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Teaching Mathematics and Computer Science

Development and assessment of non-cognitive skills among engineering students: a comparison across two universities

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Abstract. Non-cognitive skills, such as logical thinking and problem solving, are crucial for success in engineering fields. To assess these skills in undergraduate engineering students, we designed a targeted test comprising four different types of tasks. The study was conducted among students at the Faculty of Engineering at the University of Debrecen, and the Faculty of Mechanical Engineering and Informatics at the University of Miskolc. The aim of this paper is to analyze the test results, gather students' feedback, and examine the strength of the relationships between deductive reasoning, diagrammatic reasoning, and algebraic thinking.

Key words and phrases: competences, engineering students, logical thinking, abstract thinking.

MSC Subject Classification: 97C20.

Introduction

The aim of our paper is to assess the logical and abstract thinking abilities of undergraduate engineering students. The study involved 152 students from the Faculty of Engineering of the University of Debrecen and 81 students from the Faculty of Mechanical Engineering and Informatics of the University of Miskolc.

Logical thinking, as a competency, plays a fundamental role in engineering education, as the development of problem-solving skills is essential for professionals in the engineering field. Engineering activities typically involve the analysis and design of complex systems, processes, and structures, which require precise thinking. Logical thinking helps students examine problems in a consistent and structured manner, draw conclusions, and make appropriate decisions.

The development of logical thinking during engineering studies is achieved through various subjects such as mathematics, physics, and programming. These subjects contribute to refining students' analytical abilities, enabling them to effectively respond to real-world challenges and problems. Logical thinking facilitates the recognition of cause-and-effect relationships and the understanding and optimization of different technical systems and processes.

For engineers, this competency is particularly important in design and innovation processes, where solving problems requires structured, step-by-step thinking.

Overall, logical thinking is an indispensable competency in engineering education, helping students to successfully adapt to the rapidly changing technical environment and challenges.

On competences in general

The Bologna Process, starting with the Bologna Declaration (1999), brought numerous changes to the European higher education system, and simultaneously to the domestic higher education sector as well. One of the most significant innovations was the introduction of learning outcomes, which describe the output requirements achievable by the end of the learning phase.

The definition of learning outcomes aligns with the Hungarian Qualifications Framework, considering knowledge, skills, attitudes, autonomy, and responsibility in the context of defined action-level competence descriptions. The goal is to precisely articulate what a student knows, understands, and can independently do after completing a learning process, regardless of where, how, and when these competencies were acquired (Farkas, 2017).

The advantages of formulating learning outcomes in terms of competencies include:

- Laying the foundation for a learner-centered pedagogy, which prioritizes active student participation and individual development.
- Qualifications can be expressed in a language recognized and accepted by the world of work, thereby facilitating employment opportunities.

- Ensuring one of the key features of the Bologna system: the national and European recognition, comparability, and transparency of qualifications, while preserving the distinct characteristics of different national education systems.

The expected learning outcome-based approach represents a new technique, as well as a new mindset and way of thinking, which can fundamentally transform the world of education. As a result, learning processes can become more efficient and targeted, better aligning with the needs of students and the labor market (Biggs & Tang, 2011).

In general, competence means a preparedness that enables us to act effectively in different situations. We mean the preparedness that is based on knowledge and skills, but also on experience, values and attitudes. The role of the thinking ability is one of the most significant in terms of mathematical competence, but it relies on several abilities, such as systematization, combinability, deductive and inductive approaches and reasoning. These properties must be components that also work in other areas, i.e., the ability to think mathematically must become an ability that can be used in other subjects as well (Homolya & Rozgonyi, 2022).

Currently, in Hungarian higher education, the competencies to be developed in BSc, MSc, and higher education vocational training programs are contained in the so-called Training and Outcome Requirements (KKK).

The importance of logical thinking and problem-solving skills has been indirectly emphasized in the training and outcome requirements of all the examined fields (civil engineering, mechanical engineering, vehicle engineering, engineering management, electrical engineering). For example:

- Electrical engineers are capable of independently selecting and applying relevant problem-solving methods while solving professional tasks.
- In solving analytical tasks related to their field, the technical managers independently select and apply the relevant problem-solving methods.
- Vehicle engineers are capable of identifying professional problems, uncovering and articulating the theoretical and practical background required for their solution, and solving them.
- Mechanical engineers have a comprehensive understanding of the problem-solving methods related to the main theories of their field.

Abstraction, abstract thinking and logical thinking

A distinction between the activities of science and engineering concerns is suggested by Bassett and Krupczak (2022), which is, namely, the role of abstract thinking. It unites the entities that researchers imagine as existing in the world in their scientific theories; while an engineer in his/her technical designs combines existing entities with those whose existence depends on whether they are designed or not.

In the literature, in accordance with the above, abstraction is defined as a thinking process, by which a person ignores unnecessary details from the acquired information and is able to recognize connections. On the other hand, abstraction is mentioned as a product (Piaget, 1969).

The indicators of abstract thinking ability were proposed by Weintrop et al. (2016) as follows: Three aspects are distinguished, these are the reflective abstraction, the empirical abstraction and the theoretical abstraction. The indicators of reflective abstraction include problem integration, formulation, and transforming the problem into symbolic forms. The indicator of theoretical abstraction is processing the manipulation of symbols.

Advanced logical thinking is necessary for the successful acquisition of real subjects, the lack of which causes serious difficulties – among others – in technical higher education today. In the technical field, the key competences required by the labor market include among other things problem solving and critical thinking. The so-called fluid intelligence plays a fundamental role in the analysis of new problems, in the identification of patterns and relationships underlying the problems, and in the process of logical extrapolation (Cattell, 1963). One of the best-known measuring tools for this is the Raven test (Raven Progressive Matrices (RPM), see Raven et al., (1993)). The test of Paul Newton and Helen Bristoll (2024) is based on Raven's IQ test, considering the aspects of the requirements imposed on career starters in technical fields. This test measures how well the person can logically follow the sequence of symbols. It consists of simple flowcharts, during the solution of which you must be able to follow and recognize the changes in the shape, color and size of the objects. The aforementioned ability is very important for engineers, for example, when designing control systems.

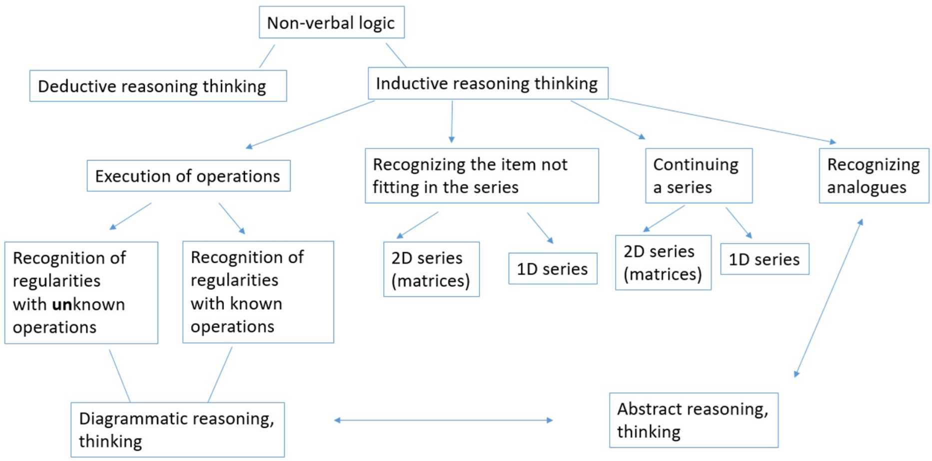


Figure 1. System for testing the relationships (partially adopted from Tóth et al., (2021))

Deductive reasoning reaches a logical conclusion based on a logical premise; and it is often called "top-down reasoning", as it moves from general information to specific conclusions. Inductive reasoning is usually contrasted with deductive reasoning and is also called "bottom-up reasoning".

Mathematics is an axiomatic discipline, which means that it does not make its findings directly based on the study of the surrounding world, experimentation, or inductive inference, as in the natural sciences in general, but deductively, i.e., using logical methods. Mathematics is primarily separated from the natural sciences by this methodological difference. Both ways of reasoning are needed for an engineer.

Diagrams and diagrammatic representations play an important role in everything from data visualization to visual programming languages. So, diagrammatic reasoning plays an important role in engineering designs.

In their article, Bronkhorst et al. (2021) investigated how 12th grade students use and apply visual and formal representations (iconic and symbolic) in logical reasoning tasks. During their research, they found that the speed and manner of transitioning from enactive and symbolic representations to symbolic representation when solving the tasks of different students is different. In their experience, it is a throwback to iconic mode that can help students support their reasoning. The importance of visual representations was emphasized in solving logical reasoning problems.

In our experience, many first-year engineering students have difficulty understanding the basic ideas of mathematics, and they have trouble deciphering the meaning of the new symbols they encounter. On the other hand, strong algebraic reasoning requires good symbolization and generalization skills.

The so-called algebraic thinking has two basic aspects (Sibgatullin et al., (2022)):

(a) the expression of increasingly generalizations and the dissemination of traditional symbol systems; and

(b) reasoning with symbolic forms, including syntactically guided manipulations of these forms.

The skills and abilities mentioned above can be said to be necessary for the successful work of a design engineer.

Research questions, the aim of the research

We do not want to use many tests with many questions, because the students' tolerance for monotony is relatively small. Thus, without the need for precise mapping of competencies, we want to create a test that is relatively diverse in terms of task types and does not take much time. Studying the relationship system illustrated in Figure 1, we are curious about the strength of the relationships in terms of deductive reasoning, diagrammatic reasoning and algebraic thinking. After testing these skills, we were curious about the students' attitudes.

About the online tasks

Before the start of the test, students received instructions on a paper (see Appendix A). There were three main task types on the e-learning test.

Task Type 1: In the first type, there are two tasks with the same structure, which are meant to measure the deductive reasoning ability of the students. The information is not given in text, which is therefore language-free; the premises are given with icons and symbols. After studying the available information, the students' task is to specify which number, Greek letter and shape each column contains (see Figure 2).

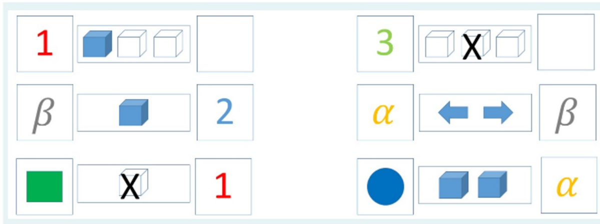


Figure 2. Information for the first task

Task Type 2: The second type of questions is devoted to measure the diagrammatic reasoning, that is, it measures how well students can logically follow ordered sequences of signals. The test consists of simple flowcharts, and the ability to perceive and interpret changes in the shape and size of shapes can be traced and plays a very important role, for example, in the analysis of engineering system processes.

The test was originally designed by the authors Paul Newton and Helen Bristoll (2024), and the time frame was 20 minutes for 35 questions, which belong to two main types (see also Appendix A):

(a) the test writers have to recognize the operations based on a flowchart;

(b) they have to guess the result of a sequence of known operations.

So, the first question type under study, (a) includes several diagrams containing combinations of letters or big symbols that can be modified with different commands. These commands are indicated by different small symbols. Each small symbol represents a rule, and these symbols can appear more than once on a chart. The meaning of the small symbols may vary from diagram to diagram. The task of the students is to follow the paths indicated by the arrows and determine what effect each command (i.e., each small symbol) has on the combinations of the big symbols. It is the students' job to apply the commands to the appropriate problem.

In the type (b), the operators may be pre-defined as in the next diagram. Each operator acts on a figure that students could be shown in the instruction. The sequence of operations is always from top to bottom. This means that students need to work from top to bottom, making a note of effect of each operator at each stage. Some of the operations involve changing the relative position of figures. Therefore, subsequent operations may need to be applied to the 'new' figure – not to the one shown (see Figure 3).

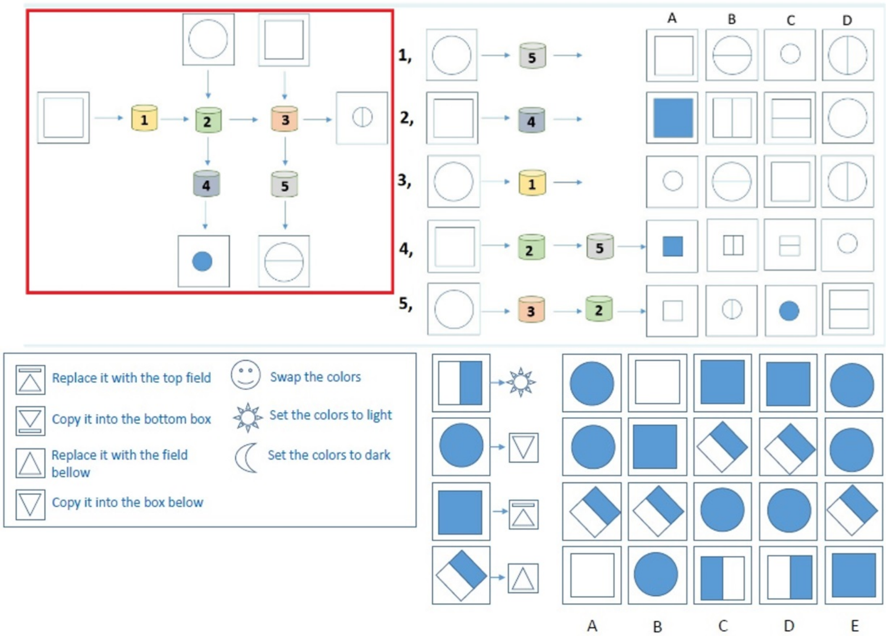


Figure 3. Questions (a) and (b) of the second type

Task Type 3: Finally, we describe the third task type. The ability to manipulate symbols is independent of language, so it can be used for comparison, as it was in the first type above. Also, abstract thinking includes some kind of information processing ability, which is why it is worthwhile to examine this through symbolic algebra tasks.

This question type mentioned was derived by Mielicki et al. (2017). The list of questions is shown in Figure 4.

In summary, there were included

- 2 questions from the first type of task (Type 1, Tasks 1–2),
- 10 questions, i.e., two times five questions from version (a) of the second type of task (Type 2 (a), Tasks 3–7 and Tasks 8–12),
- 4 questions from version (b) (Type 2 (b), Tasks 13–16), and also
- 8 questions from the third type of task (Type 3, Tasks 17–24)

in the test. Students were given 25 minutes to answer the 24 questions.

Level 1	Level 2	Level 3
$x\Delta y = 3x - y$ What is $3\Delta 6$?	$x@y = (2x - y)xy$ What is $(2@1)@3$?	$\tilde{x} = 2x + 3$ and $12 - 3\tilde{x} = 1 - 5x$ What is x?
$x * y = (xy + 1)y$ What is $2 * 1$?	$x\nabla y = y^2 - x^2 y$ What is $2\nabla(2\nabla 5)$?	$x@y = \frac{10x}{y+2}$ and $2@z = 4$ What is z?
	$x \cup y = x^y$ and $x \cap y = \frac{y^3+3}{x-3}$ What is $(3 \cup 2) \cap 3$?	$< x >= x^2 + x$ and $< y >=< y + 1 >$ What is y?

Figure 4. Tasks of the first type

Students' attitudes

Gathering feedback from students after a skill-assessment test is essential for several reasons. To evaluate the test results and to make potential interventions during future assessments, it is necessary to channel in the feedback after the survey. For the students who took the first test, we sent the feedback questionnaire a few days after the completion of the test. In this questionnaire, they were asked to evaluate both the difficulty of the task types and the time frame provided. Additionally, they were given the opportunity to leave comments. A total of 100 students from the two universities completed the feedback questionnaire.

The bar chart in Figure 5 shows that most students indicated needing 5-10 more minutes to complete the test, while only slightly more than 10% reported that the time was not enough at all.

The chart in Figure 6 illustrates the distribution of task difficulty as perceived by students after completing the test. Most of the students rated the tasks overall as average, with significant portions also categorizing them as difficult. The so-called Diagrammatic Type 1 and, respectively, Diagrammatic Type 2 tasks (abbreviated as "Diag1" and "Diag2") show a similar pattern, but higher proportion of respondents found Type 1 more difficult. The so-called "Operator" tasks had a slightly higher proportion of very difficult responses, suggesting that this type was perceived as more challenging compared to others. It should be noted that these tasks were at the end of the test, so many students did not have enough time to complete them. However, those who did have time found the operator tasks easier compared to the diagrammatic ones.

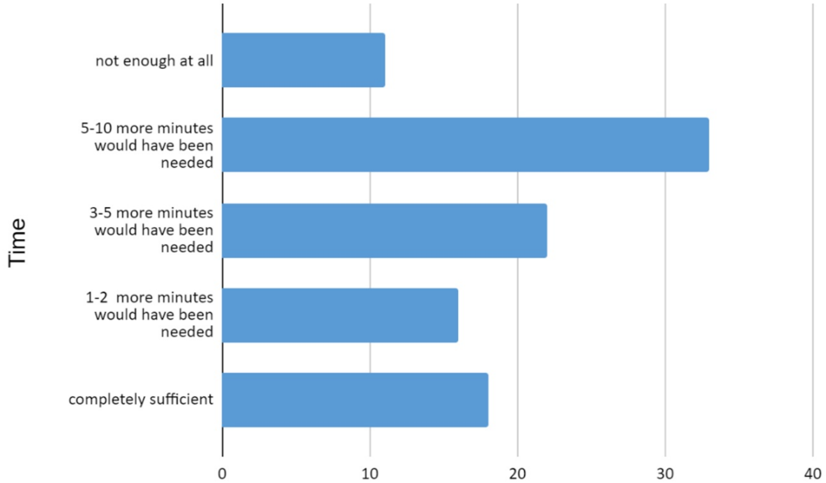


Figure 5. Tasks of the first type

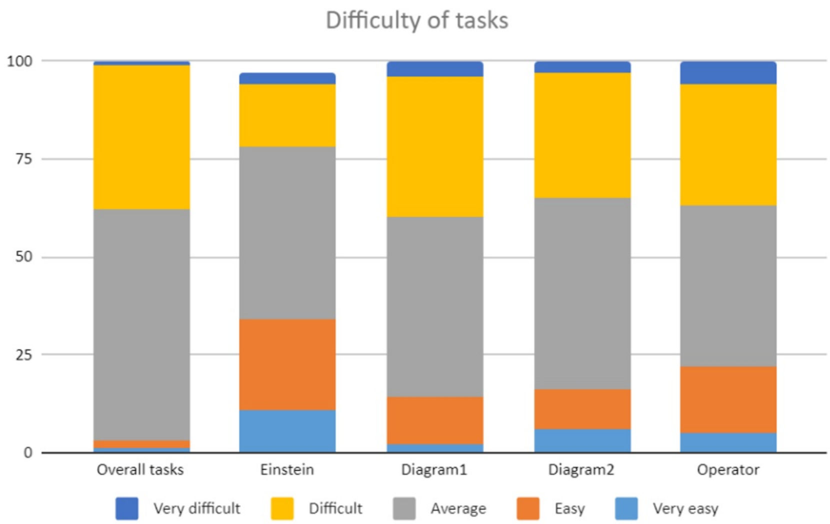


Figure 6. Tasks of the first type

Comparing the student feedback with the actual results, the “Einstein”-type task was the most successful, with an average normalized score of 0.75, and with a standard deviation of 0.27. According to the results of Diagrammatic Type 2 (the average normalized score of 0.28, standard deviation of 0.25) performed worse than for Diagrammatic Type 1 (the average normalized score of 0.4, standard deviation of 0.25). Since the feedback questionnaire was anonymous and only slightly more than 60% of students provided feedback, this could also be a reason for the discrepancy between self-reflection and actual performance. On the other hand, the mean (0.28) of Diagrammatic Type 2 is closer to the standard deviation (0.25) compared to Diagrammatic Type 1. Similarly, more students found Diag1 tasks difficult or very difficult compared to the Operator-type tasks, even though the average score for the Operator tasks $(0, 2)$ was lower.

In their additional comments and verbal feedback, students also confirmed that they feel the timing of the test (time of day, overlap with other exam periods) affects their performance.

The results of the online test

At the Faculty of Engineering of the University of Debrecen, a measurement conducted at the beginning of the semester involved 79 first-year students (58 civil engineering students, 14 vehicle engineering students, and 7 technical management students). The measurements related to the research were conducted in the second semester of the 2024/2025 academic year. The students first completed the test in March, while the retest was conducted at the end of the same semester. In May, 144 students completed the test, of whom 71 (55 civil engineering students, 10 vehicle engineering students, and 6 technical management students) participated in the retest, while 73 students from the mechanical engineering program served as the control group.

The students were not informed about the test or that they would be retested; they were unaware that their papers were categorized into focus and control groups. The students in the experimental group voluntarily undertook the completion of Diag1 tasks.

Among the civil engineering students, 11 created tasks like Diag1 tasks during the semester. Students were asked to create a logically identical, similarly typed task, each of them to create one task (see Appendix B). It can be observed that among these students, the average score achieved during the retest for the Diagrammatic Type 1 section increased by 33%, while the median value doubled.

Furthermore, as shown in Table 1, the practice of Diag1 tasks and a better understanding of the logic behind the tasks also affected the Einstein-type task. This significant increase in correlation can be explained by the fact that similar logical skills are required for solving Diag1 tasks and the Einstein task. The correlation with other types either increased slightly or as seen with Diagrammatic Type 2, decreased. Although the two types of diagrammatic tasks appear similar, different soft skills are required during the problem-solving process. Successful resolution of Diag2 tasks is essential for working memory, as it is necessary to keep multiple steps and complex processes in mind.

	Einstein	Diag2	Operator
Diag1 Pre-test	0.136	0.297	0.530
Diag1 Post-test	0.675	0.109	0.627
Progress	396%	-63%	18%

Table 1. The effect of practicing Diagrammatic Type 1 task

Strengthening working memory not only increases the effectiveness of learning but also contributes to continuous professional development, enabling engineers to quickly adapt to new technologies and solutions. Through all these factors, advanced working memory helps engineers become more successful in their dynamically changing work environments. For the students who did not complete Diag1 tasks, the correlation changes shown in Table 2 provide interesting insights. With one exception, all correlations increased significantly, which is a positive sign of improvement in learning and skill development.

	Einstein	Diag1	Diag2
Diag1	232%		
Diag2	5%	197%	
Operator	129%	75%	354%

Table 2. The change in correlation in the ‘non-practicing’ group

This indicates that students are becoming more consistent in their performance across different types of tasks. It is important to consider that the first measurement was taken at the beginning of the semester, right after the students returned from a winter break, during which they had courses ending with several assessments and an oral exam. In contrast, the retest occurred at the end of the semester, a time when students focused more on studying and preparing for exams. During the exam period, students often establish regular and intensive study routines, effectively "training" their brains. This focused effort not only enhances their knowledge retention but also strengthens cognitive skills, contributing to improved performance.

Overall, considering the data measured at the University of Debrecen, it can be stated that during the retest, we obtained stronger correlations between the scores achieved and the various types of tasks. This suggests that students' performances have become more interconnected, reflecting a deeper understanding of the material and improved application of skills across different task types.

The beforementioned logic test was administered to 81 students at the Faculty of Mechanical Engineering and Informatics of the University of Miskolc, who were enrolled in various undergraduate engineering programs. The sample included both first-year and second-year students.

Among the participants, 21 were first-year mechanical engineering students who, by the semester of the test, had completed one semester each of calculus, linear algebra, and descriptive geometry. These subjects potentially provided foundational skills advantageous for solving the test tasks. Another group comprised 17 second-year mechanical engineering students. Prior to the current semester, this group had completed two semesters of calculus, one semester of linear algebra, one semester of descriptive geometry, and an informatics course. During the semester of the test, these students were also enrolled in CAD classes, which may have further contributed to their performance. Students from both groups were encouraged to complete similar tasks to those in the test as voluntary assignments, which they could design independently. Out of these students, 21 took the opportunity, producing innovative and valuable tasks.

The third group, comprising 43 students, included first-year students from electrical engineering, vehicle engineering, and technical management programs. These students had also completed one semester of calculus and linear algebra. Additionally, the vehicle engineering and technical management students completed a semester of technical drawing. However, this group did not participate in CAD classes during the current semester, and the voluntary assignments were not offered to them. To assess the progression of all three groups, we conducted a logic test with similar tasks at the beginning and at the end of the semester. The first- and second-year mechanical engineering students had ongoing exposure to these tasks through the voluntary assignments and CAD classes, whereas the 43-member group had no such engagement. The final test coincided with the exam period, which may explain the lack of substantial improvement, potentially due to exam-related stress and fatigue. This finding suggests that the timing of assessments can significantly impact test performance.

Initially, we analyzed the results of the three groups together to explore correlations between the outcomes for each task type. Table 3 presents these correlation values.

	Diag1
Einstein	0,2232
Diag2	0,3786
Operator	0,1422

Table 3. Correlations related to Diagrammatic Type 1 (81 students)

The values in the table indicate a moderate positive correlation between tasks categorized as Diagrammatic Type 1 and Diagrammatic Type 2.

A correlation value of 0.1422 suggests a weak positive linear relationship between the operational task type and Diagrammatic Type 1. This indicates that although there is a statistically detectable relationship between the score of the Operator task type and the performance on Diag1 tasks, the strength of this relationship remains weak.

When examining the groups separately, it is noteworthy that the 17 second-year mechanical engineering students performed the poorest in Diag2 tasks compared to both other task types and the other groups. Among these 17 students, for the 4 tasks that had a maximum score of 4 points, only 1 student achieved 2 points, 8 students scored 1 point, and 8 students scored 0 points. However, 6 students from this group achieved full marks on the Einstein task.

The comparative correlation values in Table 4 reinforce these observations. While there is a strong correlation between Diag1 tasks and the Einstein tasks, there is minimal correlation between Diag2 tasks and the Einstein tasks.

The findings indicate that the strongest correlation exists between Diag1 and Diag2 tasks. This observation holds not only for the entire group of 81 students but also remains consistent across individual groups.

	Diag1
Einstein	0,7387
Diag2	0,0154
Operator	0,3696

Table 4. Correlations related to Diagrammatic Type 1 (second-year mechanical engineering students)

Follow-up measurements were conducted for each group, revealing an overall increase in correlation values (Table 5). This suggests that the coursework completed during the semester positively influenced students' performance on the tests.

Correlations related to Diag1 type	Pre-test	Post-test
Einstein	0,2144	0,5098
Diag2	0,6241	0,0908
Operator	0,0497	0,3619

Table 5. The change of the correlation values in the third group

The variation in correlation values observed in this study, like the findings at the University of Debrecen, suggests that the relationship between task types is influenced by the timing of assessments, specifically whether students are tested immediately after a winter break or at the end of an active learning period. This timing plays a critical role in shaping students' cognitive readiness and, consequently, their performance.

The decrease in the correlation between Diag1 and Diag2 tasks indicates a divergence in the working memory demands required by these two task types. This result implies that while one type may rely more heavily on immediate recall and short-term processing, the other may require integrated and more complex cognitive skills that benefit from continuous engagement and practice. Therefore, the observed differences in correlation could reflect varying cognitive loads and task-specific memory utilization during different stages of the semester.

We examined the measurements conducted at the beginning of the semester at the two universities, the results of which are summarized in Figure 7.

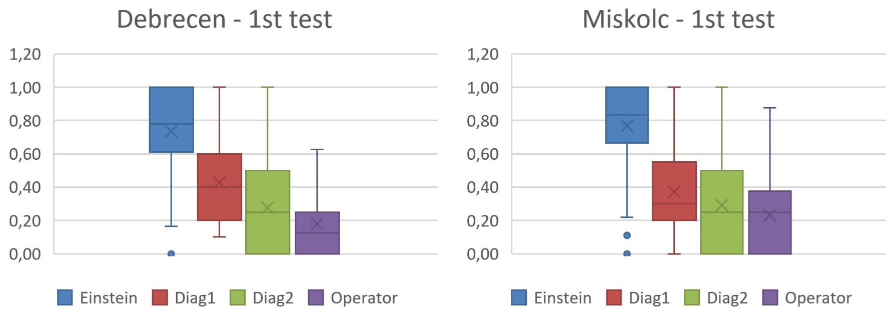


Figure 7. The boxplots of the first tests

It can be observed that the boxplot graphs of student results from the beginning of the semester at both universities are very similar. This similarity indicates that students' performance, knowledge, and skills demonstrate a comparable distribution and level in both groups, suggesting there is no significant difference in abilities between the groups, implying a uniform student performance. Furthermore, the data indicates that the testing conditions and methodologies were applied consistently across both groups. Additionally, the results suggest that both universities commenced the semester with student groups of nearly identical skill levels, indicating a homogeneous initial knowledge base and skill set.

It can also be confirmed that the timing of the measurement influences the results, as shown in Figure 8. Students with similar knowledge and skills at the beginning of the semester produced different measurement results by the end of the semester. The box plots for the second measurement and the control group no longer resemble each other as closely, indicating that external factors or changes in conditions over time contributed to these variations.

The analysis of the three box plots highlights notable similarities and differences in performance between the University of Debrecen and the University of Miskolc across the four task types. At both universities, the Einstein task type consistently achieved the highest median scores, reflecting a superior level of performance. The Operator task type has the lowest medians and variability in both cases, indicating more uniform but weaker results.

Within the University of Debrecen, a comparison between the second test and the control group revealed consistency, particularly in the Einstein group, which maintained a stable median in both scenarios. While there were slight increases in variability among the Diagrammatic Type 1 and Operator groups,

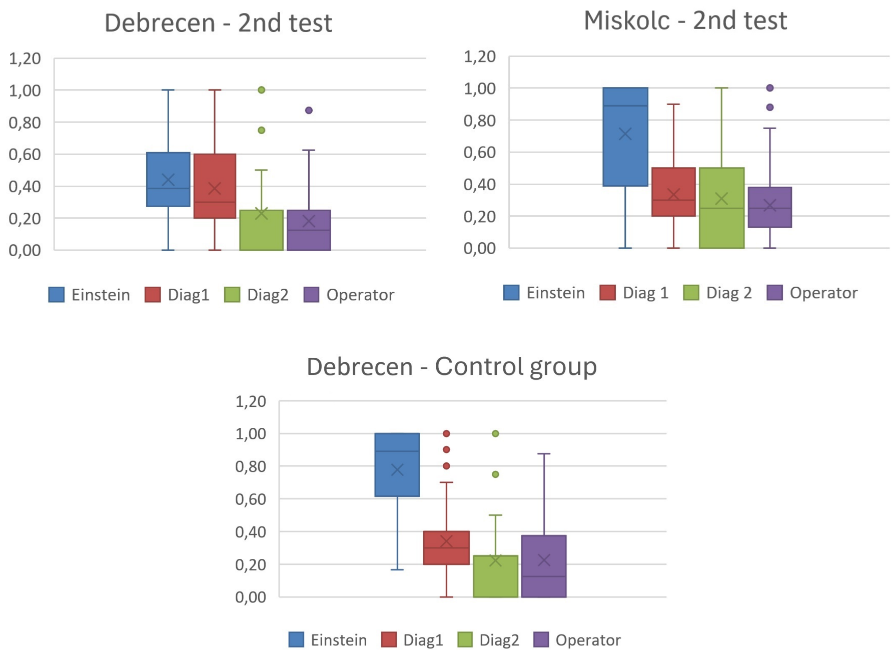


Figure 8. The boxplots of the second tests and the control group test

these differences were minimal. The presence of outliers and slight variability changes suggest potential external factors impacting these groups.

The results of the students at the University of Miskolc show slightly better overall performance in Diagrammatic Type 1 and Diagrammatic Type 2 tasks, and greater variability in the Einstein task type, suggesting a broader range of abilities. In contrast, the results at the University of Debrecen demonstrate more consistency but slightly lower medians across task types, with the control group providing insight into performance deviations within the university.

Summary

Successful engagement in STEM fields requires not only foundational professional and scientific knowledge, but also crucial non-cognitive skills such as logical thinking and problem-solving. Therefore, the aim of our research was to assess the levels of advanced logical thinking and abstraction skills through various types of tasks among engineering students in the first years of undergraduate study.

The testing was conducted simultaneously at the University of Debrecen and the University of Miskolc, with a control group also included. The main findings reveal both similarities and differences in performance across various task types.

It can be confirmed that the initial results at both universities were similar. Although there were no general improvements in test scores at the end of the semester, outliers appeared in both the retest and control group results. The timing of the tests may have influenced the outcomes, as the retests were conducted at the start of the exam period, during the final exam and project submission period, leading to lower concentration and focus among students.

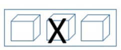
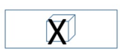
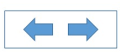
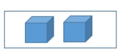
Based on changes from the original test, both universities observed an increase in the correlation between Diag1 tasks and Einstein tasks, reinforcing the relationship between diagrammatic and algebraic reasoning. However, the correlation between Diag2 tasks and Einstein tasks remained weak, highlighting different cognitive demands between these two types.

Appendix A

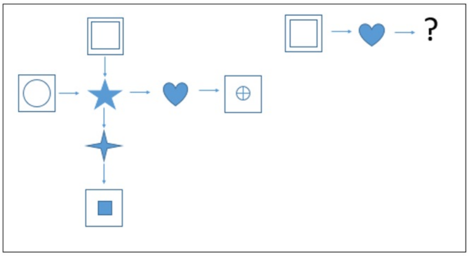
Instructions for completing the test

Completing the online test is voluntary, the test result has no impact on your studies. The test contains a total of 24 tasks.

- In **Type 1** (Tasks 1–2), 9 symbols are given, which are 3 numbers, 3 shapes, and 3 Greek letters. Their location must be found based on the given connections.

	The symbol is in the first column.
	The symbol is not in the middle column.
	The two symbols are in the same column.
	The two symbols are not in the same column.
	The symbol on the left is to the left of the symbol on the right.
	The two symbols are in adjacent columns.

- In **Type 2**, you must solve diagrammatic tasks.
  (a) Within the diagrammatic tasks, in the first and second group of questions (Tasks 3–7, Tasks 8–12), you will see one picture each, to which 5-5 questions apply. Based on the given figures, you have to invent what "process" the individual symbols/numbers represent (rotation, reflection, enlarging, reduction...). In the tasks, the effect of these "symbols/numbers" must be defined for the given figure as it is shown on the figure below.



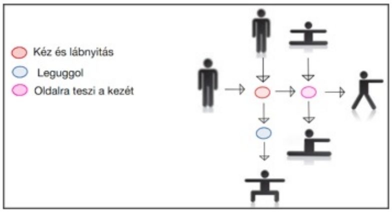
  (b) For the diagrammatic tasks belonging to the other group (Tasks 13–16), you must work with predefined symbols. For example, by using the 'Smile' symbol, the colors in the original figure are exchanged.

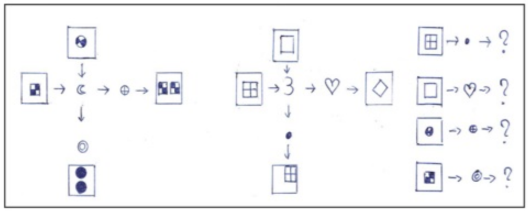
  For the questions, you must work from top to bottom with a series of 4 figures, and at each stage it is worth noting the effect of each symbol. Applying some symbols may change the original order of figures, so subsequent operations may need to be applied to the 'new' figure.

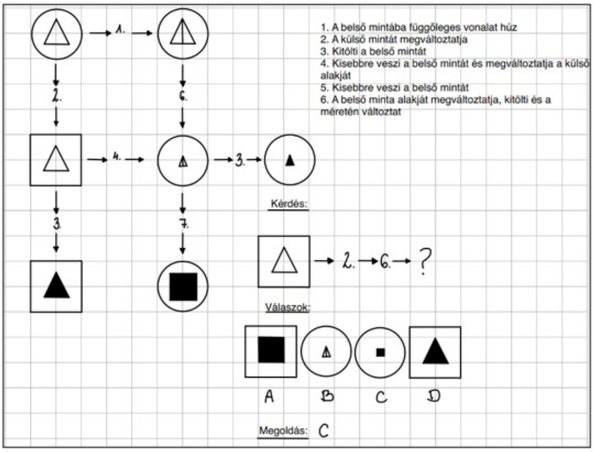
- In **Type 3** (so-called "Operator" tasks, Tasks 17–24), the question must be answered based on the operation(s) defined in the task. For instance, we know that $x * y = 2(x + 3y)$. What is $3 * 2$?

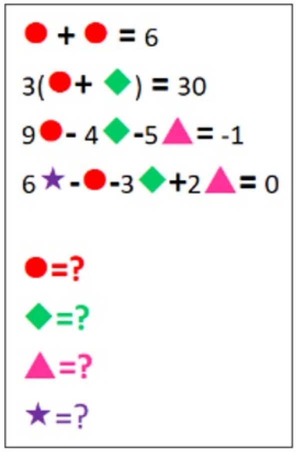
Appendix B

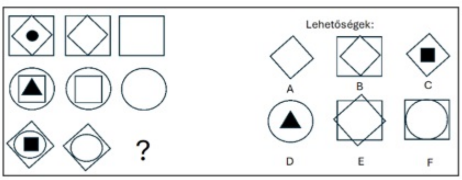
Students' work:

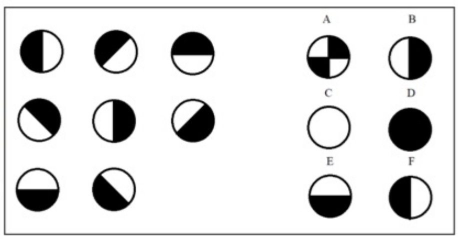


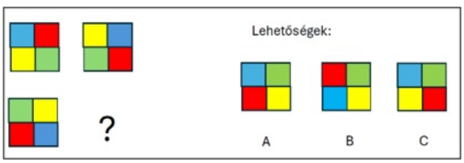












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