 5% (t = 65.876 and t = -7.310, respectively), therefore time consumption influences the result obtained in the test.

Math graduation results explain only 6.3% of the total variance. Outstanding graduation result is expected to bring approx. 22 points in the inductive test and this are expected to decrease by 1 point per weaker grade.

The results of the inductive test were analyzed by ability components, and time consumption was also examined by background variables.

Table 2. Correlative relationship between components of inductive thinking

	Continuing a 1D series	Recognizing the item not fitting in the 1D series	Recognizing analogs	Recognition of regularities with unknown operations	Recognition of regularities with known operations
Continuing a 1D series		0.292**	0.135	0.250**	0.100
Recognizing the item not fitting in the 1D series			0.251**	0.219**	0.094
Recognizing analogs				0.157*	0.245**
Recognition of regularities with unknown operations					0.211**
Recognition of regularities with known operations					

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

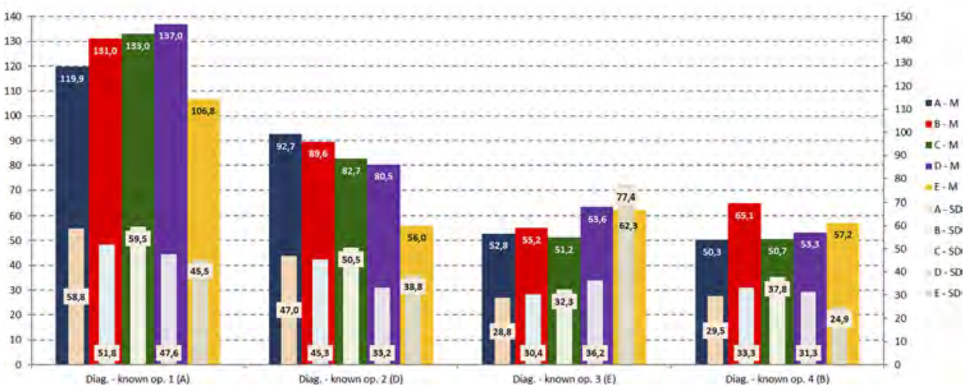

Fig. 8. The mean time consumption and standard deviation of the solutions per item of the diagrammatic problem containing known operations

No significant differences were found in terms of the ability component by gender of the students. However, in terms of time consumption, men spent significantly more time on solving the problems than women regarding total time consumption (Mann-Whitney = 2,512.500; $P < 0.05$; $M_{\mathrm{man}} = 392.99$; $M_{\mathrm{woman}} = 326.11$) as well as the continuation of the 1D series (Mann-Whitney = 2,716.000; $P < 0.05$; $M_{\mathrm{man}} = 246.32$; $M_{\mathrm{woman}} = 221.45$) and the diagrammatic tasks requiring the application of unknown operations (Mann-Whitney = 2,766.500; $P < 0.05$; $M_{\mathrm{man}} = 1{,}534.43$; $M_{\mathrm{woman}} = 1{,}409.68$). It was only the diagrammatic task requiring the implementation of known operations, which proved to be the most difficult one, where women used more time than men ($M_{\mathrm{man}} = 374.68$; $M_{\mathrm{woman}} = 396.73$), however, the difference was not significant (Mann-Whitney = 3,252.500; $P > 0.05$).

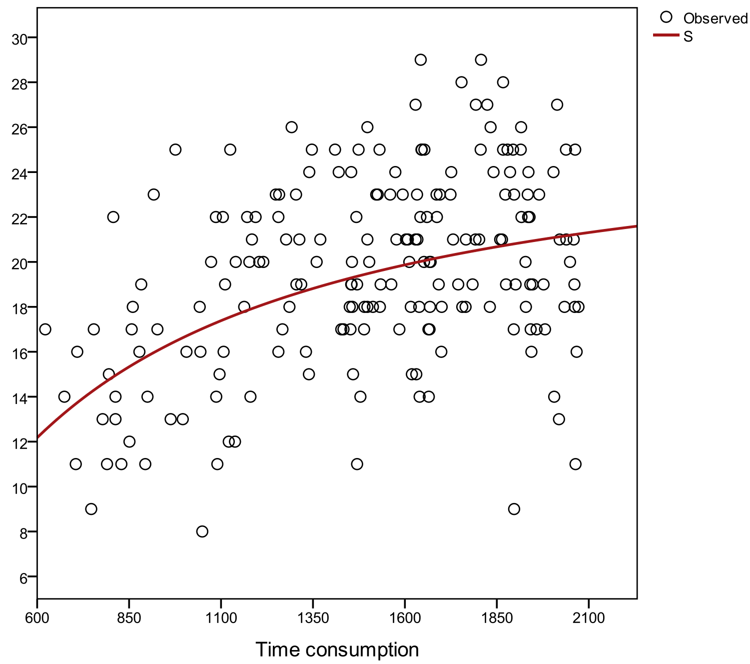

Fig. 9. The relationship between the result obtained in the inductive test and the time spent

No significant differences in the ability components of inductive thinking or time expenditure according to the student's place of residence were found either, but it can be perceived that in all cases rural students achieved the best results and spent the most time solving the tasks. The same can be stated about the parents 'education. Children of parents with tertiary education performed better and spent more time-solving tasks than the ones whose parents did not have a degree, but the differences were not significant.

Nonetheless, we did find significant differences in all ability components and time consumption according to the specialization chosen by the students (Table 3). Students in BSc

Table 3. Significance analysis of ability components and time consumption in terms of students' specialization

	Mean score			Meantime consumption		
	Task 1	Task 2	Task 3	Task 1	Task 2	Task 3
Chi-square	10.481	9.583	24.583	23.044	21.365	15.53
P	0.033	0.048	0.000	0.001	0.000	0.004
	Mean score			Meantime consumption		
	Task 4	Task 5	Inductive total	Task 4	Task 5	Inductive total
Chi-square	18.278	12.588	26.191	14.559	13.185	21.070
P	0.001	0.013	0.000	0.006	0.010	0.000

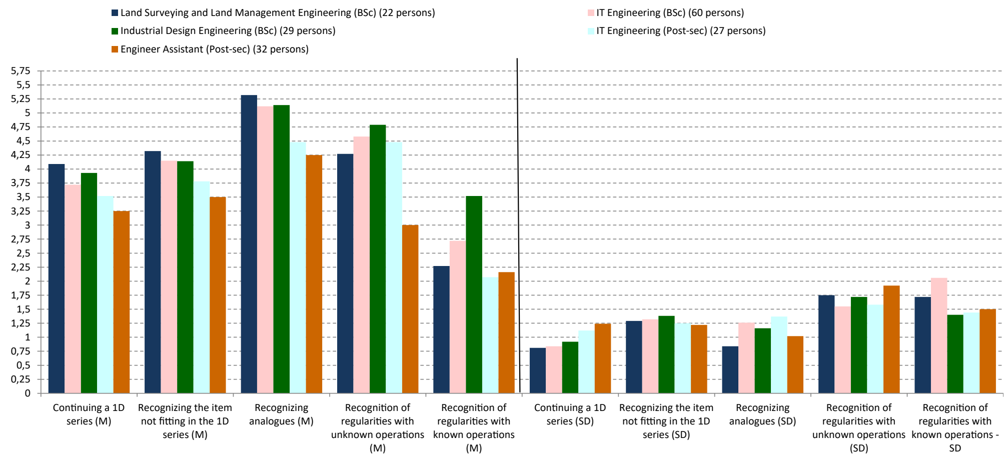

Fig. 10. Comparison of the mean scores and deviation according to the students' specialization

courses performed significantly better (Fig. 10) than students in post-secondary courses, and this is also reflected in time consumption (Fig. 11).

Participants in post-secondary courses performed worse on all competency components than their peers in BSc courses (Fig. 10), and this is also reflected in time expenditure (Fig. 11). In the latter case, the variance of post-secondary students proved to be the largest, i.e.it is their diligence and perseverance are the most diverse. In addition, they brought fewer scores from

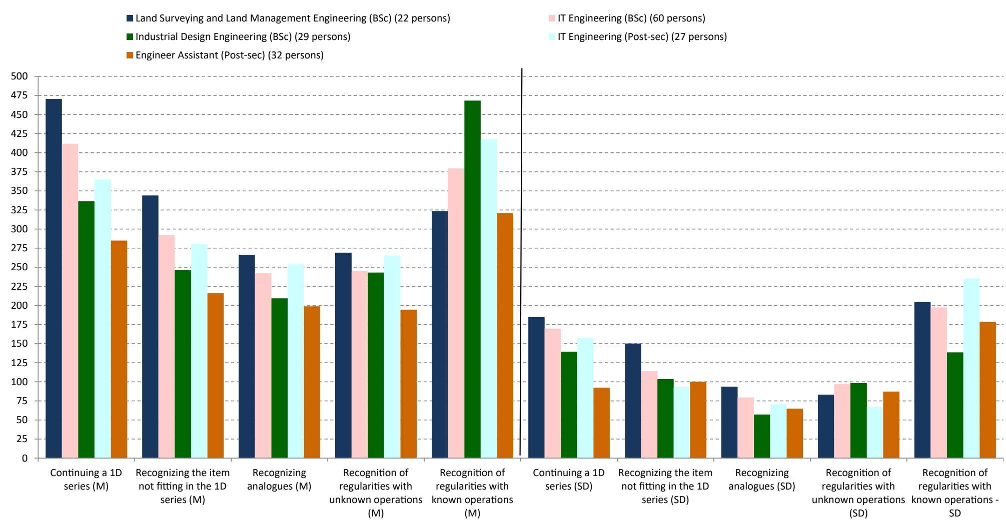

Fig. 11. Comparison of the means of time spent on task solution and values of standard deviation, by students' programs

secondary school during the admissions process. We compared their scores on math, which put students in higher education. The biggest difference appeared in the math grade. 6.8% of students in post-secondary education scored excellently (5), while 22.0% had sufficient (2) marks, the same rates were 27.9% and 9.9% for BSc students, respectively. The proportions were similar in terms of the Hungarian language and literature subject.

As for students in BSc courses, the best results – except for the two diagrammatic tasks – were achieved by students studying land surveying and land management engineering (Fig. 10), with the smallest standard deviations. They also have the highest time expenditure (Fig. 11). On the other hand, the students in the field of industrial design engineering performed the best in terms of the two diagrammatic tasks. As for their mathematics and Hungarian language and literature graduation results, 40.9% of the students majoring in surveying and landscaping engineering had excellent marks (5), while 18.2% had sufficient results. In the case of the industrial product and design engineering specialization, these two ratios were 27.6% and 3.4%. The most striking fact could be observed concerning the most difficult task. In the diagrammatic task involving known operations, industrial product and design engineering students achieved by far the best average result (Fig. 8), with the smallest standard deviation and the largest time expenditure (Fig. 9). It is most salient here that the students of this program had the lowest rate of sufficient (2) graduation results.

We examined the upper 25 percent ($N = 53$; $M = 24.72$; $SD = 1.63$) and 10 percent ($N = 28$; $M = 25.93$; $SD = 1.30$) of the students having reached the best inductive results (Fig. 12).

Compared to the total sample, in the upper 25% and the upper 10%, the proportion of students whose parents had a degree and who had a good (4) or excellent graduation result in mathematics and Hungarian language and literature (5) showed an increasing trend.

As for the distribution by program, it can be seen in Fig. 13 that the proportion of BSc students is higher amongst those with the best results, especially that of students in IT engineering.

To illustrate effectiveness, we defined the concept of *specific performance*, which was interpreted as the time required to achieve a unit score, which was defined as the quotient of time spent and the score achieved, per task. As for Task n:

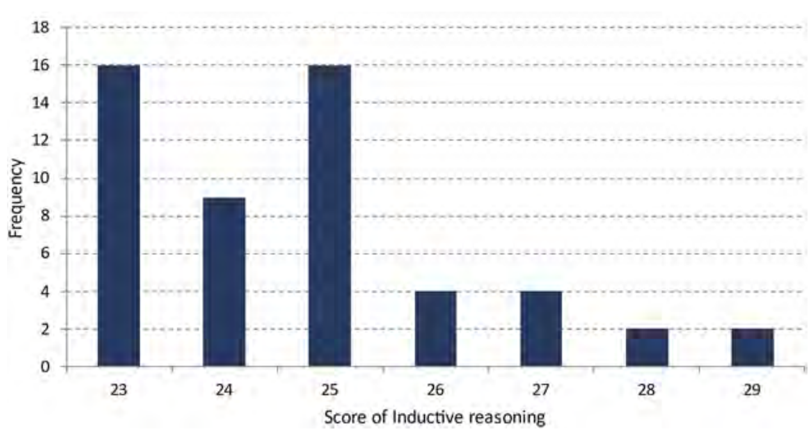

Fig. 12. Frequency distribution of the upper 25% of the students with the best inductive test results

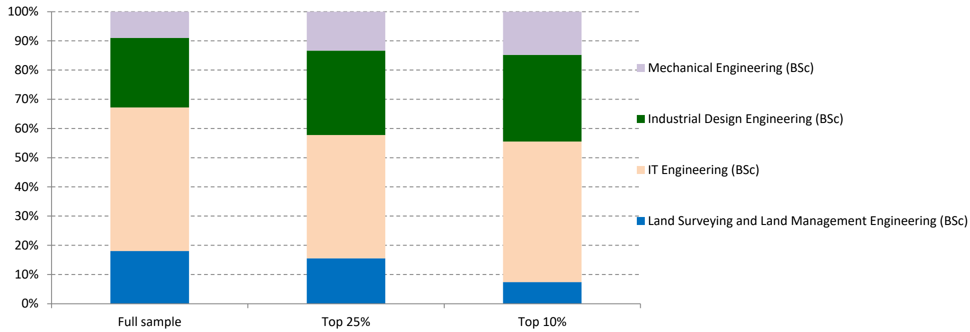

Fig. 13. Distribution of the 10% and 25% of the students with the best results in the inductive test by programs

$$\mathit{Specific\ performance}_n = \frac{\mathit{Time\ consumption(sec)}}{\mathit{Score\ in\ the\ inductive\ test}}$$

Specific performance is suitable for further differentiation of students' results and also expresses the speed of thinking. Here, the value of 300 s/point was considered a good specific performance, i.e., the students achieved a higher score with little time consumption. The values between 350 and 400 s/points were considered to be average specific performance, while those above these were considered to be weaker specific performance, i.e., it took a lot of time to achieve a unit score.

The specific performance of the 10% of the students, who best performed in the inductive test, was arranged in ascending order based on the total score achieved (Fig. 14). In the specific performance ratios, the first and last tasks were given the most weight and the recognition of

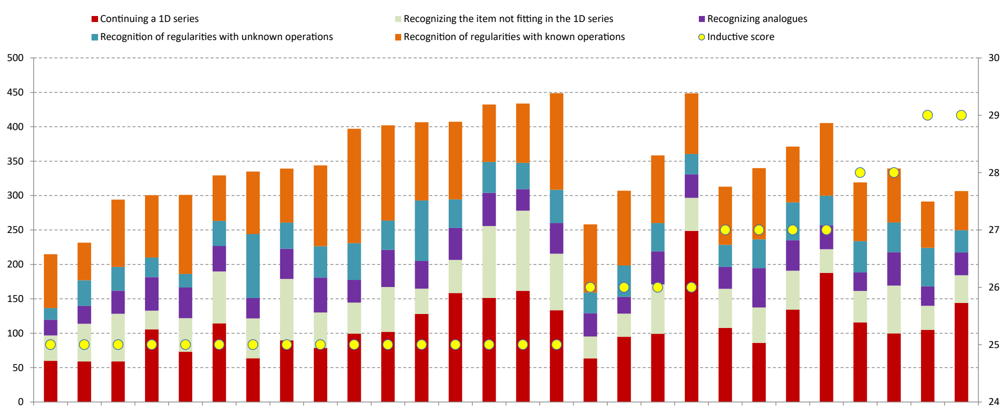

Fig. 14. Specific performance and achieved a score of the10% of the students with the best inductive test results (●)

analogs was the least, i.e., harder work had to be done for the points concerning the previous ones, while the least work was enough for the latter. The specific performance of the students with the same total score varies over a very wide range, i.e. some students had to work more (e.g. H173, H92) and some had to work less (e.g. H22, H206, H39) for a single point. The specific performance of the 4 students with the two highest scores hardly differs.

Based on the score obtained in the test and the time spent, we formed students' groups by cluster analysis (Fig. 13), and as visible, the time needed to solve the tasks served as the basis for the classification (in terms of the courses listed in Fig. 6). The first group includes the thorough ones (◆) who make full use of the available time, the second contains the considered ones (▼) and the third group includes the quick-witted and the superficial ones (●). High time consumption did not necessarily result in a good performance, and relatively low time expenditure could also lead to good results. The clusters were characterized according to cluster centroids (Table 4). The means were subjected to variance analysis. We found significant differences between the individual cluster centroids in terms of both the scores achieved (F = 9.042; P <0.001) and the time spent (F = 499.069; P < 0.001). The time consumed explains 85.7% of the variance. The reliability of the hierarchical cluster analysis was checked with the K-means algorithm, but no significant difference was found compared to the previously obtained results (Fig. 15).

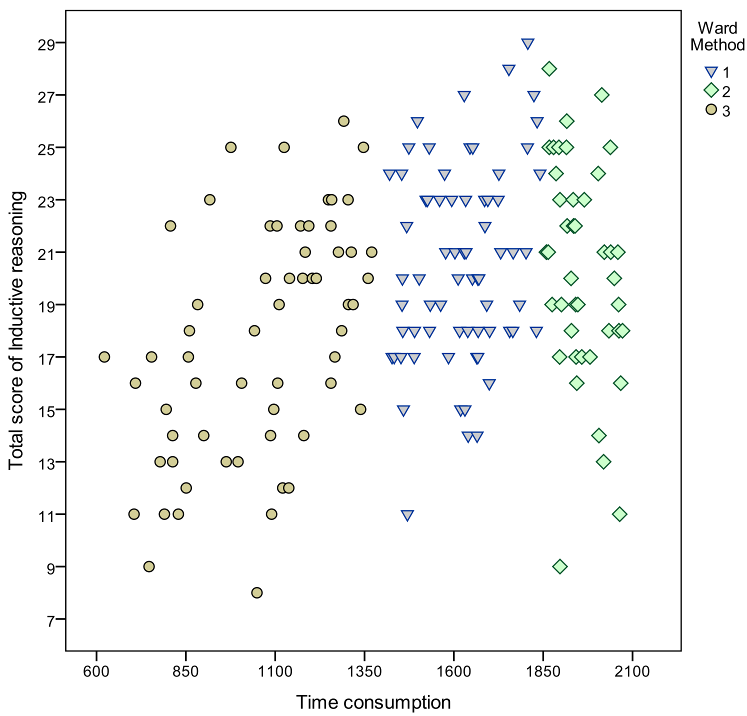

Fig. 15. Clusters formed according to time consumption and total score

Table 4. Significance analysis of the capability components and time consumption, by students' specialization

Cluster		The score achieved in the test	Time used to solve the problem
1	N	60	60
	M	17.62	1,062.35
	SD	4.44	203.62
2	N	68	68
	M	20.54	1,621.29
	SD	3.74	117.90
3	N	42	42
	M	20.19	1,959.09
	SD	4.20	68.44
Total	N	170	170
	M	19.42	1,507.48
	SD	4.30	383.88

DISCUSSION

Competencies that cannot be directly acquired via certain courses, i.e. cannot be linked to a specific discipline, but still, play a decisive role in the world of work have rarely been examined in Hungarian higher education so far. The two connecting concepts are soft skills and transversal competencies. It is true that their definition and constituent components are not clarified, nor is the relationship between the two concepts (Cornalli, 2018; Eger & Grossmann, 2004; Manpower Group, 2015; Rey, 1996; Veroszta & Nyüsti, 2015), however, problem-solving ability appears in several approaches and contexts (Tsankov, 2018; Whittemore, 2018). Components of this ability, such as inductive thinking, have been widely researched (de Koning, Hamers, Sijtsma, & Vermeer, 2002; Vo & Csapó, 2020), but not in higher education.

Inductive thinking aims to recognize regularities and anomalies by comparing properties and relations to perceive similarities and differences and to collectively perceive them. These operations can be performed in tasks involving verbal, numerical, image, or geometric figures (Klauer, 1999; Klauer & Phye, 2008). In our research, tasks containing geometric shapes were included, because such contents are common in technical training, think only of the wiring diagrams or the schematic diagrams on which the model, structure, and operation of different equipment must be understood.

212 first-grade technical students participated in the survey of inductive cognition ability, and we sought answers to three questions: (1) how can the inductive thinking of first-grade engineering students be characterized, (2) what differences does it show according to the subsamples, and (3) is specific performance apt to characterize students 'speed of thinking? The five tasks of the measuring instrument measured three types of components of inductive thinking: (1) analogical thinking (1 task, 6 items), (2) abstract thinking (2 tasks, 12 items), and (3) diagrammatic thinking (2 tasks, 12 items). An in-depth analysis of inductive thinking ability was also made possible by measuring the time spent per item.

Students achieved the best result in the analogical task, while the weakest in the diagrammatic task contained known operations. Of the tasks requiring abstract thinking, the items in terms of which the operation was aimed at changing the shape or the whole pattern caused difficulties. Changes in the position, color, and size caused fewer problems.

The advanced development of analogical thinking means that students show great sophistication in recognizing and understanding the relationships of visual structures and mapping them by analogs, which promises to be useful in processing applied science curriculum content based on abstract models.

As far as diagrammatic thinking is concerned, the items of the two tasks requiring two different approaches were subjected to a more thorough analysis, which was justified by the significant difference in the average results in favor of the unknown operations. For diagrammatic items containing unknown operations, the sequence of signals at the input and the outputs of the flowchart is known, the intermediate operations and operators must be interpreted and then selected from the four possible solutions. For the diagram items containing known operations, the signal sequence at the input of the flowchart and the intermediate operations are known, while the signal sequence at the output must be selected from five possible solutions. There was one less operator for the diagrammatic task involving unknown operations, and the good choice had to be selected from among one less possible solution. All these factors significantly reduced memory usage and time requirements, which might justify better performance. This might also be a reason for the fact that in terms of the items of the diagrammatic problem containing known operations the standard deviation among students is larger than in terms of the items containing unknown operators.

The item-by-item analysis also revealed that higher time consumption did not necessarily result in a good solution here either, however, good results required the maximum use of the available time. The relationship between the result of the inductive thinking test and the time consumed was described by an exponential function, which explains almost 21% of the total variance, in contrast to the 6% accounted for by mathematics graduation results.

Of the background variables, we observed significant differences in the components of inductive thinking ability only in terms of the students' major. And the same was true for the average time spent.

We examined the composition of the top 25% and top 10% of students with the best results according to background variables, and we found that a significantly higher proportion of them were those whose parents had a degree and whose results in their final secondary school leaving exams in mathematics and Hungarian language and literature were good or excellent.

We defined the concept of specific performance and found that it is suitable for further differentiation of students' results and can also be used to infer the speed of thinking. The specific performance of students with the same total score varies widely, the differences are mostly caused by the diverse amount of time spent on the diagrammatic task and the continuation of the one-dimensional series.

CONCLUSION

In higher education, the efficiency of pedagogical work can be increased if we have the most possible knowledge about the competencies that cannot be linked to subjects but still fundamentally determine the students' results. Getting to know the students better will help the instructors to choose the right methods. On the one hand, competence measurement can be a suitable tool for this. On the other hand, it can also contribute to the continuous monitoring of the development of soft skills and transversal competencies that are important for standing one's ground in the labor market. Finally, it also helps students get to know themselves better.

Our research having mapped the development of the components of inductive cognition (abstract, analogical, and diagrammatic thinking) and carried out in the framework of the input competence measurement strived to provide useful data for this.

We wish to repeat the research in a longitudinal form every year to monitor the developmental impact of the training on these competencies. To this end, we also consider the development of a standardized measuring instrument important.

A comparative analysis of the development of inductive cognition promises to be useful in terms of tasks involving geometric shapes and verbal and numerical items. Are these related to the nature of the programs attended by the students? For example, students in teacher education perform better on verbal tasks, while those in technical training perform better on tasks involving geometric shapes.

It is also necessary to clarify the relationship between inductive thinking and intelligence and other special abilities (e.g., spatial, mechanical, or numerical inference).

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