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Do Computer Science Students Differ from Students of Other Fields of Study in Terms of Multiple Intelligences?

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Abstract. This paper presents survey results involving students from three fields of study (computer science, business, and pedagogy), positing that computer science students exhibit distinct patterns in the spectrum of multiple intelligences compared to students in social sciences disciplines. The study involved over 300 students, revealing statistically significant differences, especially in logical-mathematical intelligence, one of the crucial intelligences according to Howard Gardner's theory and is traditionally measured by IQ indices. Statistical analysis confirms the dominance of computer science students in this intelligence. The data on student preferences were collected through self-assessment in an online questionnaire.

Keywords: multiple intelligence, psychometrics, education, suitability for the profession, personality, IT students.

1. Introduction to the Multiple Intelligences Test

Multiple intelligences, a concept developed by Prof. Howard Gardner (Gardner, 1985), suggest the existence of various equally important intelligences within each individual, which form a unique and dynamic profile, particularly influential during childhood. Gardner's extensive research (Gardner & Hatch, 1989) led to his seminal publications (Gardner, 1992; Gardner, 2002) and later evaluations of the theory's impact on education (Gardner, 2003). The theory has sparked significant academic debate, both supportive and critical (Smith, 2012; Battro, 2010; Battro *et al.*, 2010), and has seen propo-

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sitions for expansion to include additional intelligences such as spiritual, emotional, sexual, and digital intelligences.

Gardner's theory rests on two primary assertions:

1. Every person operates with a full set of at least eight intelligences, which defines our humanity.
2. Each individual has a unique intelligence profile, with intelligences developed to varying degrees.

Gardner likened the human brain to a network of relatively independent computers specialized in specific tasks. These "computers" correspond to different areas of human activity, such as:

1. Naturalistic
2. Logical-Mathematical
3. Linguistic
4. Musical
5. Visual-Spatial
6. Bodily-Kinesthetic
7. Interpersonal
8. Intrapersonal

These intelligences can also be referred to as partial or sub-intelligences, terms used synonymously in this article. Below is a brief overview of the eight intelligences based on (Wilinski *et al.* 2022).

Naturalistic Intelligence This intelligence involves understanding and appreciating the natural environment. Individuals with strong naturalistic intelligence love nature, care for the world, nurture animals, and cultivate plants. They often engage in ecological movements and support renewable energy initiatives. Careers suited to this intelligence include farmer, botanist, veterinarian, and ecologist. Children with high naturalistic intelligence excel in classifying objects and recognising patterns in nature, often enjoying outdoor activities like hiking and collecting natural specimens.

Logical-Mathematical Intelligence Highly valued in education and daily life, this intelligence involves causal thinking and perceiving the world through logical sequences and reasoning. Traditional IQ tests primarily measure this type of intelligence. Individuals with logical-mathematical intelligence excel in logic, numbers, patterns, and abstract thinking. They are curious, systematic, precise, and well-organized, making them suitable for careers as mathematicians, computer scientists, bankers, physicists, chemists, doctors, and engineers.

Linguistic Intelligence This intelligence involves the adept use of words and language. Individuals with linguistic intelligence are skilled in word choice, capturing subtle meanings, rhythm, and sound. They enjoy literature, wordplay, debates, and writing, often learning new languages more easily than others. Careers that benefit from this intelligence include writer, journalist, publicist, lawyer, teacher, and translator.

Musical Intelligence Emerging early in life, this intelligence is characterised by a love for music and sound. Children with musical intelligence enjoy singing, humming, and playing instruments. Developing this intelligence involves integrating music into daily activities, attending concerts, and encouraging musical performance and composition. In adulthood, musical intelligence manifests in a deep appreciation for music and musical skills, leading to careers in music-related fields.

Visual-Spatial Intelligence This intelligence enables understanding the world through shapes and imagery, both from the external environment and imagination. Individuals with visual-spatial intelligence think in pictures, notice details, and are sensitive to their surroundings' colours and patterns. They enjoy artistic activities, puzzles, and visualising concepts, making them suitable for careers like graphic designer, filmmaker, civil engineer, urban planner, poet, and naturalist.

Bodily-Kinesthetic Intelligence Characterised by a preference for physical activities, this intelligence is evident in children who love dance and sports, enjoy crafting, and communicate through body language and gestures. They have well-developed motor skills and spatial organisation, excelling in tasks requiring physical dexterity. In adulthood, bodily-kinesthetic intelligence is prominent in athletes, craftsmen, and sculptors.

Interpersonal Intelligence Individuals with this intelligence thrive in social settings, learning through human interaction. They are good listeners, advisors, and leaders, easily making and maintaining social connections. In children, this intelligence manifests as assertiveness, communication skills, and leadership abilities. In adulthood, it is crucial for careers in politics, administration, teaching, tour guiding, law, and the clergy.

Intrapersonal Intelligence Individuals with intrapersonal intelligence possess self-awareness, intuition, internal motivation, and a strong will. They often prefer solitary work and are introspective. Children with this intelligence are responsible, self-motivated, and capable of independent learning. In adulthood, intrapersonal intelligence is vital for researchers, thinkers, philosophers, writers, and solitary workers like computer scientists and poets.

The study involved students from WSB Merito University in Gdansk and Torun, covering three fields of study: computer science, business, and pedagogy. Students completed a 24-question test via MS Forms, previously nvalidated at other Polish and international universities (Wachala *et al.*, 2019; Wilinski *et al.*, 2022). The test was part of a Polish-American project (`https://sp22.kielce.eu/zawartosc/inteligecje-wielorakie-test`) and was designed to evaluate each student's multiple intelligences through self-assessment on a scale from 0 to 5 (see Table 1).

This survey was conducted within a highly diverse academic environment, encompassing a wide range of degree programmes in the fields of social sciences and the humanities alongside a single, albeit significantly large programme in the domain of engineering and technology. This article's authors are educators and academic staff representing various faculties and academic disciplines. The university in which this research was situated is a fee-paying institution, a context which, according to the authors, should foster a heightened sense of motivation and responsibility among students in terms of their engagement with and assimilation of knowledge. Within this

Table 1
Test for Multiple Intelligences Used in the Study
(Rate each statement from 0 to 5; 0 – does not apply; 5 – completely true for me)

Which of the statements below applies to you?	0–5
I like to sing and I sing well.	0
I love crossword puzzles and other word games.	0
I like spending time on my own.	0
Graphs, maps and graphic tables help me learn things.	0
I learn best when I can discuss new issues.	0
I like art, fine arts, photography and handicrafts.	0
In my free time, I listen to music a lot.	0
I get on well with people of different personality and interests.	0
I often think of my goals and dreams connected with the future.	0
I like learning about Earth and nature.	0
Taking care of pets and other animals brings me pleasure.	0
I like tasks related to physical movement and role play.	0
Written work is usually easy for me.	0
I find it easy to learn new material in mathematics.	0
I play or I would like to play a musical instrument.	0
I am good at such physical activities as sports or dancing.	0
I like numerical games or logic puzzles.	0
I learn best when I can perform practical exercises.	0
I love painting, drawing or designing things using a computer.	0
I often help others on my own initiative.	0
I like staying outside regardless of the weather.	0
I love challenges when a difficult, mathematical problem needs to be solved.	0
Peace and quiet while learning or thinking are important to me.	0
I read for pleasure every day.	0

environment, computer science students represent a distinct and somewhat atypical group. Owing to their unique academic and cognitive profile, the authors were particularly interested in investigating whether any measurable differences would emerge in the distribution of **multiple intelligences** between this cohort and students from other academic fields.

Students were able to rank the statements from 0 to 5, therefore achieving the score between 0 and 120 points. The following principles of self-assessment were applied:

Most students completed the survey with ease and were interested in the future comparisons and statistical results. Students rated the questions on a scale from 0 to 5, with a maximum possible score of 120 points. A student scoring zero on all items would have a vector of eight zeros, while scoring five on all items would result in a vector of eight 15-point sub-intelligences.

The following section presents the obtained results.

2. Survey Research on Students' Multiple Intelligences

The research was conducted using the MS Forms application, with the survey link distributed via email. The study involved 152 computer science students, 52 education students, and 131 business students. Data analysis was performed using the computational environments of MATLAB and partially Python.

The study focused on eight types of intelligence, as defined by Gardner, arranged in the following order:

- Naturalistic
- Logical/Mathematical
- Linguistic
- Musical
- Visual/Spatial
- Kinesthetic
- Interpersonal
- Intrapersonal

2.1. *Research on the Profiles of Computer Science Students*

The initial step was to ensure that the test questions directed at the diverse student groups did not result in a distribution of responses with reduced informational entropy. This would indicate a distribution where some answers were more frequent than others, contrary to the study organizers' intentions. This was evaluated using a polar plot for the group of computer science students (Fig. 1).

The polar plot, displaying the profiles of 153 computer science students, showed an even distribution of responses, indicating good calibration of the test – with high entropy (Fig. 1).

In order not to rely solely on an intuitive assessment of the dispersion of profiles, the variances of each subintelligence were also examined separately, adding the variances of the profile distributions of pedagogy and business students, which had not yet been presented.

These variances reduced to the standard deviation (after normalizing the results to the interval [0, 1]) were as follows, in turn, the standard deviation for the computer science group Si, the pedagogy group Sp and the business group Sb:

$$Si = [0.1765 \;\; \mathbf{0.1939} \;\; 0.1848 \;\; 0.1706 \;\; 0.1801 \;\; 0.1688 \;\; 0.1217 \;\; 0.1368] \tag{1}$$

$$Sp = [0.1799 \;\; \mathbf{0.2300} \;\; 0.1796 \;\; 0.1888 \;\; 0.1770 \;\; 0.1240 \;\; 0.1167 \;\; 0.1216] \tag{2}$$

$$Sb = [0.1711 \;\; \mathbf{0.2658} \;\; 0.1762 \;\; 0.2058 \;\; 0.2075 \;\; 0.1901 \;\; 0.1601 \;\; 0.1419] \tag{3}$$

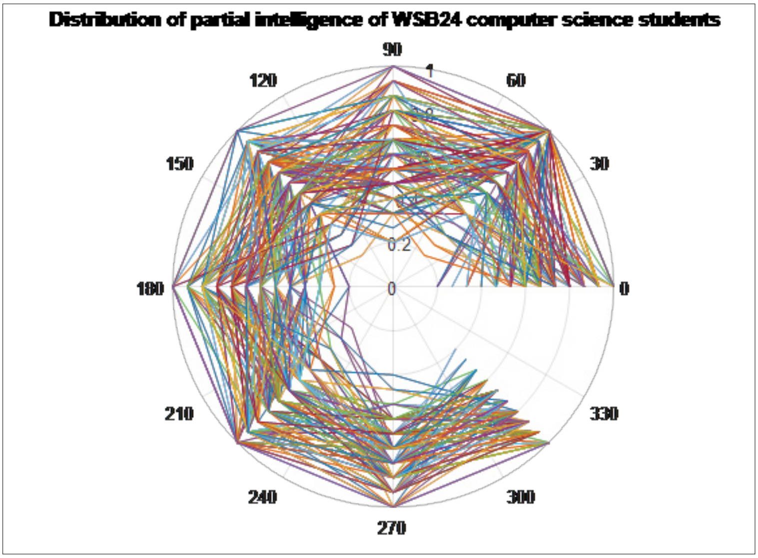

Fig. 1. Profiles of 153 computer science students. The designation of the WSB24 group denotes the group of computer science students at WSB University Gdansk.

In future studies, especially in terms of statistical hypotheses about equality or difference of mean intelligence values, the variances for mathematical and logical intelligence – the second in the above vectors 1–3 – will be important.

Of course, more important than the variances will be the mean values of the individual intelligences, which for the group of computer scientists are presented in the form of a histogram as in Fig. 2.

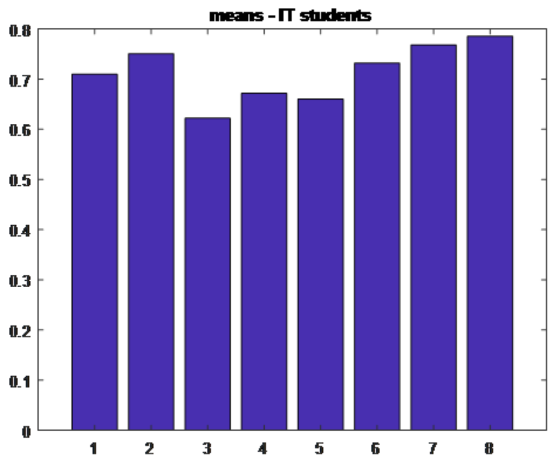

Fig. 2. Histogram of the mean values of sub-intelligences for the group of computer scientists.

In Fig. 2, the averages, after normalization, belong to the interval [0, 1]. Noteworthy is the relatively high value of three partial intelligences: mathematical and logical (second from the left), interpersonal (second from the right) and intrapersonal (last).

2.2. *Research on the Profiles of Pedagogy Students*

Similar graphs are presented for a group of pedagogy students.

Fig. 3 shows the profiles of students, similar to those in Fig. 1. There are significantly fewer students in this group -41, so this graph is filled in less.

Fig. 4 shows the histogram of average intelligence values for the group of pedagogy students.

The graph (see Fig. 4) shows a pronounced reduction in the values of the second intelligence, that is, logical-mathematical intelligence, compared with the same bar in Fig. 2.

2.3. *Research on the Profiles of Business Students*

Finally, the third group of students taking part in the survey were students of business direction. A total of 141 students participated in the survey, a group similar in size to that of IT students. Regarding the dispersion of individual student profiles visualized in Fig. 5, the students do not differ in this respect from the students of the two previously considered majors. Fig. 5 shows a similar fairly even filling of the chart space – with no densities or blanks.

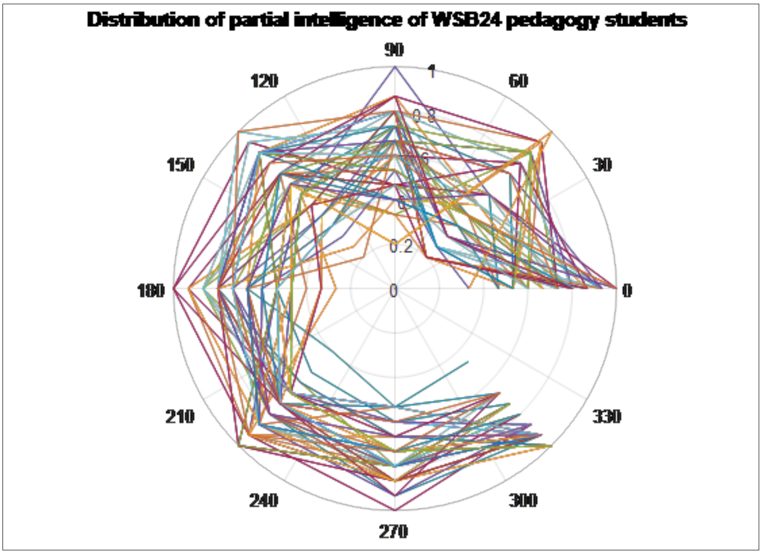

Fig. 3. Polar chart of 41 profiles of pedagogy students.

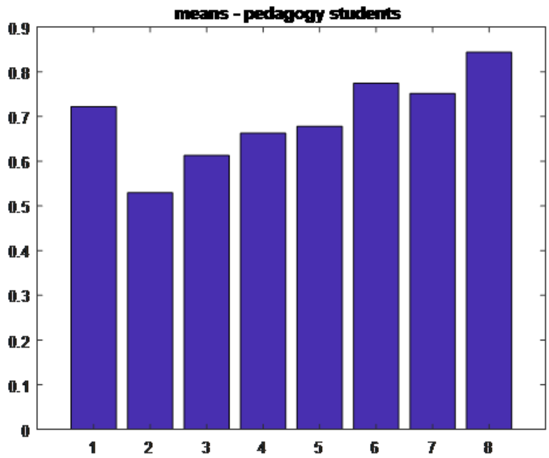

Fig. 4. Histogram of the average values of the particle intelligences of pedagogy students.

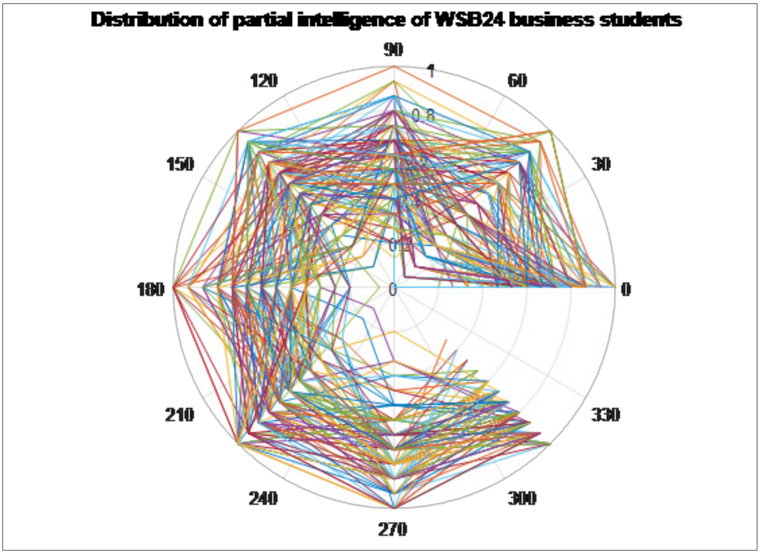

Fig. 5. Polar diagram of 141 profiles of business students.

Regarding the distribution of mean values of individual intelligences, the histogram compiled for business students (Fig. 6) is more similar to that of pedagogy students than IT students.

Summarizing this part of the study, it is possible to compare the average values of particle intelligence for the three fields of study under consideration. Using the MATLAB computing environment, in which the calculations were carried out, the following vectors of average values were extracted, successively for the three majors (Mi – for informatics; Mp – for pedagogy; Mb – for business students):

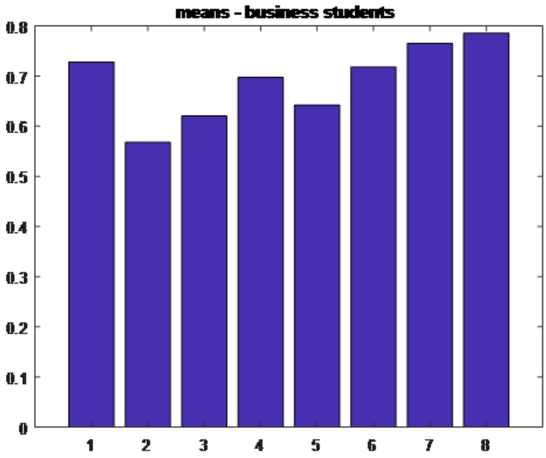

Fig. 6. Histogram of the average values of the partial intelligences of business students.

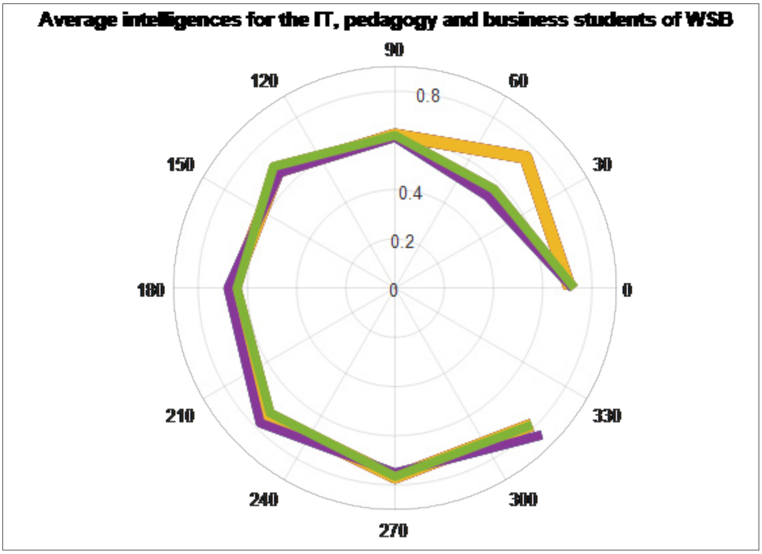

Fig. 7. Comparison of the average profiles of the three fields of study under consideration – IT (yellow), pedagogy (purple) and business (green).

$$Mi = [0.7098\ \ 0.7508\ \ 0.6222\ \ 0.6719\ \ 0.6606\ \ 0.7320\ \ 0.7682\ \ 0.7856] \tag{4}$$

$$Mp = [0.7218\ \ 0.5295\ \ 0.6128\ \ 0.6628\ \ 0.6782\ \ 0.7744\ \ 0.7513\ \ 0.8436] \tag{5}$$

$$Mb = [0.6906\ \ 0.4860\ \ 0.5715\ \ 0.6356\ \ 0.5908\ \ 0.6926\ \ 0.7425\ \ 0.7674] \tag{6}$$

After plotting the averages (4)–(6) on a common polar diagram, we will obtain the average profile for the entire student groups – Fig. 7.

After calculating the averages for the fields of study under consideration, the problem that remains to be solved is whether the differences between the averages are statistically significant.

3. Statistical Hypotheses – Statistical Analysis of Logical-Mathematical Intelligence Across Fields of Study

The graph depicting the average profiles of individual intelligences across the three academic disciplines under examination (see Fig. 7) reveals a distinct emphasis on the second key **logical-mathematical intelligence**. The figure, along with the vectors referenced earlier (4–6), indicates a substantial – indeed the most pronounced – discrepancy in this domain between students of computer science and those enrolled in the two other programmes.

The participants in the study were undergraduate students from three distinct degree programmes: Computer Science (Di), Education (Dp), and Business (Db). A purposive sampling strategy was adopted; specifically, only those students who had completed at least one year of study were included, to ensure a minimum level of disciplinary immersion. In total, the sample comprised 153 computer science students, 131 education students, and 41 business students. This distribution partly reflects the actual enrolment numbers across the programmes and was subject to availability constraints, particularly in the business student cohort. As a result, the sample was inherently imbalanced.

Despite this, the sample design satisfied the minimum requirements for non-parametric analysis (e.g. the Mann-Whitney U test), which does not rely on equal group sizes. The choice of non-parametric methods also mitigated the influence of variance in sample size, thereby ensuring the reliability of intergroup comparisons. Emphasis was placed on maximizing the analytical use of available data, avoiding artificial equalization of group sizes, which could lead to loss of meaningful information.

Accordingly, the study sought to test the following three null hypotheses concerning the equality of the average values of logical-mathematical intelligence among the groups:

H01 – The mean of Mi2 is equal to the mean of Mp2

H02 – The mean of Mi2 is equal to the mean of Mb2

H03 – The mean of Mp2 is equal to the mean of Mb2

Where:

Mi2 refers to the second component in vector (4), representing the mean logical-mathematical intelligence among computer science students.

Mp2 and **Mb2** denote the corresponding components in the average vectors for education (pedagogy) and business students, respectively.

In the assessment of these hypotheses, various statistical techniques were employed. The Student's t-test was used where assumptions of normality and homogeneity of variance were met. Variance equality was assessed using **Levene's test**; where this assumption failed, the **Welch test** was adopted as a robust alternative. In all three group pairings under consideration, these respective cases were encountered.

The study focused on examining **pairwise differences** in the mean values of logical-mathematical intelligence across the three academic groups.

Prior to data collection, the research project received formal approval from the Project Director and Faculty Authorities. All participants were fully informed about the study's aims and provided written informed consent. Participation was voluntary, anonymous, and could be withdrawn at any time without penalty.

The study employed a self-assessment questionnaire based on Howard Gardner's theory of multiple intelligence, with a particular emphasis on logical-mathematical intelligence (intelligence no. 2). This questionnaire had previously been adapted and validated for academic research in Poland (Wachała *et al.*, 2019; Wilinski & Kupracz, 2020; Wilinski *et al.*, 2022).

The survey data were organised into three matrices:

- **Di** (computer science students)
- **Dp** (education students)
- **Db** (business students)

These groups were analysed in pairs.

3.1. *Pairwise Comparisons*

This is one of the tactics that allows for the organization (sorting) of objects with specific features according to a set criterion (Koczkodaj WW. and Szybowski J., 2016).

Di vs. Db (Computer Science vs. Business)

Initial application of Levene's test using Python indicated no significant variance difference between these groups ($p = 0.12$), suggesting that a *t*-test would be appropriate. However, further analysis using the **Shapiro-Wilk test** revealed non-normal distributions in both groups. Consequently, to maintain statistical validity, the **Mann-Whitney U test** was employed.

Mann-Whitney U = 4527.5, p < 0.00001,

indicating a statistically significant difference in logical-mathematical intelligence between computer science and business students.

As a result, the null hypothesis of equal distributions was rejected in favour of the alternative.

Di vs. Dp (Computer Science vs. Education)

Similarly, the comparison between computer science and education students yielded a highly significant result:

Mann-Whitney U = 15606.5, p < 0.0000000000000005

This provided strong grounds for rejecting the null hypothesis, affirming a substantial difference in distribution.

Db vs. Dp (Business vs. Education)

In this case, the Mann-Whitney U test also reached statistical significance:

U = 3236.0, p = 0.0474

However, given the p-value's proximity to the alpha threshold of 0.05, the result must be interpreted with caution. While suggestive of a difference, it is not robust enough to draw definitive conclusions

3.2. *Effect Size Analysis*

Effect size (**r**) was calculated to assess the strength of observed differences:

Di vs. Dp: r = 0.411 – a medium effect according to Cohen's classification, indicating a substantial difference.

Di vs. Db: r = 0.242 – a small-to-medium effect, indicating a significant but less pronounced difference.

Db vs. Dp: r = 0.142 – a small effect, necessitating cautious interpretation. (Ossowski *et al.*, 2019)

3.3. *Validity of Statistical Methods*

The unequal group sizes stemmed from actual participant availability. Nevertheless, minimum sample size recommendations for non-parametric tests were met, ensuring adequate statistical power for detecting medium-sized effects ($r \approx 0.3$) at $\alpha = 0.05$ and power ≥ 0.8. The tests used (Shapiro-Wilk, Mann-Whitney U) are robust against differences in group sizes, and the calculated effect sizes further validated the strength of the findings. **Supplementary *t*-Test and Welch Test Analyses**

In additional analysis, the Student's t-test was applied to the **Di vs. Db** comparison, yielding:

$\mathbf{p = 2.36 \times 10^{-6}}$, thereby confirming the rejection of hypothesis H02.

The mean difference derived from vectors (4) and (6) were:

$$\mathbf{Mi2 - Mb2 = 0.7508 - 0.4860 = 0.2648} \tag{7}$$

This is a considerable discrepancy given the normalisation of scores within the [0, 1] interval.

In the **Di vs. Dp** comparison, **Levene's test returned p = 1.99 × 10^{-5}**, indicating unequal variances. Thus, **Welch's test** was employed, resulting in:

p = 3.71 × 10^{-18}, confirming a statistically significant difference.

Mi2 – Mp2 = 0.7508 – 0.5295 = 0.2213 (8)

For the **Db vs. Dp** comparison, Levene's test yielded **p = 0.14**, indicating equal variances. The Student's t-test was applied, producing:

p = 0.024, a result that does **not** justify rejection of the null hypothesis H03.

Mb2 – Mp2 = 0.5295 – 0.4860 = 0.0435 (9)

This represents the smallest of the observed differences and aligns with the null hypothesis of equal means.

4. Discussion

The issue of differentiating the characteristics (profiles) diagnosed among students of various fields of study and utilizing these differences in the process of career selection, or more specifically, job placement, is the subject of numerous studies. This article, through the application of Professor Gardner's multiple intelligences test, managed to observe differences between computer science students and students from two other fields under study – pedagogy and business. However, no statistically significant difference was observed between pedagogy and business students. The authors admit that a certain weakness of the applied research method presented in the form of questions in Table. 1 is its subjectivity, which comes down to self-assessment. The strength in favor of the reliability of the test is its conduct in various environments, such as students of various fields in different countries, employees of the IT sector, and high school students. All attempts have been noted in the bibliography. However, the most important argument of the authors in favor of the observed reliability and objectivity of the research are the observed results perceived both intuitively and through the formulated statistical hypotheses and the observed distribution. What is meant by intuitive perception of research results?

Namely, when we look at the polar graphs presented in this article for three fields of study (Fig. 1, Fig. 2, Fig. 3) we can see a tight and rather even filling of these graphs with student profiles. The profiles in these drawings are multi-colored broken lines (the colors are automatically assigned by the MATLAB computing environment, to facilitate finding and observing the profiles). To explain the intuitiveness of the conclusions from this image, imagine that one of the questions of the test for students was – Would you rather be healthy and rich, or poor and sick? When such (or similar) questions appeared with fairly obvious expected answers, the polar graphs would not fill the plane of the drawing so evenly. There would be clusters in these obvious coordinates of answers. We do not observe such “densities” on the graphs, which in our opinion is evidence of correctly selected questions causing a fairly even filling of the entire drawing with profiles in larger groups of respondents. Of course, this is our, the authors’, point of view. This does not change the fact that the questions are based on self-assessment and are therefore burdened with subjectivity.

What, then, is the practical utility of the conclusions drawn from this study? It is a truism that a person (including a student) as a social being is an exceedingly complex and extraordinarily difficult object of study to define. To socially benefit from such studies, they should certainly be supplemented with other observational perspectives. Computer science students, who were distinctly distinguished among these three fields of study, are still highly diverse and will exhibit various characteristics in aspects such as personality or thinking styles. Let us focus for a moment on personality studies.

Diagnosing the relationships between personality types and the work of people in various professions is the subject of many researchers’ works. Defining the concept of personality unequivocally is very challenging because there are many theories of personality and numerous diverse definitions (Kilian, 2020). J.L. Holland developed a theory of vocational personalities, according to which job satisfaction depends on the alignment between an individual’s unique characteristics and the demands of a specific job (Buszko, 2013). Holland’s model of vocational preferences, known as RIASEC, emphasizes the importance of aligning the traits of the work environment with the personality of the employee. According to this concept, these elements should be congruent; otherwise, the individual will experience dissatisfaction, lack of engagement in tasks, decreased efficiency, and increased tendency to leave the job (Miotek and Piecuch, 2012).

In this context, the research results presented here, according to multiple intelligences, offer potential and adaptability without guaranteeing a perfect fit for job placement.

The primary types in this model are:

- **Realistic (R)**: Prefers physical work requiring skills, strength, and coordination. Personality traits include shyness, reliability, perseverance, stability, adaptability, and practicality. Example occupations: mechanic, drill operator, assembler, farmer.
- **Investigative (I)**: Seeks new solutions based on logical premises, contrasting with the artist (A) who often acts intuitively. Personality traits: analytical, original, curious, independent. Suitable professions: biologist, economist, mathematician, journalist.
- **Artistic (A)**: Acts unconventionally, prefers ambiguous and unsystematic activities allowing creative expression. Dominant traits: imaginative, disorganized, idealistic, emotional, impractical. Suitable professions: painter, musician, writer, interior decorator.
- **Social (S)**: Prefers activities involving helping others and their improvement. Traits: sociable, friendly, cooperative, understanding. Best fits: social worker, teacher, counselor, clinical psychologist.

Enterprising (E): Energetic, prefers verbal activities that offer opportunities to influence others and gain power. Traits: confident, ambitious, energetic, authoritative. Suitable professions: lawyer, real estate agent, public relations specialist, small business manager.

Conventional (C): Prefers ordered, repetitive situations based on clear rules. Dominant traits: adaptable, efficient, practical, unimaginative, inflexible. Suitable professions: accountant, corporate manager, bank cashier, office worker (Robbins and Judge, 2012).

Personality traits significantly influence career choice, professional development engagement, and job satisfaction. According to the theory, satisfaction is highest and turnover lowest when personality and job are well-matched.

Analyzing the final paragraph, one might ask – what is the most suitable Holland personality type for a computer scientist, businessman, or teacher? There is no simple answer here either. The complexity of personality in any professional environment is advantageous. This Darwinian basis for social development is clearly highlighted by thinkers like Karl Popper (Popper K. *et al.*, 2012).

According to J. Misztal (2006), the contemporary individual can be complex and complicated, hence, in practice, a mix of two or even more personality types can occur. For instance, secretaries and librarians might be CSA – conventional-social-artistic types; academic teachers, nurses, social workers might be SIA – social-investigative-artistic types; mechanics, engineers, machinists might be RIE – realistic-investigative-enterprising types. Personality differences can significantly impact individual and group behaviors in an organization. Moreover, understanding personality types can assist in selecting team members (Chen and Lin, 2001), which is why many organizations use personality tests in this context.

The Myers-Briggs Type Indicator (MBTI) is the most commonly used tool worldwide for assessing personality (Kennedy, 2006). It is a personality test comprising several questions about how people feel or act in specific situations. Based on responses, individuals are classified as extraverted or introverted (E or I), sensing or intuitive (S or N), thinking or feeling (T or F), and judging or perceiving (J or P) (Robbins and Judge, 2012). It is assumed that we utilize each of these eight personality aspects, but we have natural preferences in each area, much like the preference for using one hand more than the other. Neither pole of preference is inherently better or more desirable than the other (MBTI Report, 2014). The principle of equal value of each assessment component is consistently upheld from titular intelligence to personality trait studies.

When forming a team from employees with defined personality types, their particular traits should be considered. For example, extroverted employees feel more comfortable in teamwork, in contrast to introverted employees who prefer working individually in quiet settings (Komarnicka and Jankowski, 2019). The second rule pertains to how information is perceived: through hard evidence and facts or relying on intuition, inner thoughts, and imagination. The former prefers routine and order, focusing on details, while the latter rely on unconscious processes and look at the big picture. These individuals are eager to perform new tasks, think a lot about new possibilities, and solve problems by combining several ideas and possibilities. Another pair is logic and feeling, which indicate how decisions are made. The former solves problems with reason and logic, while the latter rely on personal values and emotions. The final pair is judging and perceiving, where judging individuals want to control, have a planned and orderly approach to the external world, and make decisions quickly, while perceiving individuals prefer a flexible and spontaneous approach to the external world and make decisions slowly.

Together, these classifications describe 16 personality types. Each type is different and has its strengths and weaknesses, helping individuals understand themselves and others. This typology appears to be well-suited to business realities, especially with characteristic names derived from business roles such as strategist, mentor, innovator, inspector, or director.

However, this division is not rigid and permanently assigned to an individual. Personality can be changed and shaped throughout life. Here are a few examples: INTJs are visionaries. These individuals are characterized by original thinking and a strong drive to achieve their goals. They are skeptical, critical, independent, determined, and often stubborn. This role can be imagined for a computer scientist, a teacher, or a company owner. ESTJs are organizers. They are realists, think logically and analytically, are decisive, and often have natural technical and business talents. They like to organize and manage activities. This personality may be particularly attractive to business representatives. ENTPs are conceptualists (Robbins and Judge, 2012), innovative, individualistic, versatile, and entrepreneurial. They can solve difficult problems but often neglect routine tasks. These traits seem attractive to entrepreneurs and creative computer scientists, less so for educators.

The MBTI is not the only, and perhaps not the best, indicator for determining a person's personality type, but due to its properties, it has been chosen as a potential measure to assess personality types. It is a popular indicator used in both academic and industrial settings, serving as a tool for skill development, team collaboration, and shaping interpersonal relationships (Chen, 2005). Its popularity is confirmed by over three million individuals who have taken the MBTI test and that it is the most frequently used personality test in American corporations (Chen and Lin, 2004).

Correctly identifying employees' potential by determining preferences, predispositions, and professional interests early in their development, particularly during their studies, allows for the optimal design of their careers. Professional preferences express a person's personality and actions; work aligned with one's preferences and predispositions not only increases motivation and employee efficiency but also allows for the fulfillment of individual needs and personal development. To ensure that career choices lead to future satisfaction, the decision should be thoughtful and aligned with predispositions, which include abilities, skills, interests, and competencies. Factors such as intelligence, temperament, personality, abilities, interests, health, needs, and values are essential, as well as external factors like family, school, and peers. Another personality model, commonly known as the Big Five by P. Costa and R.M. McCrae, has established relationships between personality dimensions (i.e., extraversion, agreeableness, conscientiousness, emotional stability) and job performance (Barrick and Mount, 2024). This feature forms the basis of many significant personality theories. The more frequently a behavior occurs, indicating the intensity of a trait, the more typical it is for that individual's personality (Karczla, 2017).

All choices made by an individual are a composite of their personality traits. For example, there is a clear link between personality traits and the selection of a field of study. Research findings on the diversification of students in different fields of study are inconclusive. However, the conclusions suggest a distinct relationship between the degree of specificity of the field studied and adaptive skills.

Students in scientific and practical fields, such as mathematics, business, and education (pedagogy), demonstrate significantly less difficulty in adapting compared to their peers studying in general fields like Polish philology. A discrepancy in personality traits is observed between students of scientific fields and those in humanities and arts. Moreover, the more practical the field of study, the better the adaptive skills exhibited by its students (Połeć, 2002). Other correlations between the field of study and characteristics, such as those of extroverts and introverts, confirm that extroverts are practical, open, impulsive, energetic, easily form social contacts, and prefer movement and activity. Conversely, introverts are less sociable, reserved, prefer peace and order, are uninterested in the external world, are diligent, and prefer reading books to conversing with people. They favor occupations that do not require frequent contact with people. It appears that the fields of study considered in this research (computer scientists, educators, entrepreneurs) clearly indicate the first group.

In our opinion, the potential competencies resulting from the distribution of Gardner's intelligence could be interpreted as follows, taking into account the specifics of the fields of study.

If, for example, because of such tests, a student is found to lack mathematical and logical intelligence, then on the basis of such tests, he should consider the correctness of the decision to continue computer science studies.

In summary, personality traits significantly influence the choice of both the field of study and future occupation. It is essential to match an employee's personal traits to the demands of the work environment, enabling them to apply their preferences, inclinations, or skills effectively. Only then will they be more engaged, interested in the content of their work, and, most importantly, able to achieve personal success. The conducted research using Gardner's multiple intelligences can thus be regarded not as a guideline for choosing a profession but rather as a tool for selection to avoid a career mismatch. In light of the research, this selection tool can be verified logical-mathematical intelligence, without which it would be challenging to develop in typical, traditional IT professions (programming, web development, database management, AI, and similar fields).

Certainly, education in the IT environment (and work in this environment) can influence the change of mathematical-logical sub-intelligences. However, they can also be destructive. The authors have a lot of evidence of how in academic environments, mainly in free education, which does not threaten the life interests of a student without special motivation to study, they can and in a large number of cases they end in the first year of studies after the student realizes the difficulties that he encounters in this field when he is deprived of this natural Gardnerian mathematical-logical intelligence. Prof. Gardner emphasized that all intelligences are equal, therefore not everyone has to be a computer scientist, they can successfully make a career in life based on other personal abilities.

Based on the conducted research on the differences in logical-mathematical intelligence between students of computer science and students of other fields, several important conclusions can be drawn regarding the nature of these differences and their sources. The research results suggest that the higher level of logical-mathematical intelligence observed in computer science students may have two possible causes: an innate predisposition or the effect of educational experiences provided by the study program. On the one hand, computer science students may already demonstrate higher logical-mathematical intelligence before starting their studies, which may have prompted them to choose this field. A higher level of analytical, mathematical and problem-solving abilities may be an innate feature that predisposes to study fields such as computer science. It is worth noting that the initial selection for computer science studies may attract people who already show higher abilities in these areas at the recruitment stage, which affects the structure of the student group. On the other hand, curricula in fields such as computer science are intensively focused on the development of logical thinking skills, solving mathematical and analytical problems. Long-term contact with mathematical and computer science material, solving complex problems and algorithms may affect the further development of logical-mathematical abilities, regardless of the initial level of these skills. Therefore, the research results may suggest that intensive education in this area leads to the strengthening of these abilities, regardless of their innate level. These changes may be the effect of the educational process, which develops specific skills as part of the studies, broadening the scope of logical-mathematical intelligence in students. However, it should not be forgotten that these two causes – innate predispositions and the influence of educational experiences – may cooperate. Students who already have certain predispositions in the area of logical-mathematical intelligence can more effectively acquire the knowledge and skills offered in the computer science studies program. In turn, people with lower initial predispositions, although they may not initially demonstrate higher intelligence in this area, can significantly improve their mathematical-logical abilities through appropriate education.

Taking the above into account, the conclusions of the research suggest that a higher level of logical-mathematical intelligence among computer science students is not only the result of innate predispositions, but also the result of the specificity of the curriculum that effectively develops these abilities. Such conclusions emphasize the importance of appropriate educational experiences, which can have a decisive impact on the development of intelligence, regardless of the initial level of students' abilities.

The analysis of contemporary publications indicates a continuous and ongoing interest in the issue of multiple intelligences. Helding L. (2009), Elena (2016), Maruna (2023). There are also critical attitudes towards this theory, attributing to it the features of a neuromyth (Waterhause, 2023). In general, favorable attitudes prevail, seeing in the theory the potential for inspiration and exploration of every young person.

Using methodological patterns, it can be summarized that every scientific theory is not a dogma and can and even should be accepted with skepticism and can be attacked. The authors support this theory using a powerful research tool, which is statistics. It confirms the validity of the relationships and their practical, especially educational, significance. The researchers – co-authors are familiar with the case of creating a music band among previously unknown students after revealing their musical interests to Gardner's father-in-law, and are familiar with spontaneous volunteering inspired by similar profiles or interests in postgraduate studies in a scientific discipline other than the one originally chosen.

The authors admit that a certain weakness of the applied research method presented in the form of questions in Table 1 is its subjectivity, which comes down to self-assessment. The strength of the test reliability is its conduct in various environments, such as students of various fields in various countries, employees of the IT sector, high school students. All attempts were noted in the bibliography. However, the most important argument of the authors in favor of the observed reliability and objectivity of the research are the observed results perceived both intuitively and through the formulated statistical hypotheses and the observed distribution. What is meant by intuitive perception of research results? Well, when we look at the polar graphs presented in this article for three fields of study (Fig. 1, Fig. 2, Fig. 3), we can see that these graphs are tightly and rather evenly filled with student profiles. The profiles in these drawings are multicolored broken lines (the colors are automatically assigned by the MATLAB computing environment to facilitate finding and observing profiles). To explain the intuitiveness of the conclusions from this image, imagine that one of the questions in the student test was – Would you rather be healthy and rich, or poor and sick? When such (or a similar) question appeared with fairly obvious expected answers, the polar graphs would not fill the plane of the drawing so evenly. There would be clusters in these obvious coordinates of the answers. We do not observe such "densities" on the graphs, which in our opinion is evidence of correctly selected questions causing the entire drawing to be filled with profiles quite evenly in larger groups of respondents. Of course, this is our, the authors', point of view. This does not change the fact that the questions are based on self-assessment and therefore burdened with subjectivity.

5. Conclusion

Students in scientific and practical fields (mathematics, computer science, economics, or commerce) exhibit better adaptive skills and capabilities, such as greater maturity, independence, higher intelligence, and lower levels of neuroticism and psychoticism. Students in humanities and arts (philology, pedagogy) show greater adaptation difficulties, more frequent occurrences of anxiety or low mood, conflicts with their surroundings, a sense of lower self-worth, and higher levels of neuroticism and psychoticism (eccentricity, social distance) (Połeć, 2002). Additionally, research results indicate that students in scientific fields are characterized by an internal locus of control, which is associated with greater independence and self-reliance in action. In contrast, students in humanities display an external locus of control (Długosz, 1991), meaning that events in their lives are perceived as resulting from external factors beyond their control, such as fate, chance, or the influence of other people or higher forces.

Studies have shown that differences in personality traits between students of computer science, pedagogy and business can significantly affect the choice of field of study. Computer science students showed higher logical-mathematical intelligence, which may suggest that their predispositions to analytical thinking and solving problems in a systematic and logical manner are crucial in the context of their future careers. In turn, students of fields such as pedagogy, characterized by a higher level of interpersonal intelligence, may prefer professions requiring communication skills and working with people, which fit their personality. Choosing fields related to social assistance, education or counseling may therefore be a natural effect of their innate predispositions. Despite the general differences in personality profiles, certain similarities can be observed within each of the student groups, which also affect the choice of career path. Computer science students, in addition to their strong predispositions to solving mathematical problems, often display traits such as independence, autonomy, and a tendency to analytical thinking, which favors working in isolation or in teams that require great precision and attention to detail. These types of personalities fit the IT work environment, which is characterized by demanding technical tasks and often the individual nature of work. The study also observed that students of technical fields, such as computer science, are more likely to choose fields that require strict analytical and technical skills, which may result from both their innate predispositions and educational experiences that develop logical and mathematical abilities. In the context of people studying pedagogy or business, their personality traits (greater sensitivity to the needs of others, interpersonal skills) may explain their tendency to work in areas that involve contact with people and helping others solve problems. In the case of computer science students, a higher level of logical-mathematical intelligence is clearly associated with a predisposition to choose technical studies, where analytical and mathematical skills are key. In turn, students of humanities, such as pedagogy and business, showed a tendency to use interpersonal and verbal intelligence, which could be a factor that influenced their choice of courses related to working with people and organizing business activities.

Educational experiences, including curricula in various fields of study, have a great impact on the development of specific abilities and personality traits. In the case of computer science students, who during their studies receive intensive training in mathematics, logic, programming and data analysis, these experiences can strengthen their predisposition to take up work in the IT industry, which requires a high level of logical-mathematical intelligence. In turn, students of pedagogy, engaging in internships and projects related to education, develop social skills, which influences their choice of future career in professions that help others.

Despite noticeable differences, common personality traits can also be seen within student groups that can influence their choice of career path. For example, computer science students demonstrate the ability to concentrate and work on complex problems, which is essential in the technology industry, while students of education and business demonstrate qualities such as empathy, teamwork and communication, which make them excellent in professions related to education or management. In summary, the differences and similarities in personality traits observed in the study have significant implications for career choices, as well as for the effectiveness of education in various fields of study. The choice of studies seems to result from both students' innate predispositions and educational experiences, which are intended to develop their skills and prepare them for professional challenges.

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