The Development of Engineering Students' Analogical Reasoning

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Abstract: Based on the Industry 4.0 strategy, problem-solving and, in this context, analogical reasoning has become crucial for successful placement and positioning in the labor market. Therefore, its development and monitoring is a priority. The goal of our research was to explore the development of analogical thinking in first-year engineering students who have completed their high school studies and are now starting their engineering studies. In the present study, 241 first-year engineering students of Óbuda University participated. The students enrolled in the BSc in Computer Engineering and BSc in Electrical Engineering have more advanced analytical skills and higher thinking speed. Cluster analysis was used to identify and characterize three groups.

Keywords: labor market competencies; problem-solving competencies; analytical thinking; analogical reasoning; engineering education

1 Problem Statement

Technological development and changes in job and occupational structures are transforming the demand for skills at a faster pace than ever before. In addition to technology-related knowledge, non-cognitive, or soft skills are becoming increasingly important for individuals in the 21st Century labor market environment. The industrial revolution of the 21st Century, Industry 4.0, has created a need for a workforce that can meet the demands of the times. In parallel with the transformation of the industrial environment, there is also a need for a radical overhaul of education at the level of public, vocational, and higher education.

Education 4.0 is the name given to this renewed education that prepares for the needs of the 21st Century labor market.

The World Economic Forum 2018 report provides a summary of the skills for which demand is forecast to increase or decrease between 2018 and 2022 [1]. The international research presented in Figure 1 shows that the increasing demand is mainly for intellectual occupations. At the forefront are analytical thinking (examined in our current research), strategic thinking, creativity, and planning skills. The skills listed below, which are in declining demand, are also worth observing. Thanks to automated and robotic production lines, which are gaining ground in Industry 4.0, the manual dexterity of workers is typically less needed. Research shows that the need for literacy and mathematical skills is also declining. However, without these skills, we believe that more complex cognitive processes, such as analytical thinking and complex problem-solving, which are considered more important, cannot be achieved. Many of these skills may be in decline because they can already be partially automated by artificial intelligence, but this trend is likely to continue in the future.

2018	2022 Increasing demand	2022 Decreasing demand
• Analytical thinking and innovation • Complex problem solving • Critical thinking and analysis • Active learning and learning strategies • Creativity, originality and initiative • Attention to detail, reliability • Emotional intelligence • Reasoning, problem solving and brainstorming • Leadership and social influence • Coordination and time management	• Analytical thinking and innovation • Active learning and learning strategies • Creativity, originality and initiative • Technological design and programming • Critical thinking and analysis • Complex problem solving • Leadership and social influence • Emotional intelligence • Reasoning, problem solving and brainstorming • Systems analysis and evaluation	• Dexterity, persistence and precision • Memory, verbal, auditory and spatial skills • Management of financial and material resources • Technology installation and maintenance • Reading, writing, mathematics and active listening • Managing staff • Quality control and safety awareness • Coordination and time management • Visual, listening and speaking skills • Technology use, supervision and control

Figure 1

Skills Demand Forecast 2018-2022, Source: [1] based on own ed.

In 2020 Szilágyi and colleagues [2] conducted a survey among employers in Hungary, and the results of the survey showed that cooperation skills, developmental skills, digital competencies, theoretical professional competence, professional ambition, creativity, emotional intelligence, cognitive flexibility, communication skills, autonomy, complex problem-solving skills, critical thinking skills of students leaving university were rated between good and medium. Students' practical professionalism, decision-making, decision-making skills, use of a foreign language, and negotiation skills were rated as weaker. Students' work experience was rated the weakest of the general competencies. Kis and colleagues [3] also conducted their study among employers in Hungary. According to their results, the top 5 soft skills expected by employers are responsibility, reliability, motivation, teamwork ability, and results orientation.

Miranda et al [4] identified key transversal competencies as core competencies to be developed in higher education in the era of Education 4.0. One of these is critical thinking, which encourages students to immerse themselves in real-world problems by applying various problem-solving techniques. Another area of emphasis in this study is collaboration through activities that promote individual participation of group members by sharing responsibility among participants; therefore, each participant is responsible for solving part of a complex problem or project. At the same time, students should demonstrate their ability to interact and work on joint projects. Communication in higher education takes the form of activities that encourage students to express their ideas effectively in oral, graphic, or written form, or any digital format. Creativity and innovation are present through activities that encourage students to implement creative and innovative problem-solving in design, development, and research.

Education 4.0 defines education as a lifelong experience that puts the responsibility for developing skills on the learner, with teachers and mentors at their side as facilitators. To achieve Education 4.0, existing education systems need to be modernized, which requires investment. According to the World Economic Forum's Education 4.0 paper, problem-solving, including analogical thinking, is a key competence that the renewed education system must contribute to developing. This is why we chose to focus our research on this essential 20th Century skill, among young people starting their technical university studies. The research we present in this paper, explores analogical reasoning, an important and fundamental component of problem solving.

There are two systems in the cognitive structure, the symbolic system, and the associative thinking system. [5] In the symbolic or rule-based thinking system, abstract real-world problems are thought about and solved using symbolic representations and rules. [6] The associative or similarity-based thinking system is where we think about problems through associations or similarities with other known information. Thinking processes are guided by networks of concepts and relationships, called schemas. One function of the associative, similarity-based thinking system is analogy thinking [5].

Analogy refers to the transfer of structural information from a source system to a target system [7] by focusing on syntactic relationships between objects in a domain. Structure mapping [5] [8] [9] reveals the relationships between structures and entities. Knowledge transfer is achieved through mapping or matching processes that consist of finding correspondences between two systems [7] [10].

In other words, the analogy is the identification of certain aspects of one element (the known or base domain) that are similar to certain aspects of another element (the unknown or target domain). The base domain and the target domain are not similar in all aspects, but through structure mapping, the relational structure of the base and target domains is found to be similar [9] [10]. Structure mapping allows new schemas to be built based on inductive, deductive, or analogical inference and prediction [11] [12]. Inferences undergo a transformation that brings the two elements close enough to each other to allow mapping and transfer from the base to the target schema, shed light on causal relationships, and allow the construction of causal mental models or schemas.

2 Aims, Questions and Measurement Tools

The aim of this research was to map the development of analogical thinking in first-year engineering students who have completed their secondary school studies and are starting their engineering studies.

The research sought to answer the question: what are the characteristics of analogical thinking and speed of thinking of first-year engineering students?

The research used the inductive reasoning test developed by Psychometric Success WikiJob Ltd. The test designers based their instrument on the theories of single and multi-factor intelligence and took into account labor market considerations in its development [13].

The test authors developed a complex three-factor measure to assess inductive reasoning. It is suitable for testing abstract, diagrammatic, and analogical thinking. The present study presents the results obtained in assessing the latter ability.

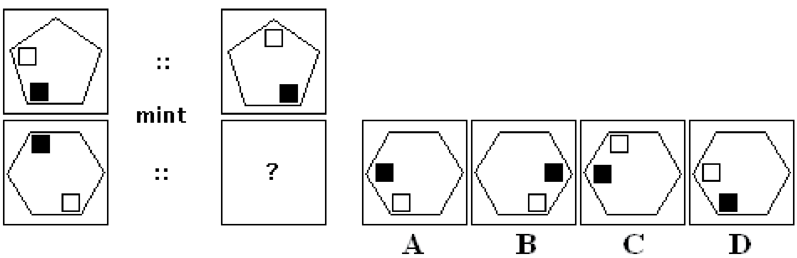

Figure 2
One of the items in the analogical reasoning test

The instrument used in this research consisted of five types of tasks (continuation of a series, recognition of out-of-series items, two types of diagrammatic tasks, and recognition of analogies), with six items per type. In this study, the results obtained for the six items measuring analogy reasoning (Figure 2) are presented.

The generative analogy [20] is about recognizing the relationship and thus solving the problem not only in terms of formal features (shape, size, color, pattern) but also in terms of changes in structure.

The research used a background questionnaire to assess the socio-demographic data of the students, their previous academic achievements, and their inferential reasoning ability using the APM-I version of the Raven test [14]. The online version of the instruments was used in the research. The present study is related to research assessing the development of inductive reasoning [15]. Both tests were found to be reliable, with Cronbach's alpha = 0.829 for the Raven test and 0.873 for the analogy test.

3 Research Participants

The 241 first-year engineering students admitted to the Alba Regia Technical Faculty and the Rejtő Sándor Faculty of Light Industry and Environmental Protection Engineering at Óbuda University participated in the research. The socio-demographic data of the students were as follows:

- 32.0% (77 students) female, 68.0% (164 students) male
- 34.9% (84 students) had a father and 39.8% (96 students) had a mother with a degree; 26.9% (65 students) had both parents with a degree
- 8.3% (20 persons) aged 18, 40.7% (98 persons) aged 19, 29.9% (72 persons) aged 20, 12.0% (29 persons) aged 21, 5.4% (13 persons) aged 22, 3.7% (9 persons) aged 23 or older

In their previous studies, they achieved the following results:

- 50.6% (122 persons) graduated from high school, 48.5% (117 persons) from vocational school
- Only 0.8% (2 persons) of the compulsory school-leaving certificate subjects were Hungarian language and literature, 5.4% (13 persons) mathematics, and 2.5% (6 persons) history
- 63.5% (153) had some level of foreign language knowledge: 0.8% (2) at the primary level, 47.3% (114) at the intermediate level and 11.6% (28) at the advanced level in English; 0.4% (1) at primary level, 7.5% (18) at intermediate level and 1.2% (3) at the advanced level in German; 0.4% (1) at primary level, 1.2% (3) at intermediate level and 0.4% (1) at advanced level in other languages
- The results of the Hungarian language and literature and mathematics A-levels are shown in Figure 3, which clearly shows that more than a quarter of the students achieved intermediate or below, which makes it very difficult for them to study technical subjects in later life.

As far as the students' university studies are concerned, it can be seen that all of them are enrolled in BSc courses, the distribution of which is shown in Figure 4. The vast majority of those admitted to the various degree courses attended, i.e., representativeness ranges between 74% and 100%.

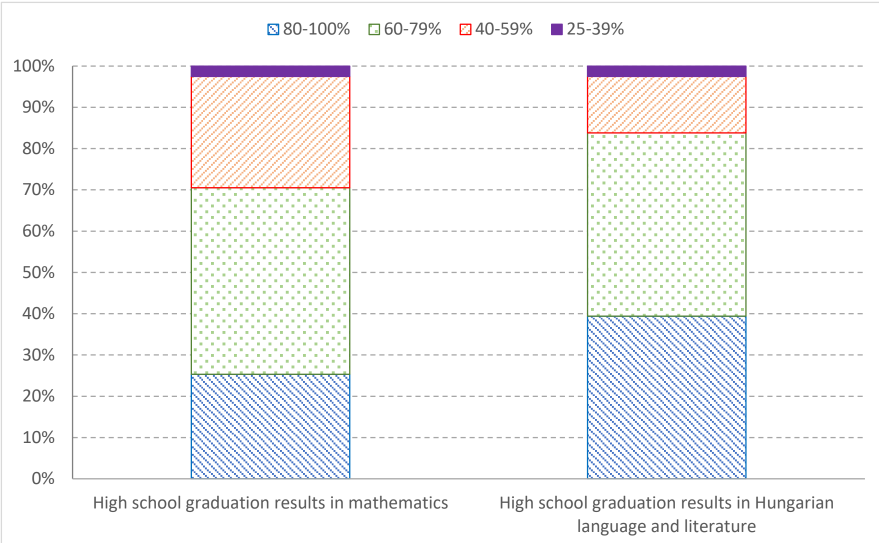

Figure 3
Graduation results

The results of students in each degree program were also compared. 46.2% (18 students) of the students enrolled in surveying and land surveying engineering obtained intermediate (40-59%), 5.1% (2 students) obtained satisfactory (25-39%) results in mathematics, 33.3% (23 students) of the students enrolled in computer engineering obtained intermediate and 1.4% (1 student) obtained satisfactory results in mathematics, while students in other fields of study obtained much better results. 41.4% (12 students) of mechanical engineering students achieved good (60-79%) and the same number of students achieved excellent (80-100%) results in mathematics, while 60.0% (15 students) of environmental engineering students achieved good and 20.0% (5 students) excellent results in mathematics. There is a significant correlation between the choice of major and the mathematics matriculation score ($\chi 2$=29.409; p=0.014), the strength of the relationship is moderate (Cramer's V=0.202; p=0.014), with mathematics predicting 12.8% of the ability to predict which major one will study at university. Analysis of the residuals revealed that a prominent mathematics score is significantly associated with the choice of Mechanical Engineering (Adjusted Residual= 2.1) and Industrial Product and Design (AD= 2.3), while a medium score is associated with the choice of Land Surveying (AD= 2.9).

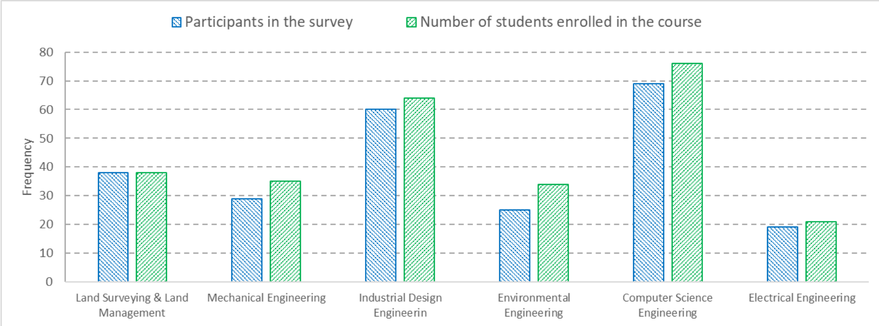

Figure 4
Distribution of students by field of study

Looking at the co-occurrence of the two subjects, it can be seen that the result in mathematics is equal to or less than the result in Hungarian language and literature. The highest proportion of students achieved good results in mathematics and the majority of them also did well in Hungarian language and literature.

There is no significant correlation between mathematics A-level results and having a GCSE in English and having an intermediate or advanced level English language exam, but it can be said that in all merit categories, the proportion of students with a GCSE at the intermediate or advanced level is 85%, while the proportion with an intermediate or advanced level English language exam is above 55%. Even out of the 6 students with a satisfactory level of Mathematics, 4 have an intermediate level of English, 4 have an intermediate level and 1 has an advanced level.

Mathematics A-level is associated with the highest educational attainment of the fathers (χ^2=25.036; p=0.037), with a significantly higher proportion of fathers with a degree among the better-performing students. This is also true for mothers, but the relationship is not significant.

Since the proportion of students who graduated from a vocational school was very high, we examined the graduation outcomes of these students. Almost 40% of the students had taken an intermediate or advanced level examination in a vocational preparation subject, and a higher proportion of them had a good or medium level in mathematics than those who had not taken such an examination.

We also administered the Raven intelligence test to the students in the study. The Progressive Matrices test is an excellent measure of inferential reasoning ability, which includes the ability to recognize meaning-ordering principles, new insights, and the ability to recognize connections that may not be obvious at first glance. In John Carroll's model of cognitive ability, the Raven test is a measure of inductive reasoning [14]. Carpenter et al. concluded that such items measure the ability to decompose problems into sub-problems and to manage a hierarchy of goals and subgoals that arise in the course of problem-solving [15].

Since deductive reasoning, ability plays a crucial role in engineering education [16] [17] [19] and is related to analytical thinking [18], a 12-item version of the Raven test (APM-I) was used in this research.

The test allows a quick assessment but is less differentiating while contributing to the general characterization of students' logical thinking. On the 12-item test, 68.4% of students (165 students) scored between 11 and 12, corresponding to an IQ of 126-132, 45 scored 10 (IQ 120-124), 16 scored 9 (IQ 116-118), 6 scored 8 (IQ 108-114) and 9 scored 5-7 (IQ 91-106). For the latter, the lack of interest in the measurement is questioned, and therefore the time taken was analyzed. The average time spent by the 241 students on the Raven test was 324.37 sec (SD= 115.399 sec; 95% Confidence Interval for Mean: 309.72 - 339.01 sec). The average time spent by the 9 students with the lowest scores was 263 sec, with one of them spending 99 seconds (5 points, IQ 91-95) and the other 699 seconds (7 points, IQ 102-106) on the 12 items. In their case, it is suggested that they were unmotivated in solving the test.

Using Rose's categorization, we turned our attention to characterizing students with low (bottom 10%) and high (top 10%) intellectual abilities [21].

The average time spent by students with high intellectual ability was 334.88 sec (N= 165; SD= 107.348; 95% Confidence Interval for Mean: 318.38 - 351.39 sec; Min= 160 sec; Max= 645 sec).

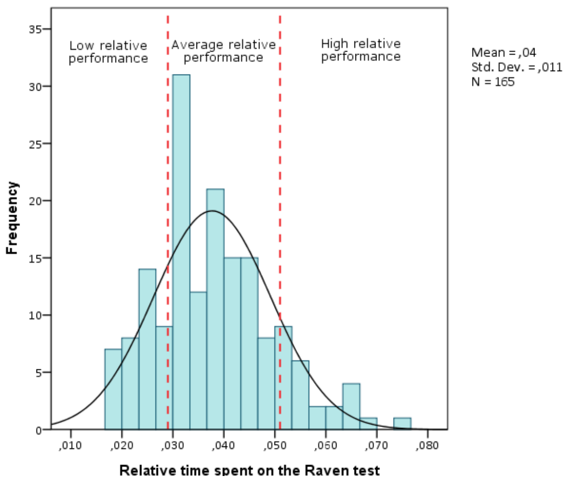

Figure 5
Distribution of the relative performance of students with high intellectual ability

The concept of relative performance, defined as the ratio of the score on the Raven test to the time taken, was introduced to capture performance (Figure 5).

In this case, high relative performance means that the student has achieved a high score with less time. These students quickly recognized the logical relationships between the elements of the matrix and applied them to select the missing element.

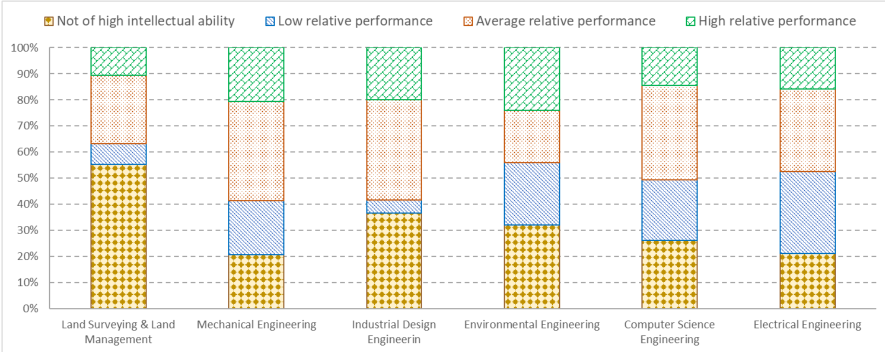

Figure 6
Percentage of Raven test relative performance categories by profession

While students with low relative performance did so more slowly. Relative performance on the Raven test also seems to be a suitable proxy for the speed of thinking in Carroll's model.

Figure 6 shows the proportion of students by the subject who did not achieve high intellectual performance on the Raven test. In this respect, the highest proportions of students are found in surveying and land surveying engineering and industrial product and design engineering. On the other hand, we gave the proportion of the three relative performance categories. Among students with high intelligence, more than 20% of environmental engineers have a high relative performance, i.e., speed of thinking. Among electrical engineering students, the proportion of students with low relative performance is the highest, and the proportion of students with no high intellectual ability is the lowest.

4 Results of the Research

Table 1 shows the descriptive statistical indicators for each of the five task types. The best average results were obtained for the task measuring analogical reasoning (Task 3), while the weakest results were obtained for the diagrammatic task involving known operations (Task 4). Taking into account the time taken to solve the tasks and the average scores, it can be concluded that the analogy task did not seem difficult for the students. If we compare the average results of the individual tasks by discipline, we find that in almost all cases, the best results were obtained by the Computer Engineering and Electrical Engineering students, despite their relative performance in the Raven test not being outstanding. Taking the average scores into account, there were significant differences between disciplines for the other tasks, except for the 'odd one out' task.

Table 1
Descriptive statistical indicators of the sample by task

Descriptive statistical indicators			Task 1	Task 2	Task 3	Task 4	Task 5
Whole sample	N		241	241	241	232	217
	M		3.65	4.15	4.77	4.13	2.58
	SD		1.267	1.374	1.325	1.891	1.662
	95% Conf. int.	Low.	3.49	3.98	4.61	3.88	2.35
		Up.	3.81	4.33	4.94	4.37	2.80
	Percentiles	25%	3	3	4	2	1
		50%	4	4	5	5	2
		75%	5	5	6	6	4
	Spending time	M	381.95	260.28	206.01	203.91	357.20
		SD	237.723	126.353	77.545	76.800	135.120
Courses	Land surveying & Land Man.	M	3.18	3.77	4.31	3.45	2.06
		SD	1.355	1.459	1.704	2.089	1.608
	Mechanical Engineering	M	3.83	4.48	5.03	4.67	2.85
		SD	1.256	1.430	1.149	1.981	1.562
	Industrial Design Eng.	M	3.62	4.40	4.73	4.53	2.32
		SD	1.236	1.238	1.201	1.736	1.696
	Environmental Engineering	M	3.12	4.16	4.08	3.46	2.39
		SD	1.269	1.405	1.470	1.841	1.500
	Computer Science Eng.	M	3.94	3.99	5.09	4.13	2.92
		SD	1.187	1.300	1.067	1.774	1.735
	Electrical Engineering	M	4.05	4.26	5.28	4.35	3.29
		SD	1.079	1.628	1.179	1.869	1.383
	Kruskal-Wallis	χ^2	16.922	9.412	16.543	12.682	11.450
		p	0.005	0.094	0.005	0.027	0.043

Note: Task 1 - Continuing a series; Task 2 - Recognize an out-of-series element ("odd one out" task); Task 3 - Recognize an analogy; Task 4 - Diagrammatic task (unknown operations); Task 5 - Diagrammatic task (known operations)

The results for the Raven test were also very similar, but no significant difference between the disciplines was observed due to the small number of items. There, too, the electrical engineering students produced the best mean score (M= 11.26; SD= 0.806). On the other hand, the results in the Hungarian language and literature and mathematics do not reflect this. In Mathematics, 78.9% of Electrical Engineering students and only 65.2% of Computer Engineering students achieved good or excellent marks, while three of the other four subjects had a higher percentage. The situation is not much better in the mother tongue.

To investigate the relationship further, we conducted a Spearman's correlation analysis of the components of the matriculation results, the Raven test, and the inductive reasoning test (Table 2, from the main diagonal upwards).

The mathematics matriculation result shows inverse proportionality with all ability components, with a low correlation coefficient. However, the Raven test indicates a medium level of correlation with all ability components of inductive reasoning, with the second strongest correlation with analogical reasoning.

From the relationship between the Raven test scores and the inductive reasoning test components, we filtered out the bias of mathematics, and since the correlation, coefficients decreased slightly (10-20%), it can be said that mathematics subject knowledge does reflect the development of these skills to some extent (Table 2, below main diagonal). No such bias was observed for the mother tongue.

Table 2

Correlational relationship between graduation, Raven's test, and inductive test scores

	1	**2**	**3**	**4**	**5**	**6**	**7**
1. Mathematics Baccalaureate		-0.247**	-0.251**	-0.178**	-0.207**	-0.281**	-0.216**
2. Raven test			0.357**	0.291**	0.382**	0.436**	0.308**
3. Continuation of the series		0.309**		0.286**	0.379**	0.288**	0.249**
4. "Odd one out" recognition		0.249**	0.233**		0.279**	0.352**	0.182**
5. Analogy recognition		0.384**	0.379**	0.268**		0.388**	0.350**
6. Diagrammatic - unknown operations		0.426**	0.272**	0.351**	0.375**		0.433**
7. Diagrammatic - known operations		0.266**	0.192**	0.134**	0.300**	0.393**	

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

Based on the item-by-item analysis of the analogy recognition task (Figure 7), it can be seen that tasks of varying difficulty were created, with the best average score being the first item and the weakest the fourth item. The average time spent was highest for item 4 and lowest for item 5, i.e., the difficult task made the students think. Relative analogy performance (score/time) was also determined, with item 4 being the most difficult (0.012 points/sec) and item 5 the easiest (0.049 points/sec), suggesting that the greater time expenditure behind the good score on item 1 may have been due to the novelty of this task type.

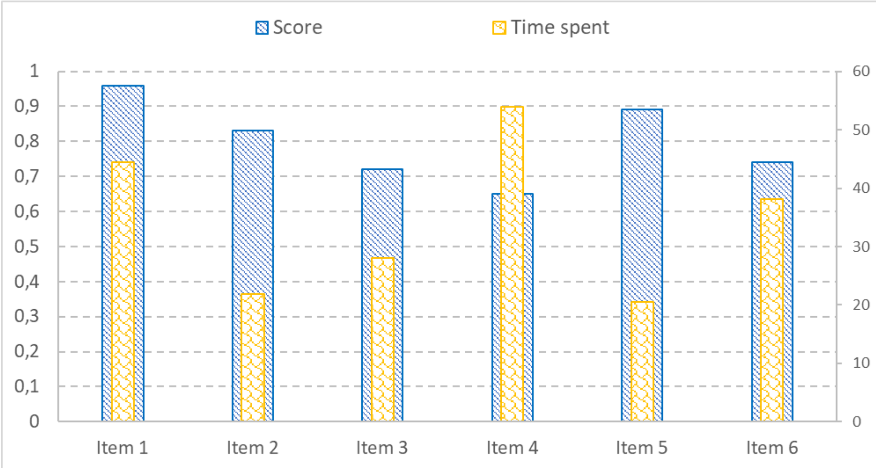

Figure 7
Average score and time spent on analog items

Comparing the average scores of the six items by profession, significant differences were found for items 4 and 6 (Table 3). For item 4, students in computer engineering and electrical engineering had the best average scores, while for item 6, students in mechanical and electrical engineering had the best average scores. The results of the electrical engineering students are supported by the fact that they also scored well on the Raven test and their mathematics final examination results were quite good (78.9% good to excellent), although their relative performance on the Raven test was not high. The students in surveying and land surveying had the poorest results in mathematics (51.3% fair and average) and also performed poorly on the Raven test, which may explain why they scored the lowest on all the tasks in the inductive reasoning test, including the analogy test.

When analyzing time expenditure, only the most difficult item, item 4, showed a significant difference among the students of different programs. For this item, the higher the time needed, the better the result was. For the other items, a higher average score required less time.

There was no significant difference between the scores of the analogy items by gender of the students, while the scores of the analogy items for time spent were significantly lower than the scores of the 1st group. ($M_{Male} = 46.94$; $SD_{Male} = 21.191$; $M_{Female} = 37.29$; $SD_{Female} = 13.393$; $\chi^2 = 14.053$; $p = 0.000$) and item 4 ($M_{Male} = 57.59$; $SD_{Male} = 37.266$; $M_{Female} = 47.77$; $SD_{Female} = 29.003$; $\chi^2 = 4.764$; $p = 0.042$). Also, for the other items, women spent less time solving than men, i.e., their relative performance was higher.

For item 4, there was a significant difference (χ^2=8.350; p=0.039) in the mathematics maturity scores: 80-100% for M=0.76; SD=0.429; 60-79% for M=0.65; SD=0.480; 40-59% for M=0.60; p=0.493; 25-39% for M=0.20; SD=0.447.

For the other items, the higher the mathematics A-levels of the student at university, the more likely he or she was to solve the problem well. In terms of time spent, there was a significant difference for items 4 (χ^2=6.063; p=0.043) and 5 (χ^2=7.536; p=0.024) (Figure 8), but for all items, it is clear that the worse the mathematics A-levels the student had, the more time he or she spent thinking about the analogy task.

Table 3

Mean score and time spent on analogy items by programs

Descriptive statistical indicators			Item3	Item4	Item6	Item3	Item4	Item6
			Score			Spending time		
Courses	Land surveying & Land Man.	M	0.61	0.55	0.68	27.24	49.11	22.29
		SD	0.495	0.504	0.471	15.645	31.003	13.837
	Mechanical Engineering	M	0.83	0.59	0.86	30.39	59.11	20.46
		SD	0.384	0.501	0.351	10.454	22.202	9.359
	Industrial Design Eng.	M	0.64	0.66	0.75	25.81	49.43	18.29
		SD	0.483	0.477	0.439	13.978	30.688	7.901
	Environmental Engineering	M	0.68	0.44	0.52	24.50	45.92	22.13
		SD	0.476	0.507	0.510	12.687	35.787	11.498
	Computer Science Eng.	M	0.77	0.81	0.74	30.86	62.86	21.88
		SD	0.425	0.396	0.444	21.657	44.093	10.671
	Electrical Engineering	M	0.89	0.67	0.94	26.78	59.22	18.50
		SD	0.323	0.485	0.236	9.046	29.824	6.233
	Kruskal-Wallis	χ^2	9.299	14.542	12.968	7.079	11.987	3.854
		p	0.098	0.013	0.024	0.215	0.042	0.571

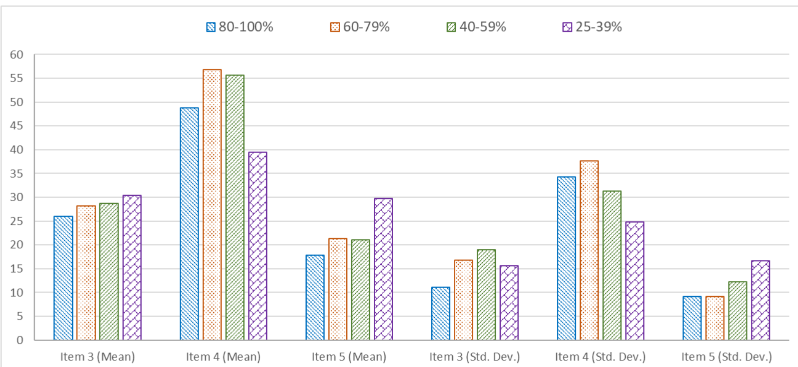

Figure 8

Mean scores and time spent on analogy items by mathematics examination results

The three items that proved most difficult were analyzed in more detail (Figure 9). On average, those with good answers spent the most time on the item. In all three cases, there was a higher number of marked incorrect answers, with item 3 being 'A', item 4 'B', and item 6 'D'. The average time taken for these was slightly less than the time taken for the correct answer.

Item 4 (Figure 2) required two rotations. The white square was rotated clockwise and the black square was counterclockwise. Several of them selected the answer 'B'. The problem here may have been that in the unknown analogy, the underlying plane axis is not a pentagon but a hexagon. In item 3, the incorrect answer 'A' failed to notice that one of the elements was turned, while the others were reflected and changed color. In item 6, the incorrect solution D is very similar to the correct solution B, except that the pattern is in the opposite direction.

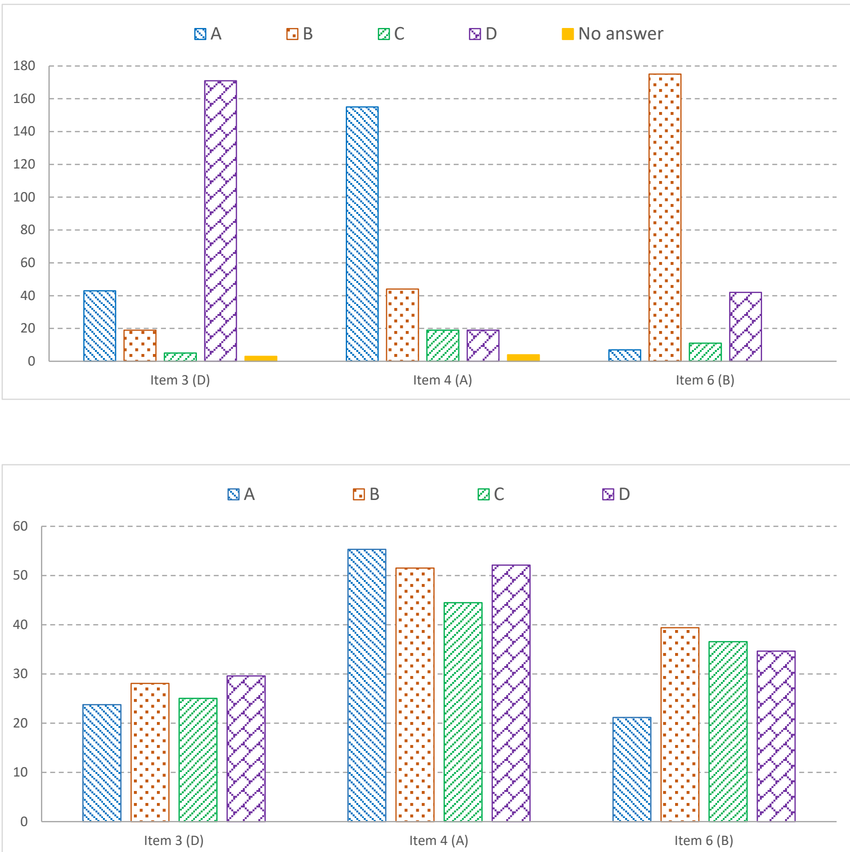

Figure 9

Solutions and times for the two most difficult analogy items

17.5% of men (28 respondents) and 20.8% of women (16 respondents) marked the incorrect answer "B" for item 4. In terms of professions, land surveyors (31.6%), mechanical engineers (24.1%) and environmental engineers (24.0%) were the most likely to have marked 'B' incorrectly, while only 11.8% of computer engineers and 17.7% of electrical engineers marked this response.

The average age of those who marked this incorrect answer was 19.86 years (SD=0.930 years), most of their parents were not graduates, and their mathematics scores were medium to good, with an average score of 10.16 on the Raven test (SD=1.430 points), their analogy recognition test scored 3.66 (SD=1.119), they spent an average of 213.7 seconds (SD=72.720 sec) on the six problems, and they scored an average of 15.9 (SD=3.753) on the full inductive test. In other words, their overall performance was below average.

Cluster analysis was used to categorize the scores on the analogy test. Using Ward's procedure, 3 clusters were identified (Table 4) in terms of analogy recognition development: advanced (C1), moderately advanced (C2), and not advanced (C3).

Average times to task completion in each cluster were also given. It can be seen that the poorer results are explained by lower time expenditure with larger variances. The average time spent in the three clusters is significantly different (χ^2=8.347; p=0.015). The reliability of the cluster analysis was checked using the K-means procedure, but no significant differences were found compared to the cluster centroids obtained previously.

Table 4

Cluster centroids and standard deviation

C		Test score	Time taken to complete the task (sec)
1.	N	158	158
	M	5.59	213.69
	SD	0.494	66.798
2.	N	60	60
	M	3.67	202.43
	SD	0.475	91.802
3.	N	21	21
	M	1.81	154.19
	SD	0.402	91.967
Total	N	239	239
	M	4.77	205.64
	SD	1.325	77.605

The composition of each cluster was characterized by background variables (Table 5). Weaker analogy scores are associated with weaker scores in other areas (Maths and Hungarian matriculation, Raven's test, inductive test), with significantly higher proportions of students in this cluster in surveying and land surveying, and environmental engineering. The majority of students in this cluster have parents who are not graduates, have a vocational secondary school leaving certificate, and a higher proportion of students are in college. Behind the better analogy scores are better matriculation, Raven's test, and inductive test scores, parents are mostly graduates, and a significant proportion of students in computer engineering, electrical engineering, and mechanical engineering belong to this cluster.

Table 5

Interpreting clusters

Cluster	C1	C2	C3	Connection
Score achieved	5-6 points	3-4 points	1-3 points	χ^2=478.000; p=0.000
Time spent	150-260 sec	110-290 sec	60-240 sec	χ^2=8.347; p=0.015
Place of residence	with parents, in dorm	with parents	in dorm	χ^2=21.028; p=0.021
Profession	Computer Eng., Electrical Eng., Mechanical Eng.	Industrial Design Eng.	Land Surveying, Environmental Eng.	χ^2=33.556; p=0.000
Graduation results in Math	80-100%; 60-79%	60-79%; 40-59%	40-59%; 25-39%	χ^2=27.342; p=0.000
Raven test result	11-12 points	10-11 points	less than 10 points	χ^2=56.806; p=0.000
Total inductive test score	19-24 points	12-18 points	9-14 points	χ^2=87.508; p=0.000

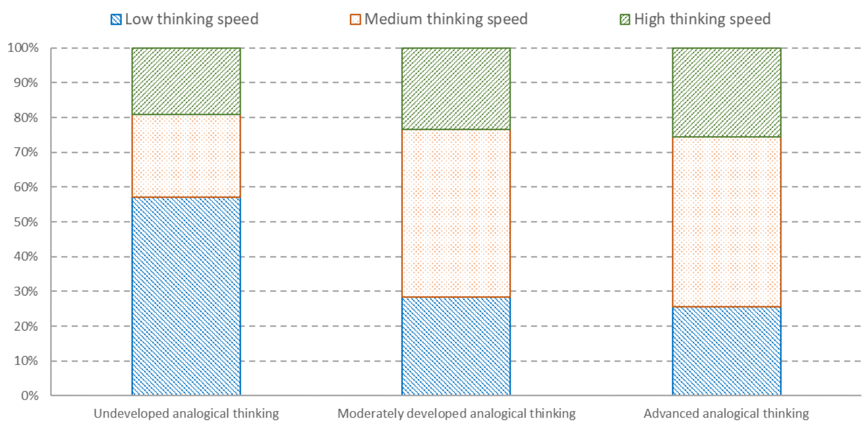

Figure 10

The relationship between thinking speed and performance on the analogy recognition test

Finally, we compared the speed of thinking measured by the Raven test with the results of the inductive test (Figure 10). It can be seen that undeveloped analogical thinking is associated with low thinking speed, while developed thinking is mostly associated with medium to high thinking speed.

Conclusions and Future Work

The aim of this study was to reveal the development of analogical thinking among first-year engineering students, as analogy, in particular generative analogy, plays an important role in the modeling and design of engineering structures and technological processes. It is therefore important to know the development of this ability and the methods used to develop it in young people starting their studies in engineering higher education. Inductive reasoning, including analogical reasoning, is also an important element of soft skills, which are important in the labor market, i.e., their development prepares people for real engineering jobs.

The results of the research are useful from several points of view, on the one hand, they support the development of new methodologies that also develop incomplete soft skills, and on the other hand, they can also be a predictive factor in terms of career suitability and can draw attention to deficiencies where skill development is necessary to avoid dropout. The comparative analysis of the inductive reasoning test by discipline shows that for almost all ability components, the highest scores were achieved by students in Computer Engineering and Electrical Engineering, although the proportion of high relative performers in terms of speed of reasoning was higher in Mechanical and Environmental Engineering. Analogy recognition has a moderately strong correlative relationship with performance on the Raven and diagrammatic tests. Item 4 of the test proved to be the most difficult to solve, yielding significant results across disciplines. Computer Engineering and Electrical Engineering students scored the best in terms of analogical reasoning and speed of reasoning, while Surveying and Land Surveying Engineering and Environmental Engineering students scored the weakest. This may be due to the high proportion of students with low reasoning skills and a medium mathematics A-level among these two disciplines. This is also supported by the fact that a weaker math score indicates a greater need for time on the analogy test.

A more in-depth analysis of the more difficult items reveals that all of them have a higher number of marked incorrect answers, where the logical relationship is only partially well identified. The performance of all the students who marked these incorrect answers was below average, with a high proportion of students in land surveying and environmental engineering.

Through cluster analysis, three analog performance categories were identified: developed, intermediate and underdeveloped. Each cluster was well characterized by socio-demographic background variables and occupational affiliation, and at the same time, correlations were found with performance in other areas (mathematics and Hungarian matriculation exams, Raven test, inductive test). A strong correlation was found between the speed of thinking and the results of the analogy test.

Liu and Liang's research [22] also pointed out the differences in the problem-solving processes of students in different majors. While engineering students focused on specific tasks in the experiment, the humanities students preferred the contextual aspects of the task.

In our previous research, we examined another important element of problem solving, inductive thinking [23], and in the future we aim to examine another element, diagrammatic thinking. Diagrammatic thinking is especially important in the field of engineering and IT, in the case of circuit diagrams, understanding the operation of equipment, analyzing system processes, software error correction and system design.

The limitation of our research is that the sample covered first-year students of two faculties, further research can be extended to higher years and other faculties in order to get an even more complex picture of analogical thinking.

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